



Energy-aware scheduling and berth allocation for ferries under phased cold ironing upgrades

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ABSTRACT

Many ferry ports are undergoing a phased transition from fully diesel-powered vessels to hybrid ferries capable of connecting to shore power while berthing. This transition raises new operational challenges: when several hybrid ferries arrive simultaneously, limited cold ironing capacity may force some vessels to revert to auxiliary diesel engines, undermining scheduling efficiency and resource use. To address this issue, we develop a tri-objective mixed-integer programming model for energy-aware ferry scheduling and berth allocation. The model jointly minimises vessel-related CO₂ emissions, reduces grid capacity exceedances that constrain port operations and energy storage, and improves berth utilisation. It captures key logistical and operational complexities of ferry ports, including tightly coupled ferry schedules and berth availability driven by short sea crossings with predictable arrival times, berth-vessel compatibility constraints across multiple operators, and immediate berthing requirements, thereby necessitating an integrated berth allocation and scheduling model. Using empirical data from a major Western European ferry port, our computational experiments demonstrate that the proposed approach can reduce berthing-related CO₂ emissions by up to 70% depending on demand patterns and fleet composition. From the perspective of ferry operators, total daily emissions across crossings and berthings decline by 5–9% as hybrid adoption increases. Even in the absence of hybrid vessels, the model identifies opportunities to cut emissions by 12–40% compared with business-as-usual scheduling through more efficient utilisation of berth capacity. The results highlight how integrated berth allocation and energy-aware scheduling, framed as a logistics optimisation problem, can deliver both operational efficiencies and substantial environmental benefits, offering ports a practical pathway to manage the hybrid transition without immediate large-scale infrastructure expansion.

1. Introduction

Decarbonisation has become a defining priority for the maritime sector, with digitalisation providing complementary tools to accelerate this transition (Yang et al., 2025). Ports face mounting pressure to reduce emissions from vessel manoeuvring, anchoring, and berthing, which contribute significantly to local air pollution and public health risks (Wan et al., 2021; Cammin et al., 2020). Mitigation strategies can be broadly classified into technological solutions, low-carbon fuels, market-based instruments, and operational

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A. Abbreviations

BESS	Battery Energy Storage System
BAU	Business-As-Usual scheduling
EAS	Energy-Aware Ferry Scheduling

B. Sets

$\mathcal{T}$	Set of time periods
B^H	Set of berths equipped with cold ironing
B^D	Set of berths without cold ironing
$\mathcal{V}^H$	Set of hybrid ferries
$\mathcal{V}^D$	Set of diesel ferries
$\mathcal{K}$	Set of possible crossing numbers per ferry within the scheduling horizon
$\mathcal{N}$	Set of demand types

C. Capacity, emission, and cost-related parameters

C^G	Available electricity grid capacity per period
C^{BESS}	Energy capacity of the Battery Energy Storage System
E_i^H	Emission rate per period for hybrid ferry $i \in \mathcal{V}^H$ during electric berthing
E_i^D	Emission rate per period for diesel ferry $i \in \mathcal{V}^D$ during diesel berthing
P_b	Penalty associated with activating berth $b \in B^H \cup B^D$ during the scheduling horizon
M	A sufficiently large positive constant

D. Time-related and operational parameters

τ	Fixed round-trip duration of a ferry, defined as the time from departure at Port A until return, including outward and return sailing times between Ports A and B and the berthing duration at Port B (excluding berthing at Port A)
b_i	Berthing duration of ferry $i \in \mathcal{V}^H \cup \mathcal{V}^D$ at Port A
θ_i	Power required by hybrid ferry $i \in \mathcal{V}^H$ during berthing
ℓ_v	Length of the acceptable embarkation time window for demand type $v \in \mathcal{N}$
λ_{tv}	Number of demands of type $v \in \mathcal{N}$ that must start loading within time window ℓ_v starting from period $t \in \mathcal{T}$
d_{iv}	Capacity of ferry $i \in \mathcal{V}^H \cup \mathcal{V}^D$ for demand type $v \in \mathcal{N}$ per crossing
a_i^1	Earliest possible arrival time of ferry $i \in \mathcal{V}^H \cup \mathcal{V}^D$ for its first berthing
δ_i	Maximum allowable delay of the first berthing of ferry i relative to a_i^1
q_{ib}	Binary compatibility parameter equal to 1 if ferry i can be assigned to berth b

E. Decision variables

x_{itb}^k	Binary variable equal to 1 if ferry i begins its k th berthing at berth b in period t
y_{itb}^k	Binary variable equal to 1 if ferry i occupies berth b in period t during its k th berthing
O_b	Binary variable equal to 1 if berth b is activated during the scheduling horizon
ψ_t	Binary variable equal to 1 if electricity demand exceeds grid capacity in period t
w_i^1	Time between the earliest available time of ferry i and the start of its first berthing
R_t	Remaining energy stored in the BESS at the start of period t , bounded between 0 and C^{BESS}

optimisation (Joung et al., 2020; Grigoriadis et al., 2024; Alamouh et al., 2020). Among these, energy-aware operational measures are particularly attractive as they can deliver tangible greenhouse gas (GHG) reductions without requiring substantial infrastructure investment.

Cold ironing, also known as onshore power supply, enables berthed vessels to switch off their auxiliary diesel engines and draw electricity from shore, thereby reducing both emissions and noise (Wang et al., 2024a; Uzun et al., 2024). Reported CO₂ reductions vary depending on vessel type, operational profile, and grid energy mix, with estimates of 57.2% at Kaohsiung (Chang and Wang, 2012), 25% across UK ports (Hall, 2010), 38.44% at Eskişehir-Tavşanlı (Bakar et al., 2024), and potential savings of three megatons annually across European ports (Stolz et al., 2021). Globally, more than 200 ports now provide cold ironing facilities, serving approximately 2500 vessels (Liu et al., 2025). While adoption is expanding—particularly in European ports—significant barriers persist, most notably limited grid capacity and high installation costs. For example, at Aberdeen ferry port, installation cost £6.6 million (€7.4 million) with a seven-year payback period (Innes and Monios, 2018), and similar cost concerns have been reported in Chinese ports.

Cold ironing adoption has been slower in the container shipping sector due to greater retrofitting challenges, higher power requirements, and irregular schedules (Kumar et al., 2019). In contrast, onshore power is particularly well suited to ports with

frequent vessel returns, such as short-strait ferry terminals.¹ Operators such as DFDS and P&O are increasingly deploying hybrid propulsion for Roll-on/Roll-off ferries, enabling them to operate on electricity during berthing and improving overall efficiency (Colarossi and Principi, 2023). Ferries' fixed routes, relatively small size, and high call frequency make them strong candidates for hybrid or fully electric propulsion. This motivation is further reinforced by emerging green shipping corridor initiatives. For example, under the Clydebank Declaration,² the UK has committed to establishing at least six green shipping corridors by 2026, many of which are strongly focused on short-sea ferry routes such as Holyhead–Dublin, Dover–Calais, and Liverpool–Belfast. These services involve short, frequent, and highly predictable crossings, making them suitable candidates for early adoption of zero-emission technologies, including cold ironing, full electrification, methanol, or hybrid propulsion systems.

However, ports serving multiple hybrid ferries face a specific operational challenge: when several ferries arrive and berth in close succession, their combined cold ironing demand can exceed the supply available from the grid and any Battery Energy Storage Systems (BESS). As BESS requires time to recharge after discharge, it may be unable to meet peak demand (Iris and Lam, 2019; Gong et al., 2024), forcing some vessels to revert to diesel auxiliary engines and reducing both environmental benefits and the return on investment in shore power infrastructure. While BESS can smooth short-term demand fluctuations by storing energy during off-peak periods and supplying it during peaks (Iris and Lam, 2019), its charging is feasible only when cold-ironing demand remains below grid capacity. Moreover, BESS capacity is finite and its repeated charge-discharge cycling accelerates degradation. Consequently, reliance on BESS alone cannot fully address the cyclical and synchronised nature of ferry operations or prevent simultaneous charging of multiple vessels. Its deployment is further constrained by high capital costs (Gong et al., 2024; Zhen et al., 2022), limited space availability, and gradual performance deterioration.

A complementary solution to mitigating peak demand is load shifting, which involves optimising vessel timetables and berth assignments to distribute electricity demand more evenly. This is particularly relevant in ferry operations, where short, regular crossings result in predictable but tightly coupled schedules. However, most existing berth allocation and vessel scheduling models either overlook energy constraints altogether (Mao et al., 2022; Yu et al., 2022b; Wang et al., 2024c) or assume that all berths are fully equipped with shore power and have adequate capacity—conditions rarely met in practice, especially during the early phases of decarbonisation investment. Moreover, the operational complexities of multi-operator ferry terminals, such as fixed departure intervals, interdependent round trips, and diverse service reliability requirements, have received limited attention in energy-aware scheduling research. These operational characteristics also imply a strong interdependence between vessel scheduling and berth allocation. Given the high predictability of ferry arrival times and the operation of fixed, high-frequency shuttle services, vessels are expected to berth immediately upon arrival under normal operating conditions. Scheduling decisions must therefore be consistent with berth availability and compatibility, making an integrated approach to berth allocation and vessel scheduling operationally essential in ferry terminals.

This study addresses these gaps by developing a tri-objective mixed-integer programming model that simultaneously optimises the initial berthing times, berth assignments, and service termination times of ferries, while explicitly considering port cold ironing constraints, grid capacity limits, BESS charging and discharging cycles, the presence of multiple ferry operators, and varying demand requirements with different ticketing schemes of fixed and flexible types. The objectives are to minimise CO₂ emissions, minimise grid exceedance to reduce reliance on BESS and extend battery lifespan by limiting charging and discharging frequency, and improve berth utilisation by avoiding unnecessary use of berths, particularly cold ironing-equipped berths that require costly maintenance. The proposed framework provides a cost-effective operational strategy that mitigates cold ironing limitations and maximises the benefits of transitioning to hybrid ferries across all phases of the transition, from the initial stage to full adoption. It prevents reversion to diesel engines during peak demand periods without requiring major infrastructure upgrades, thereby supporting a smoother phased transition towards net zero. This research fills a critical gap in the literature on energy-aware ferry scheduling by integrating phased, limited cold ironing upgrades with berth allocation and vessel scheduling, while capturing the operational complexities of multi-operator ferry ports and their diverse demand satisfaction requirements.

The remainder of this paper is structured as follows: Section 2 provides a concise review of relevant literature and identifies research gaps. Section 3 defines the problem and outlines the methodology. Section 4 presents the proposed tri-objective MIP formulation. Section 5 discusses computational results and evaluates the model's effectiveness in supporting a phased transition toward hybrid ferries. Finally, Section 6 summarises the findings and suggests avenues for future research.

2. Literature review

Balancing environmental protection with operational efficiency and economic growth has become a central challenge for ports worldwide (Bjerkkan and Seter, 2019). Among the available mitigation measures, cold ironing systems, which allow vessels to connect to shore-side electricity while berthed, have attracted increasing attention as an effective means of reducing local air pollution and greenhouse gas emissions. In response to tightening environmental regulations and growing public concern over port-related emissions, many ports have begun to deploy shore power infrastructure.

As shown in Table 1, ports in Europe have been early adopters of cold ironing, followed by ports in the United States and China. Shore power systems have been implemented for a wide range of vessel types, including RoRo and RoPax ferries, container ships,

¹ EPA Shore Power Technology Assessment at US Ports

² UK Government, COP26: Clydebank Declaration for Green Shipping Corridors

Table 1

Installation year and ship types for representative world ports equipped with shore power systems.

Year	Port name	Country	Ship types	Year	Port name	Country	Ship types
2000	Gothenburg	Sweden	RoRo, ROPAX	2010	San Diego	USA	Cruise
2000	Zeebrugge	Belgium	RoRo	2010	San Francisco	USA	Cruise
2001	Juneau	USA	Cruise	2011	Prince Rupert	Canada	Container
2004	Piteå	Sweden	RoRo	2011	Rotterdam	Netherlands	Various types
2004	Los Angeles	USA	Container, Cruise	2011	Oslo	Norway	Cruise
2005	Seattle	USA	Cruise	2012	Ystad	Sweden	Cruise
2006	Kemi	Finland	ROPAX	2013	Trelleborg	Sweden	ROPAX
2006	Kotka	Finland	ROPAX	2015 ^a	Hamburg	Germany	Cruise
2006	Oulu	Finland	ROPAX	2017 ^b	Guangzhou	China	Container
2008	Antwerp	Belgium	Container	2020 ^c	Helsingborg	Sweden	ROPAX
2008	Long Beach	USA	Tankers	2021 ^d	Southampton	UK	Cruise
2009	Vancouver	Canada	Cruise	2022 ^e	Shanghai	China	Container
2009	Lübeck	Germany	ROPAX	2024 ^f	Stockholm	Sweden	Cruise
2010	Karlskrona	Sweden	ROPAX	2024 ^g	Asyaport	Turkey	Container

Legend: ROPAX = Roll-on/Roll-off passenger vessels (ferries).^a Data for ports between 2000 and 2015 are based on [Kumar et al. \(2019\)](#).^b World Port Sustainability Program (2017). Available at: sustainableworldports.org.^c Nordic Innovation (2020). Available at: nordicinnovation.org.^d Associated British Ports (2021). Available at: transportenvironment.org.^e Maritime Gateway (2022). Available at: maritimegateway.com.^f Port of Stockholm (2024). Available at: portsofstockholm.com.^g Offshore Energy (2024). Available at: offshore-energy.biz.**Table 2**

Onshore power availability in major ports worldwide.

Year	Ports	Availability	Obstacles
2024	83 surveyed European ports ^a	58%	Insufficient grid infrastructure at 45% of ports
2024	Ports in the USA ^b	8–10%	Upgrading connections to the electrical grid
2023	Ports in China ^c	84%	Cost of shore power use and lack of standardisation ^d

^a European Sea Ports Organisation (2024). *ESPO Environmental Report 2024*. Available at: espo.be.^b United States Environmental Protection Agency (2024). *Shore Power Technology Assessment at U.S. Ports*. Available at: epa.gov; and International Council on Clean Transportation (2024). *ID-181–US-shore-power_final.pdf*. Available at: theicct.org.^c Hellenic Shipping News (2023). *China leads world in utilising shore power*. Available at: hellenicshippingnews.com.^d International Chamber of Shipping (2023). *Evaluating China's Decade of Electrification*. Available at: ics-shipping.org.

tankers, and cruise vessels. This diversity reflects both the technological feasibility of shore power across vessel classes and the increasing policy emphasis on reducing emissions in port and coastal areas.

Despite this progress, the large-scale deployment of cold ironing remains constrained by several structural barriers. As summarised in [Table 2](#), limited grid capacity, high capital investment requirements, and, in some regions, a lack of technical standardisation continue to hinder widespread adoption ([Innes and Monios, 2018](#)). Even in regions with relatively high levels of shore power availability, ports often face challenges in meeting simultaneous electricity demand from multiple vessels without costly grid upgrades.

These barriers underscore the need for operational optimisation approaches that can maximise the utilisation of limited cold ironing infrastructure while avoiding or deferring costly grid upgrades. In this context, energy-aware decision-making at the operational level has emerged as a promising avenue for reducing emissions without requiring large-scale infrastructure expansion.

To establish the operational context and the relevance of focusing on ferries, [Section 2.1](#) first summarises the key operational characteristics of short-sea ferry services. The subsequent sections review relevant optimisation literature on energy-aware ship scheduling, energy-aware berth allocation, and multi-objective optimisation in berth allocation and scheduling.

2.1. Operational characteristics of short-sea ferry services and related literature

Berth allocation and vessel scheduling problems have been extensively studied in the context of container terminals and long-haul shipping ([Li et al., 2023](#); [Zheng et al., 2025](#); [de Andrade and Menezes, 2023](#)). By contrast, comparatively limited attention has been devoted to ferry operations and ferry terminal management. Existing ferry-related studies are dispersed across several problem domains, including fleet scheduling, vessel traffic management, and terminal operations, and are often developed in isolation. As a result, the interaction between ferry schedules, berth availability, and terminal-level decision-making remains under-explored, particularly in settings where energy and infrastructure constraints play a central role.

Within the ferry literature, several studies have examined scheduling and service planning problems under fixed-route and short-sea operating conditions. For instance, vessel traffic scheduling models have been proposed for busy passenger Ro-Ro terminals with restricted harbour basins, with the objective of improving safety and operational efficiency by optimising vessel movements and reducing waiting times (Jia et al., 2023). Other contributions focus on demand-driven fleet scheduling and service planning in high-density short-sea corridors, highlighting issues related to capacity utilisation, capacity sharing and alliances among ferry operators, schedule regularity, and the handling of multiple demand types (Wang et al., 2025; Lai and Lo, 2004; Yan et al., 2007). While these studies provide valuable insights into ferry scheduling and fleet-level decision-making, berth allocation at the terminal level is typically treated implicitly or omitted altogether.

A smaller body of work has explicitly considered berth-related operational issues in Ro-Ro and ferry terminals. Among related contributions, Hein et al. (2020) develop a multi-objective optimisation framework for the operational scheduling of a single hybrid ferry equipped with shore-to-ship power and onboard energy storage, explicitly accounting for battery degradation and energy-related costs. Their study explores degradation-aware energy management and ship-side operational trade-offs under both grid-connected and sailing modes. However, the optimisation is formulated at the individual vessel level and does not capture interactions among multiple ferries, berth availability, or terminal-wide coordination constraints.

Beyond vessel-centric approaches, berth allocation models have been applied to Ro-Ro ferry ports with limited dock capacity to mitigate scheduling conflicts and reduce vessel waiting times (Arianti et al., 2025). Discrete-event simulation methods have also been used to evaluate daily operational decisions in Ro-Ro terminals, capturing berth utilisation, vehicle handling processes, and associated economic and environmental impacts (Iannone et al., 2016). In addition, optimisation models addressing berth-side operational processes, such as dual cycling of loading and unloading activities, have demonstrated potential reductions in turnaround time, fuel consumption, and CO₂ emissions (Jia et al., 2022). Nevertheless, these studies typically address berth operations in isolation and do not jointly optimise ferry schedules, berth activation, and energy-related constraints over a planning horizon.

In contrast, the broader berth allocation literature has predominantly focused on container terminals, where vessel arrivals are uncertain, service times are long, and queuing at berth is an accepted operational feature. Comprehensive surveys document a wide range of deterministic and stochastic berth allocation formulations developed under these assumptions (Li et al., 2023; Dai et al., 2008; Rodrigues and Agra, 2022; Makhado et al., 2025). These modelling assumptions differ fundamentally from those observed in ferry terminals. Ferry services operate according to fixed schedules, arrival times are highly predictable due to short sea crossings, and timetables are designed to avoid waiting at berth under normal operating conditions. As a result, conventional container-terminal berth allocation models cannot be directly transferred to ferry contexts without substantial modification.

Beyond the identified gaps in existing literature, ferry operations exhibit a set of distinctive operational characteristics that further motivate the development of a dedicated modelling framework. These characteristics make ferry terminals particularly suitable candidates for shore power deployment and, at the same time, imply that suboptimal scheduling decisions can significantly undermine potential emission reductions when cold ironing capacity is limited (Bakar et al., 2024; Wang et al., 2024b; Qi et al., 2020). Ferry services typically involve high-frequency and tightly coupled round trips on fixed short-sea routes, with short and relatively standardised berthing durations driven by Ro-Ro operations and rapid turnaround requirements. Schedules at both ends of the route are synchronised, and immediate berthing under normal operating conditions is essential to maintain timetable integrity (Mangan et al., 2002). Moreover, the frequent connection and disconnection of shore power during successive ferry calls can generate repeated and time-correlated peaks in electricity demand at the terminal, creating operational challenges that cannot be addressed through infrastructure provision alone (Iris and Lam, 2019; Khan et al., 2022).

In particular, short-sea ferry services exhibit the following operational characteristics:

- high-frequency, tightly coupled round trips on fixed short-sea routes,
- short and operationally standardised berthing durations driven by Ro-Ro processes and rapid turnaround requirements,
- synchronised timetables with immediate berthing expected at both ends of the route under normal operating conditions,
- frequent connection and disconnection of cold ironing systems, generating repeated and temporally correlated peaks in electricity demand, thereby making energy-aware scheduling an effective mechanism for demand smoothing.

These characteristics imply that ferry arrival times are not independent stochastic inputs but are determined by cyclic timetable decisions. As a result, scheduling the initial departure time effectively determines the entire sequence of future port arrivals, distinguishing ferry scheduling from traditional berth allocation settings with exogenous arrival processes.

From an environmental perspective, although container ships and bulk carriers dominate global maritime CO₂ emissions, ferry RoPax and Ro-Ro vessels contribute a smaller but non-negligible share, estimated at approximately 5% of total shipping emissions.³ Importantly, ferry emissions are concentrated in and near densely populated port and coastal areas due to frequent port calls, amplifying their local environmental and public health impacts (Ramacher et al., 2018). At the same time, techno-economic studies indicate that Ro-Ro and Ro-Pax ferries operating on short and repetitive routes exhibit strong potential for hybridisation and electrification when supported by shore power and battery energy storage systems (Lindberg, 2025). These operational profiles are well aligned with energy-aware scheduling and berth allocation strategies that exploit predictable arrival times and regular berthing windows to achieve significant emission reductions, even in early transition phases with limited cold ironing capacity.

Taken together, the reviewed literature highlights a clear research gap. While ferry scheduling, Ro-Ro terminal operations, and berth allocation have each been studied in isolation, there is a lack of integrated optimisation models that jointly consider ferry

³ OECD, Environment and maritime transport, 2023

schedules, berth allocation, and energy-related constraints in terminals undergoing phased decarbonisation. This study addresses this gap by developing an energy-aware integrated berth allocation and scheduling framework tailored to multi-operator ferry terminals with limited and evolving cold ironing infrastructure.

2.2. Energy-aware ship scheduling

Traditional vessel scheduling in liner shipping has evolved to incorporate energy considerations, addressing decisions such as sailing speed, departure time, routing, and port calls to reduce fuel use and emissions. Slow steaming and just-in-time arrivals are examples of such strategies, aligned with the IMO's Carbon Intensity Indicator (CII) regulations (Fagerholt et al., 2010; Kontovas, 2014). Optimisation models have targeted sailing speed and routing to minimise both costs and environmental impacts (Fagerholt et al., 2010, 2015; Dulebenets et al., 2017; Dulebenets, 2018), examined trade-offs between fleet size and emissions (Ronen, 2011), and addressed uncertainties in port turnaround times (Qi and Song, 2012).

The literature has also begun to consider electric and hybrid vessels, integrating voyage scheduling with onboard energy management for generators and battery systems (Shang et al., 2016). Recent models account for propulsion dynamics (Gao et al., 2022), uncertainty in energy supply (Pan et al., 2022), speed variation (Angkasa et al., 2023), environmental conditions (Tian et al., 2023), and power availability constraints (Yang et al., 2024).

Despite these advances, most existing studies focus on long-haul container ships operating on weekly or monthly schedules. In contrast, short sea ferry operations, characterised by frequent crossings between ports, repeated shore power connections, and short berthing duration, require a distinct approach. Different from the past literature, this study aims to optimise daily ferry schedules while accounting for port constraints such as cold ironing availability and limited power capacity.

2.3. Energy-aware berth allocation

The berth allocation problem (BAP) traditionally involves assigning arriving vessels to berths and scheduling docking times to avoid simultaneous use of the same berth, which could cause anchorage delays (Bierwirth and Meisel, 2015; Ursavas and Zhu, 2016). While earlier work largely focused on minimising vessel waiting time and improving berth utilisation, recent studies have expanded the scope to incorporate environmental considerations, such as emissions reduction (Fang et al., 2019).

Some studies address emission reduction under deterministic (Du et al., 2011) and stochastic (Yu et al., 2022a; Zhen et al., 2021) arrival conditions, as well as integrated quay crane scheduling to minimise emissions and delay without using cold ironing (Wang et al., 2019). Others have specifically considered berths equipped with shore power. At the strategic level, optimisation models have been proposed for allocating onshore power facilities under uncertain vessel arrivals (Peng et al., 2019, 2021). At the operational level, berth allocation has been integrated with energy scheduling under power demand constraints (Mao et al., 2022; Zhang et al., 2022), time-of-use tariffs, and green technology availability (Yu et al., 2022b, 2023), as well as carbon pricing schemes (Wang et al., 2024c).

To date, a significant share of studies in the aforementioned areas has focused on container terminals. However, the distinct operational profile of ferry services, characterised by short turnaround times, high-frequency arrivals that restrict opportunities for BESS recharging, and tightly interlinked schedules, demands a fundamentally different optimisation approach. These conditions create additional complexity in meeting the required electricity demand without forcing some hybrid ferries to revert to their diesel engines, particularly during the early phases of cold ironing adoption when shore power capacity is severely limited and many berths remain without upgrades.

2.4. Multi-objective optimisation in berth allocation and scheduling problems

In practice, berth allocation and scheduling problems are inherently multi-objective, as port authorities and terminal operators must simultaneously consider service efficiency, resource utilisation, operational cost, environmental performance, and, in some cases, vessel or customer priority.

Much of the classical berth allocation literature formulated the problem with a single dominant objective, typically time-based measures such as waiting time or makespan, while other considerations were incorporated implicitly (Barbosa et al., 2016). Although these objectives represent different and often conflicting stakeholder interests, most early studies optimised only one criterion explicitly and addressed others through constraint formulations rather than modelling them within a multi-objective framework.

Among the first studies to explicitly adopt a multi-objective perspective, Cheong et al. (2007) and Cheong et al. (2009) demonstrated that berth allocation objectives represent competing interests between ports and shipping lines and should therefore be optimised concurrently. Building on this insight, Cheong et al. (2010) further formalised prioritisation-related performance alongside time-based measures and employed Pareto-based evolutionary algorithms to generate sets of non-dominated berth schedules, enabling decision-makers to explore trade-offs without fixing objective weights a priori.

Subsequent research has widely employed evolutionary and metaheuristic methods to analyse trade-offs among berth allocation objectives. For example, Hu (2015) proposed a bi-objective dynamic berth allocation model balancing delay-related performance and daytime operation preference. Similar Pareto-based approaches have been applied to service differentiation, robustness-oriented scheduling, and integrated berth and terminal resource allocation, generally treating objectives as compensatory and allowing performance improvements in one objective to offset deterioration in another.

More recent work has incorporated environmental and energy-related objectives, particularly in ports equipped with shore-side electricity supply. Yue et al. (2025) developed a multi-objective berth scheduling model that jointly considers shore power availability and emission outcomes. In related directions, Hu (2020) modelled low-emission berth allocation by optimising sailing speed and mooring time, while Peng et al. (2021) and Zhang et al. (2022) integrated berth allocation decisions with shore power allocation and port energy system scheduling. These studies highlight the close interaction between berth allocation, energy management, and environmental performance, while still relying predominantly on trade-off-based decision structures.

In contrast, lexicographic optimisation is appropriate when objectives are non-compensatory and must be satisfied in a strict priority order. Two representative applications of this approach in berth allocation are the disruption-driven berth schedule recovery model of Zhang et al. (2016) and the fully fuzzy multi-objective berth allocation formulations proposed by Pérez-Cañedo et al. (2020) and Pérez-Cañedo et al. (2022), in which lexicographic ranking criteria are argued to be methodologically preferable to linear ranking functions for the associated fuzzy multi-objective programming problems.

Overall, the literature indicates that no single multi-objective optimisation method is universally superior. Pareto-based approaches are suitable when objectives are compensatory and lack a clear priority hierarchy, whereas lexicographic optimisation is more appropriate when objectives correspond to binding policy targets or physical infrastructure constraints. Accordingly, the lexicographic framework adopted in this study reflects a strict priority structure in which emissions reduction dominates, followed by minimising grid capacity exceedances, thereby limiting reliance on battery energy storage systems (BESS). Berth utilisation and maintenance-related considerations are treated as lower-priority objectives. This formulation ensures that improvements in lower-priority objectives cannot compensate for deterioration in higher-priority ones.

2.5. Research gaps and contributions

In contrast to much of the existing literature, which often treats vessel scheduling and berth allocation as sequential or loosely coupled decisions, ferry operations require these decisions to be addressed simultaneously due to tightly synchronised schedules and berth compatibility constraints. Despite advancements in shore power integration, the literature review reveals several critical gaps, as summarised in Table 3. Firstly, existing studies often assume that all berths are uniformly equipped with cold ironing, overlooking real-world scenarios in which only a limited number of berths have access to shore power due to financial constraints. This assumption overlooks the operational challenges that arise when the available shore power capacity is insufficient to serve multiple vessels simultaneously, which is a common constraint in ports with partial or phased infrastructure upgrades. Further research is needed to investigate mixed-infrastructure environments, where both hybrid and diesel ferries operate under limited cold ironing availability, assessing their impacts on scheduling, berth allocation, and overall energy consumption.

Secondly, previous studies have rarely considered the energy sources used for cold ironing. In particular, limited attention has been paid to the role of BESS, which are crucial for managing peak electricity demand and enhancing the feasibility and sustainability of shore power deployment (Buonomano et al., 2023).

Finally, while decarbonisation efforts in the maritime sector have become a growing focus, they have largely overlooked the distinct operational characteristics of ferries. This gap is especially evident in the context of energy-aware scheduling and berth allocation optimisation (Winnes et al., 2015).

It should be noted that speed optimisation and vessel routing decisions, which frequently appear in studies of deep-sea container and bulk shipping, are not included in the present model. Ferry services operate as short-distance shuttle services on fixed routes with highly standardised sailing times and strict safety and timetable constraints. As a result, neither routing flexibility nor slow-steaming strategies are operationally meaningful in this context. The primary decision levers are therefore scheduling and berth allocation under energy constraints rather than routing or speed selection.

Our study addresses critical gaps in the literature by making two key contributions:

- **Energy-aware scheduling model for ferries:** A novel berth allocation and scheduling framework specifically designed for ferry operations. Unlike existing models, this approach integrates cold ironing constraints, interdependent ferry crossing schedules, and diverse ticketing schemes across multiple operators. By incorporating these operational complexities, the model enhances both energy efficiency and service reliability.
- **Facilitating a gradual transition from diesel to hybrid ferries:** A tri-objective mixed-integer programming (MIP) model is developed to minimise CO₂ emissions, reduce grid capacity exceedances to limit the frequency of BESS charging and discharging, thereby extending battery lifespan, and reduce berth utilisation to lower long-term port maintenance costs. The model determines optimal berth allocation and ferry scheduling to meet both environmental and cost objectives for ferry operators and ports along the gradual transition pathway from diesel to hybrid ferries. Rather than relying solely on costly infrastructure upgrades, it maximises the potential benefits achievable even with limited cold ironing capacity in each phase.

3. Research problem and methodological framework

This study addresses the operational challenges faced by short-strait ferry ports transitioning from diesel-powered to hybrid or fully electric vessels. A short-strait ferry is characterised by frequent, short-distance crossings and typically carries vehicles, passengers, or both between two ports. Ferry schedules at one port are directly linked to those at the corresponding port. Once the timetable is set for one side of the route, the timetable at the opposite port is consequently determined.

Table 3

Overview of energy-aware optimisation models for ship scheduling and berth allocation.

References	Objective Function	Decision Variables	Constraints
Scheduling multiple ships with multiple port calls			
Fagerholt et al. (2010)	Minimise emissions	SS	Time windows for service initiation
Fagerholt et al. (2015)	Minimise operational costs	SS, VR	Time windows at ports
Dulebenets et al. (2017)	Minimise route service costs	SS, VR	Emissions per voyage leg
Dulebenets (2018)	Minimise route service costs	SS, VR	Transit time requirements
Ronen (2011)	Minimise operational and investment costs	SS, FS	Service frequency
Qi & Song (2012)	Minimise fuel consumption and emissions	VS	Uncertainties in port times and frequency requirements
Scheduling one ship with multiple port calls			
Shang et al. (2016)	Minimise emissions and operational costs	VGS	Power generators and energy storage systems
Gao et al. (2022)	Minimise emissions and operational costs	VGS	Propulsion power variations and equipment lifespan losses
Pan et al. (2022)	Minimise emissions, investment, and operational costs	VGS	Uncertainties in energy generation
Angkasa et al. (2023)	Minimise generation cost and ESS wear cost	VGS	Ship speed variations
Tian et al. (2023)	Minimise economic and environmental costs	VGS	Influence of wind and waves on speed
Yang et al. (2024)	Minimise economic and environmental costs	VGS	Power supply capacity
Berth allocation without onshore power supply			
Du et al. (2011)	Minimise emissions	BA	Deterministic arrival and handling times
Yu et al. (2022), Zhen et al. (2021)	Minimise emissions	BA	Uncertain arrival and handling times, QCA
Wang et al. (2019)	Minimise emissions and ship stay time	BA, QCA, TA	Time window satisfaction
Berth allocation with onshore power supply			
Peng et al. (2019)	Minimise investment, fuel costs, and emissions	BA, OPA	Ship arrival uncertainty
Peng et al. (2021)	Minimise installation and usage costs of onshore power supply	BA, OPA	Ship arrival uncertainty
Mao et al. (2022)	Minimise fuel and electricity consumption costs	BA, ES	Meeting power demands
Zhang et al. (2022)	Minimise operational costs and delayed ship departures	BA, ES	Uncertainty in power generation
Yu et al. (2022)	Minimise shore power usage, departure delay, and emissions	BA, QCA	Onshore power availability, TOU tariffs
Yu et al. (2023)	Minimise delay, fuel, shore power usage, and port fees	BA, QCA	Availability of green technologies, TOU tariffs, incentives
Wang et al. (2024b)	Minimise operational, energy costs, and emissions	BA, QCA	OPA, and quay crane productivity
Berth allocation with onshore power supply and scheduling multiple ships with dual port calls			
Present study	Minimise emissions, power grid exceedance, and berth usage	BA, DFS	Cold ironing availability and power supply capacity via grid and BESS
Legend: SS = Sailing speed, VR = Vessel routing, FS = Fleet size, VS = Vessel schedule, VGS = Voyage and generation schedule, DFS = Daily ferry scheduling, BA = Berth allocation, QCA = Quay crane assignment, TA = Yard Truck assignment, OPA = Onshore power assignment, ES = Energy schedule			

This research is motivated by a real-world industry challenge faced by a Western European ferry port in Country A, referred to as Port A. Port A provides berthing services as well as embarkation and disembarkation for ferries operating between itself and another Western European port, Port B, located in Country B. As shown in Fig. 1, two types of ferries operate between Ports A and B: diesel-powered ferries and hybrid ferries. Hybrid ferries provide significant environmental benefits, as they can switch off their diesel engines and draw electricity through cold ironing while berthed, during harbour manoeuvres, and during acceleration and deceleration when entering or leaving the port.

Three ferry operators, labelled 1, 2, and 3, each operate three ferries between Ports A and B. These operators have reached an agreement with both ports to implement a phased transition towards net-zero emissions. This transition is structured into four phases, during which diesel-powered ferries are progressively replaced by hybrid ferries, while cold ironing infrastructure is gradually expanded through incremental upgrades to both grid capacity and Battery Energy Storage Systems (BESS).

An explicit modelling assumption adopted in this study is that the aggregate cold-ironing capacity available at the ferry terminal, provided jointly by the electricity grid and BESS, is sufficient to meet the berthing requirements of all hybrid ferries, provided that ferry schedules are appropriately designed. This assumption reflects standard decarbonisation practice in ferry ports, where onshore power-supply infrastructure is typically deployed ahead of, or in parallel with, vessel retrofitting programmes. Such sequencing is commonly driven by regulatory requirements and public incentives that prioritise early investment in shore power in order to enable subsequent fleet transition. It is important to note, however, that grid capacity alone is not sufficient at all times, particularly during high peak demand periods when multiple hybrid ferries berth simultaneously. For this reason, BESS with finite capacity is deployed at berths equipped with cold ironing. The BESS is charged during periods when electricity demand is below grid capacity and discharged during peak periods when cold-ironing demand temporarily exceeds grid supply. The combined use of grid capacity

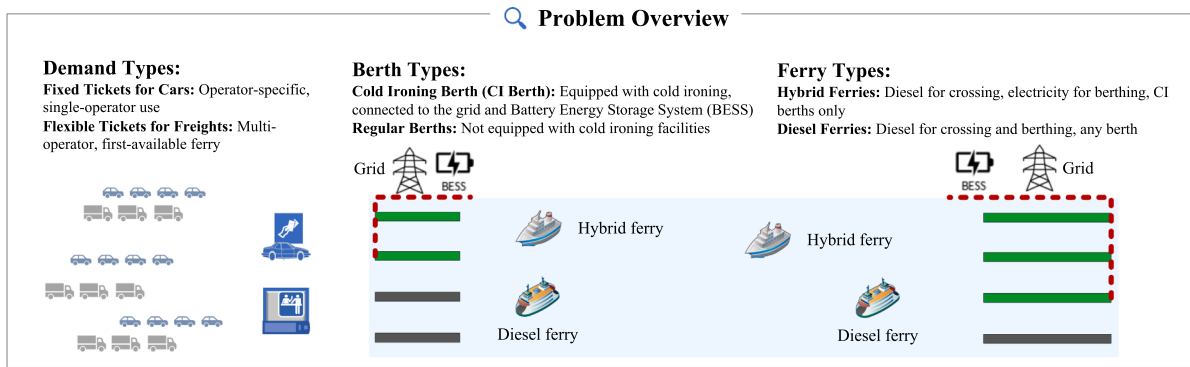


Fig. 1. Schematic illustration of demand, berth, and ferry types in a hybrid-transitioning port.

and BESS therefore ensures that hybrid ferry berthing requirements can be satisfied without reverting to diesel operation, provided that ferry schedules are energy-aware and appropriately coordinated.

This assumption is grounded in the empirical investment roadmap of the case study port, where grid reinforcement and BESS deployment were dimensioned to support the targeted level of hybrid adoption under coordinated scheduling. The optimisation problem therefore investigates whether operational coordination alone is sufficient to avoid systematic reliance on diesel fallback during peak demand periods, rather than assuming unlimited infrastructure capacity.

Under this assumption, hybrid ferries are never required to berth at unequipped berths or to wait idly for shore power access. Instead, the optimisation problem is responsible for coordinating ferry schedules and berth assignments such that hybrid ferries arrive at cold-ironing-equipped berths exactly when required. This ensures uninterrupted operations, avoids unnecessary waiting, and prevents reversion to diesel operation while alongside.

With the support of an advanced national power grid and more favourable conditions for infrastructure investment in Country B, Port B has already upgraded its power grid and is on track to install a sufficient number of cold ironing systems and BESS units to support the phased introduction of hybrid ferries by multiple operators. In contrast, Port A faces significant challenges due to limited capital investment, transmission capacity constraints, and ageing grid infrastructure. As a result, upgrading the grid at Port A to the required level is expected to take at least a decade. The present numerical application reflects a real-world green corridor in which Port A constitutes the binding constraint for decarbonisation due to limited grid capacity and phased shore power deployment, while Port B has already completed the required infrastructure upgrades over the planning horizon considered. This assumption is introduced solely to reflect the empirical investment sequence observed in the case study and does not restrict the applicability of the proposed optimisation framework.

Short-sea ferry operations are governed by fixed and synchronised schedules. Once berthing times and departure sequences are determined at Port A, the corresponding arrival and berthing pattern at Port B is automatically fixed through predetermined sailing times and cyclic round-trip operations. Consequently, optimising ferry berthing at Port A directly determines the temporal distribution of ferry arrivals at Port B. This structural coupling implies that energy-aware scheduling at the bottleneck port not only mitigates grid and cold-ironing constraints locally, but also reduces the likelihood of simultaneous berthing of multiple hybrid ferries at the opposite port. As a result, even when Port B faces limited cold-ironing capacity, the resulting schedule smooths electricity demand, avoids high peak shore power consumption, and reduces the need for hybrid ferries to revert to auxiliary diesel engines while berthed.

In addition, the transition to shore power at Port A presents several operational challenges, including technical constraints related to fast connection and disconnection, as well as the need for rapid charging due to short turnaround times and fixed berthing durations. A key limitation is the restricted cold ironing capacity, which depends jointly on available grid capacity and BESS resources. Minimising reliance on BESS by avoiding grid capacity exceedance is therefore essential, as it prolongs BESS lifespan by reducing charge–discharge cycles and improves overall energy reliability by preserving BESS primarily as a backup resource. Fig. 1 summarises the key features of the problem under investigation. It illustrates the heterogeneity of ferry and berth types and highlights the resulting need to jointly determine berthing times and berth assignments.

These challenges are further compounded by the presence of multiple ferry operators, each publishing independent schedules and competing for limited market share. Addressing this complexity requires a coordinated, energy-aware operational framework that jointly optimises ferry scheduling and berth allocation while maximising utilisation of cold ironing infrastructure and supporting decarbonisation objectives. The resulting problem constitutes a multi-criteria decision-making setting involving multiple stakeholders, including port authorities, ferry operators, energy suppliers, and technology providers. In this study, the problem is formulated as a multi-objective optimisation in which ferry operators and the port authority collaboratively determine ferry schedules and berth assignments. In practice, ferry operators determine service capacities based on booked tickets or historical demand, while the port authority manages berth allocation and berthing times to ensure safe, coordinated, and operationally feasible services.

The case study examined in this research focuses on Port A, where grid capacity and cold ironing constraints are more restrictive than at Port B. Despite these differences, ferry scheduling at Port A remains fully aligned with operations at Port B. The ferry schedule

determines each vessel's initial berthing time and service termination time, with ferries operating continuously from their first berthing until the end of service. Berth allocation is subject to physical constraints, including vessel length and water depth. Consequently, ferries can only be assigned to compatible berths, rendering berths effectively operator-specific, with each operator's vessels allocated to designated berth locations. Although certain ferries may be compatible with only a subset of berths due to physical or operational constraints, berth allocation remains a non-trivial decision variable. Even when the number of hybrid ferries equals the number of cold-ironing-equipped berths, the model determines which berths to activate and how to temporally distribute ferry berthings so as to avoid simultaneous shore power demand peaks and minimise operational costs.

The proposed optimisation framework is applicable across a wide range of corridor configurations. If Port B is less constrained than Port A, the optimised schedule generated for Port A yields a smooth and low-peak berthing pattern at Port B. If Port B is more constrained, the same schedule limits overlapping hybrid ferry berthings, thereby reducing reliance on auxiliary diesel engines during berthing. Even in the extreme case where Port B is not equipped with cold-ironing infrastructure, the energy-aware schedule reduces emissions through the elimination of unnecessary crossings and improved utilisation of hybrid vessels.

Energy-aware ferry scheduling and berth allocation can shift peak electricity demand associated with ferry charging, minimise the number of cold ironing units required in each transition phase, and optimise overall berth usage. Without energy-aware scheduling and effective berth allocation, simultaneous berthing of multiple hybrid ferries in excess of available cold ironing capacity would force vessels to revert to diesel auxiliary engines, undermining both environmental benefits and the substantial investments made by ports and ferry operators.

In this study, ferry scheduling and berth allocation are formulated as a single integrated optimisation problem rather than as two separate decision layers. Vessel scheduling determines the timing of each ferry's initial berthing and subsequent round-trip cycles over the planning horizon, while berth allocation specifies which berth each ferry occupies in each time period, subject to compatibility and mutual exclusivity constraints. Ferry services operate on short sea crossings with highly reliable arrival times and fixed round-trip patterns, and the scheduling of hybrid and diesel ferries must remain fully consistent with berth availability and berth type, that is, whether the berth is equipped with cold ironing or is conventional. Likewise, berth allocation decisions must respect the temporal structure imposed by ferry schedules. Importantly, grid capacity for cold ironing is limited, and the schedules of hybrid ferries directly influence grid capacity exceedance at the berth level. These characteristics make it operationally infeasible to decouple energy-aware scheduling from energy-aware berth allocation in ferry terminals, thereby necessitating an integrated formulation for ferry scheduling and berth allocation.

Berth allocation decisions are often integrated with vessel scheduling decisions (Rodrigues and Agra, 2022). In classical berth allocation problems, vessel arrival times are treated as exogenous inputs, while the optimisation focuses on assigning vessels to berths and determining berthing duration. Although limited flexibility may be allowed to adjust berthing times in order to reduce departure delays when berth capacity is tight (Imai et al., 2007), the term "berthing time" in this literature refers to the berthing service interval, including both the start and completion of service, rather than to a timetable design decision.

In contrast, in short-sea cyclic ferry operations, vessel arrival times are endogenous outcomes of timetable design. The initial berthing time determines the starting point of a cyclic round-trip service pattern, while berthing durations remain fixed and operationally standardised. Once this initial time is set, all subsequent arrivals follow from the fixed round-trip duration. This formulation reflects the practical operation of ferry service timetables used by many ferry operators, such as Wightlink Ferries in the UK⁴ and Scandlines operating between Denmark and Germany.⁵ In these services, the timetable defines the cyclic sequence of departures and arrivals, from which subsequent berthing times follow. The proposed formulation therefore integrates cyclic ferry timetable design with berth allocation.

While this study is motivated by a short-strait ferry corridor, the modelling framework is generic at the level of the mathematical formulation and is applicable to a broader class of regular short-distance shipping services, including Ro-Ro shuttle services, cruise vessels, river barges, and small coastal or general cargo ships operating in shuttle services. These services share key operational characteristics with ferries, namely fixed schedules with reliable arrival times, frequent port calls, and operation at smaller ports or inland terminals that typically do not accommodate large ocean-going vessels. By contrast, direct application of the framework to long-haul container or bulk shipping would require substantial modifications to account for fundamentally different voyage lengths, energy demand profiles, port-call frequencies, and speed or routing flexibility.

3.1. Phased transition roadmap for hybrid ferry integration

Fig. 2 presents the progressive shift from diesel to hybrid ferries across four transition phases for each ferry operator. For each phase, the figure summarises the corresponding evolution of fleet composition, planned upgrades to power grid and Battery Energy Storage System (BESS) capacity, and the gradual increase in the number of berths equipped with cold ironing relative to conventional berths. These projections account for electricity demand growth and budgetary constraints, thereby outlining a realistic and implementable transition pathway for accommodating the increasing adoption of cold ironing as more ferries convert to hybrid propulsion systems.

⁴ <https://www.wightlink.co.uk/plan-your-journey/timetables>

⁵ <https://www.scandlines.com/departures/?route=puttgarden-rodby&date=05-03-2026>

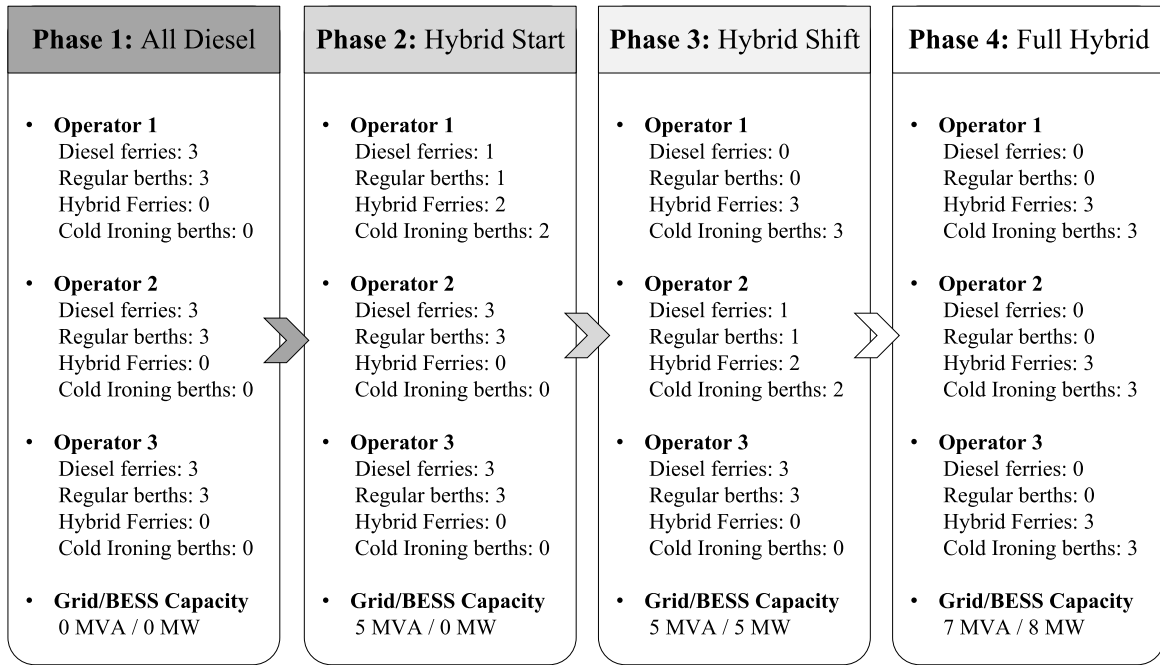


Fig. 2. Decarbonisation transition phases.

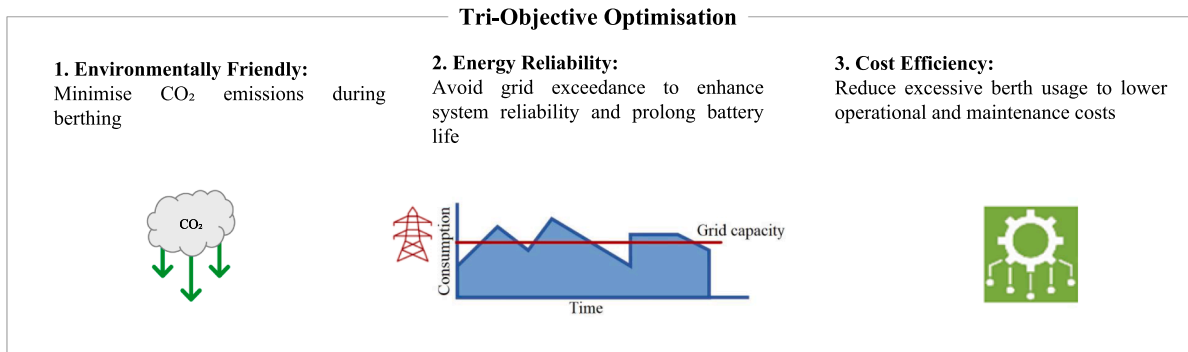


Fig. 3. Key optimisation objectives.

3.2. Tri-objective model for energy-aware ferry scheduling with cold ironing limitations

To optimise ferry operations under cold ironing constraints, this study proposes a novel tri-objective mixed-integer programming (MIP) model for energy-aware scheduling and berth allocation. As shown in Fig. 3, the overarching aim of the model is to support the port in implementing a phased transition towards decarbonisation, while balancing three key and potentially competing objectives: environmental sustainability, energy reliability, and cost efficiency.

These objectives are embedded within a lexicographic optimisation framework, reflecting the priority structure communicated by the port authority and ensuring that improvements in lower-priority objectives do not compromise higher-priority operational goals.

- **Minimise carbon emissions:** Reduce CO₂ emissions during berthing by prioritising the assignment of hybrid ferries over diesel ferries wherever feasible and by avoiding unnecessary crossings.
- **Enhance energy reliability:** Minimise periods in which cold ironing demand exceeds available grid capacity, thereby reducing reliance on the Battery Energy Storage System (BESS).
- **Improve cost efficiency:** Minimise unnecessary berth activation in order to reduce operational and maintenance costs, particularly for berths equipped with cold ironing.

The proposed model jointly determines ferry schedules and berth assignments for two ferry types, hybrid and diesel, over a defined scheduling horizon. Hybrid ferries are allocated exclusively to berths equipped with cold ironing, ensuring they operate on electricity

while docked in line with the study's decarbonisation objective. Diesel ferries, by contrast, can berth at any available berth. The model explicitly coordinates hybrid ferry assignments with cold ironing availability to ensure that electricity demand remains within supply limits and to avoid fallback to diesel operation.

The first energy-aware objective prioritises the use of hybrid ferries to minimise CO₂ emissions. For a round trip between Port A and Port B, the total journey duration is $b_i + \tau$, where b_i denotes the berthing duration at Port A and τ represents the elapsed time from departure at Port A to return, including sailing and berthing at Port B. For example, if $b_i = 1$ h and $\tau = 4$ h (3 h of sailing and 1 h of berthing at Port B), the total round-trip duration is 5 h. Throughout the scheduling horizon, each ferry's round trips are arranged sequentially to ensure continuous service. Once assigned, each ferry operates continuously over a defined time window without idle gaps. This structure respects operational constraints, enforces feasible berthing windows, and determines ferry departure times endogenously through optimisation.

In ports equipped with shore power, temporary grid capacity exceedance events may occur when the instantaneous electricity demand from vessels connected to cold ironing exceeds the maximum import capacity of the grid. In such periods, the shortfall is covered by discharging the Battery Energy Storage System (BESS) over short time intervals. These exceedance events are operationally feasible and do not imply a violation of physical grid limits or an interruption of port operations. Ferry services therefore continue normally, with all vessels remaining fully supplied with electricity while berthed.

Frequent reliance on grid exceedance is nevertheless undesirable in practice, as it accelerates BESS degradation through repeated charge–discharge cycles, increases operational complexity and the risk of power management failures, and may lead to additional costs or penalties imposed by grid operators. Ports therefore aim to limit exceedance events and to preserve the BESS primarily as a contingency and peak-shaving resource rather than as a routine energy supply.

Accordingly, grid capacity exceedance is explicitly represented in the model through binary variables and associated constraints, and the second optimisation objective minimises the number of periods in which cold ironing demand exceeds grid capacity and must be partially supplied by the BESS.

The model assumes fast-charging capability for the BESS, allowing it to fully recharge within the remaining time of each period after hybrid ferry charging is completed. This assumption reflects commercially available high-capacity port-scale battery systems deployed in several ferry terminals, where rapid charging and discharging are technically feasible within short operational intervals.⁶ This assumption enables effective utilisation of surplus grid capacity without introducing inter-period charging dependencies.

Given the significant costs associated with berth operation and maintenance, the third objective seeks to minimise the number of activated berths when fewer berths are sufficient to meet demand. Efficient scheduling can demonstrate that operations remain feasible with a limited subset of berths, thereby reducing avoidable maintenance expenditure. To reflect this, the model applies a penalty to each activated berth, weighted by berth-specific operating and maintenance costs.

Although berth infrastructure is already constructed, activating and operating a berth incurs non-negligible ongoing costs. These include the allocation of staff and safety personnel, operation and upkeep of linkspans, ramps, and boarding bridges, as well as additional inspections, monitoring, and mandatory testing of electrical and safety systems.

Berths equipped with cold ironing impose substantially higher operating and maintenance requirements due to the need for regular certification and servicing of shore-to-ship electrical interfaces. During the early phases of transition, when the number of hybrid ferries remains limited, the port therefore seeks to operate the minimum number of berths required to maintain uninterrupted service.

The third objective captures this operational preference by penalising berth activation rather than infrastructure availability. It does not imply decommissioning of berths, but reflects the port's intention to avoid activating additional berths unless they deliver clear operational benefits. Consistent with this rationale, the berth activation objective is placed last in the lexicographic priority order.

Three key operational decisions form the backbone of the proposed optimisation framework:

- the initial berthing time of each ferry within a defined flexibility window,
- the assignment of berths to ferries during each time period, and
- the termination time of each ferry's service.

Under normal operating conditions, ferry schedules are designed to avoid waiting at berth, and arrival times are generally highly reliable due to short sea crossings. Ferry terminals are therefore planned and operated such that sufficient berth capacity is available when schedules are appropriately designed.

Although waiting can occur under exceptional circumstances such as adverse weather, mechanical failures, or unexpected traffic disruptions, these situations fall outside standard operating practice and are not considered in this study. Accordingly, the model represents normal operating conditions in which ferries berth immediately upon arrival and proceed through their scheduled round trips without queuing.

While ferry timetables are designed to avoid systematic queuing under normal operating conditions, ports may activate additional berths in practice to provide operational robustness against disruptions such as adverse weather or technical failures. The present model deliberately abstracts from such robustness buffers in order to isolate the interaction between ferry scheduling and limited

⁶ For example, onshore charging systems supporting electric ferries are equipped with dedicated battery energy storage systems to provide high power during fast charging of vessels (e.g., Leclanché onshore BESS installations for ferry charging). See: <https://www.leclanche.com/wp-content/uploads/2022/05/Zero-Emission-Ferry-and-Onshore-Battery-Energy-Storage-System.pdf>.

cold-ironing capacity during normal operations. This abstraction does not imply that additional berths are unnecessary in practice; rather, it reflects a modelling focus on energy-aware coordination under nominal system states.

Incorporating flexible time windows for initial berthing allows ferries to commence their first journey at different periods, reflecting realistic operational practices. By jointly optimising these decision layers, the model ensures that resulting schedules are both energy-efficient and operationally feasible.

Each ferry has strict capacity limits for freight vehicles and passenger cars due to deck height, weight, and space constraints. While car passengers purchase operator-specific tickets, freight vehicles typically operate under flexible annual contracts that allow boarding of the earliest available ferry regardless of operator. In the model, demand is indexed by v , with $|v| = 4$ in the case study port. Ferry capacities and demand compatibility vary by operator and vessel. Embarkation windows are predefined and aligned with published timetables, and berthing durations are treated as fixed and sufficient to accommodate all loading activities. This operational setup eliminates the need to explicitly model vehicle loading times.

Beyond demand allocation, the model ensures that once a ferry begins its first berthing, all subsequent crossings and berthings proceed without delay, preserving schedule interdependence and avoiding service disruption. Electricity usage at berths is dynamically managed to remain within the combined capacity of the grid and the BESS. Energy-aware scheduling distributes electricity demand over time and allows sufficient recharging of the BESS, reducing reliance on storage as a primary energy source and preserving its availability for contingency use.

4. Mathematical formulation of the energy-aware ferry scheduling (EAS) model

This section provides the formal mixed-integer programming (MIP) formulation for the proposed energy-aware scheduling model introduced in Section 3.2.

Mathematical model

$$\min Z_1 = \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{V}^H} \sum_{b \in \mathcal{B}^H} \sum_{k \in \mathcal{K}} E_i^H y_{itb}^k + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{V}^D} \sum_{b \in \mathcal{B}^D} \sum_{k \in \mathcal{K}} E_i^D y_{itb}^k \quad (1)$$

$$\min Z_2 = \sum_{t \in \mathcal{T}} \psi_t \quad (2)$$

$$\min Z_3 = \sum_{b \in \mathcal{B}} P_b O_b \quad (3)$$

s.t.

$$\sum_{b \in \mathcal{B}^H \cup \mathcal{B}^D} \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{V}^H \cup \mathcal{V}^D} \sum_{\tau=1}^{t+\ell_v-1} d_{iv} x_{i\tau b}^k \geq \sum_{\tau=1}^t D_{\tau v}, \quad \forall t \in \{1, \dots, |\mathcal{T}| - \ell_v + 1\}, v \in \mathcal{N} \quad (4)$$

$$\sum_{b \in \mathcal{B}^H \cup \mathcal{B}^D} \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{V}^H \cup \mathcal{V}^D} \sum_{\tau=1}^{t+\ell_v-1} d_{iv} x_{i\tau b}^k \geq \lambda_{iv}, \quad \forall t \in \{1, \dots, |\mathcal{T}| - \ell_v + 1\}, v \in \mathcal{N} \quad (5)$$

$$\sum_{b \in \mathcal{B}^H \cup \mathcal{B}^D} \sum_{i \in \mathcal{T}} t x_{itb}^k \geq -M \left(1 - \sum_{i \in \mathcal{T}} \sum_{b \in \mathcal{B}^H \cup \mathcal{B}^D} x_{itb}^k \right) + \sum_{b \in \mathcal{B}^H \cup \mathcal{B}^D} \sum_{i \in \mathcal{T}} t x_{itb}^{k-1} + b_i + \tau, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D, k \in \mathcal{K} \setminus \{1\} \quad (6)$$

$$\sum_{b \in \mathcal{B}^H \cup \mathcal{B}^D} \sum_{i \in \mathcal{T}} t x_{itb}^k \leq M \left(1 - \sum_{i \in \mathcal{T}} \sum_{b \in \mathcal{B}^H \cup \mathcal{B}^D} x_{itb}^k \right) + \sum_{b \in \mathcal{B}^H \cup \mathcal{B}^D} \sum_{i \in \mathcal{T}} t x_{itb}^{k-1} + b_i + \tau, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D, k \in \mathcal{K} \setminus \{1\} \quad (7)$$

$$x_{itb}^k \leq \sum_{\tau=1}^{t+b_i} y_{i\tau b}^k - (b_i - 1)x_{itb}^k, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D, b \in \mathcal{B}^H \cup \mathcal{B}^D, k \in \mathcal{K}, t \in \{1, \dots, |\mathcal{T}| - b_i\} \quad (8)$$

$$R_t \leq C^{BESS}, \quad \forall t \in \mathcal{T} \quad (9)$$

$$R_t \leq R_{t-1} - \left(\sum_{i \in \mathcal{V}^H} \sum_{k \in \mathcal{K}} \sum_{b \in \mathcal{B}^H} \theta_i y_{i(t-1)b}^k - C^G \right), \quad \forall t \in \mathcal{T} \setminus \{1\} \quad (10)$$

$$\sum_{i \in \mathcal{V}^H} \sum_{k \in \mathcal{K}} \sum_{b \in \mathcal{B}^H} \theta_i y_{itb}^k \leq C^G + R_t, \quad \forall t \in \mathcal{T} \quad (11)$$

$$\sum_{i \in \mathcal{V}^H} \sum_{k \in \mathcal{K}} \sum_{b \in \mathcal{B}^H} \theta_i y_{itb}^k - C^G \leq M \psi_t, \quad \forall t \in \mathcal{T} \quad (12)$$

$$w_i^1 \leq \delta_i, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D \quad (13)$$

$$\sum_{i \in \mathcal{V}^H \cup \mathcal{V}^D} \sum_{k \in \mathcal{K}} y_{itb}^k \leq 1, \quad \forall t \in \mathcal{T}, b \in \mathcal{B}^H \cup \mathcal{B}^D \quad (14)$$

$$\sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{V}^H \cup \mathcal{V}^D} \sum_{k \in \mathcal{K}} y_{itb}^k \leq M O_b, \quad \forall b \in \mathcal{B}^H \cup \mathcal{B}^D \quad (15)$$

$$\sum_{b \in B^H \cup B^D} \sum_{t \in \mathcal{T}} tx_{itb}^1 = a_i^1 + w_i^1, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D \quad (16)$$

$$\sum_{b \in B^H \cup B^D} \sum_{t \in \mathcal{T}} tx_{itb}^k \leq |\mathcal{T}|, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D, k \in \mathcal{K} \quad (17)$$

$$\sum_{k \in \mathcal{K}} \sum_{t \in \mathcal{T}} x_{itb}^k \leq M q_{ib}, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D, b \in B^H \cup B^D \quad (18)$$

$$\sum_{t \in \mathcal{T}} \sum_{b \in B^H \cup B^D} x_{itb}^k \leq \sum_{t \in \mathcal{T}} \sum_{b \in B^H \cup B^D} x_{itb}^{k-1}, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D, k \in \mathcal{K} \setminus \{1\} \quad (19)$$

$$\sum_{b \in B^H \cup B^D} \sum_{t \in \mathcal{T}} x_{itb}^k \leq 1, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D, k \in \mathcal{K} \quad (20)$$

$$x_{itb}^k \leq y_{itb}^k, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D, b \in B^H \cup B^D, k \in \mathcal{K}, t \in \mathcal{T} \quad (21)$$

$$w_i^1, R_i \geq 0, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D \quad (22)$$

$$x_{itb}^k, y_{itb}^k, O_b, \psi_t \in \{0, 1\}, \quad \forall i \in \mathcal{V}^H \cup \mathcal{V}^D, b \in B^H \cup B^D, k \in \mathcal{K}, t \in \mathcal{T} \quad (23)$$

The proposed mixed-integer model aims to fulfil all demands within an acceptable time window while enhancing the overall operational and environmental efficiency of hybrid and diesel ferry scheduling. In objective functions (1) to (3), three key factors within the scheduling horizon are minimised: carbon emissions during berthing, grid capacity exceedances, and penalised berth usage, due to its impact on future repair and maintenance costs. Constraints (4) and (5) ensure that all demand is met within the acceptable time window, including cars with fixed operator-specific tickets and freight with flexible multi-operator tickets. They are applied separately to each demand type $v \in \mathcal{N}$, not to an aggregated total. Both are required because $\ell_v > 0$ for several demand types, allowing flexibility in boarding times. If all $\ell_v = 0$, either constraint alone would suffice, but with $\ell_v > 0$, both are essential for accurate and realistic demand satisfaction. Constraints (6) and (7) define the sequence of start times for consecutive berthings, reflecting real-world ferry operations where, once service begins, scheduled crossings continue without idle gaps. They impose both lower and upper bounds so that, if both berthings occur, the k th starts exactly $b_i + \tau$ periods after the $(k-1)$ th, where b_i is the berthing duration in the port where allocation is made and τ is the sailing time, including berthing at the other port and returning. Formulating this as two inequalities rather than one equality preserves feasibility when fewer crossings are scheduled, as unused berthings automatically relax the timing requirement. Constraint (8) specifies the time periods during which each berth is occupied by a ferry after the berthing process begins. Together, these constraints explicitly couple scheduling decisions with berth occupancy, ensuring that temporal and spatial feasibility are enforced simultaneously. Constraint (9) ensures that the energy stored in the BESS does not exceed its capacity. Constraint (10) dynamically calculates the available BESS energy for each period based on the energy used or recharged in the previous period. Constraint (11) limits electricity usage in each period to the combined capacity of the grid and BESS. Finally, Constraint (12) activates the exceedance grid capacity variable for any period in which the grid capacity is surpassed. Constraint (13) ensures that the start of the initial berthing for each ferry's first crossing does not exceed the allowable time window. Constraint (14) specifies that each berth in each period can be occupied by no more than one ferry. The assumption of immediate berthing under normal operating conditions is enforced through the scheduling and berth allocation constraints. Constraints (6) and (7) ensure that once a ferry enters service, its sequence of round trips proceeds without interruption, while Constraint (14) enforces berth exclusivity and prevents overlapping berth assignments that would otherwise generate waiting. Constraint (15) determines whether a berth is used or not during the scheduling horizon. Constraint (16) ensures that each ferry starts berthing within a reasonable time window from its earliest available berthing time. Constraint (17) ensures that all scheduled ferry berthing begin before the end of the scheduling horizon. Constraint (18) ensures each operator's ferries are restricted to their designated berths. Constraint (19) ensures that if the $(k-1)$ th crossing of a ferry is not completed, the subsequent crossings cannot take place. Constraint (20) states that the berthing of each crossing of each ferry cannot start on more than one berth. Constraint (21) ensures that if a ferry crossing starts from a berth, the berth remains occupied for the duration of the berthing and cannot serve another ferry during that time. Finally, Constraints (22) and (23) ensure the continuity and binary nature of the decision variables, respectively.

5. Computational experiments

The computational experiments were conducted using empirical data from Port A with the aim of benchmarking how the proposed energy-aware scheduling and berth allocation model can deliver significant environmental benefits without requiring extensive upgrades or costly investments in cold ironing infrastructure. The experiments evaluate the sufficiency of planned infrastructure and compare operational performance under alternative scheduling strategies across different decarbonisation phases.

5.1. Parameter setting based on empirical data

This subsection presents the empirical calibration of model parameters, integrating information on Port A's infrastructure configuration, vessel characteristics, and demand patterns. These inputs were derived from operational records and historical demand statistics to ensure that the optimisation model reflects realistic port conditions.

Infrastructure configuration and case study parameters

We take one day of 24 h as the scheduling horizon, i.e., $|\mathcal{T}| = 24$ h. Fig. 2 provides an overview of the port configuration and key input parameters used in the model, including cold ironing infrastructure availability (B^H and B^D), electricity grid capacity (C^G),

BESS capacity (C^{BESS}), and planned upgrades across transition phases. It also shows the phased adoption of hybrid ferries ($\mathcal{V}^H$ and $\mathcal{V}^D$) and the berth assignment structure, where the binary parameter q_{ib} is set to 1 or 0 depending on the designated berths for each operator. $\mathcal{K}$ is calculated to be 4 for each ferry over a 24-h time horizontal, reflecting that each round trip takes 6 h.

Ferry services at Port A operate nearly identical crossing time and berthing duration for both operational and logistical reasons. All ferries follow the same route between Port A and Port B. With designated berths per operators, turnaround processes are standardised, resulting in almost identical berthing duration. We assume equal berthing durations for all ferries ($b_i = 1$ h for all $i \in \mathcal{V}^H \cup \mathcal{V}^D$) and a uniform sailing time ($\tau = 5$ h). The electrical engineer at Port A estimates an average energy consumption rate of $\theta_i = 5$ MW would be required to charge auxiliary engines of ferries. Likewise, CO₂ emissions during berthing are estimated to be equal across hybrid ferries (2000 kg CO₂/h) and across diesel ferries (6706 kg CO₂/h), based on available data.

The earliest possible berthing time for all ferries is set as $a_i^1 = 1$, and $\delta_i = 24$ provides sufficient flexibility for initial berthing. Berths equipped with cold ironing are penalised at twice the rate of regular berths to reflect their higher operational and maintenance costs, with P_b values set to 200 and 100 for cold ironing and regular berths, respectively.

There are $\mathcal{N} = 4$ demand types: three operator-specific car demand types and one flexible multi-operator freight demand. Based on 200 demand instances generated from the scenarios described in the following subsection, λ_{iv} was specified for each ferry operator and each of the four demand types. Ferry capacities for car demand (d_{iv} , $v = 1, 2, 3$) vary by operator and vessel. For Operator 1, the three vessels have capacities of 200, 200, and 195. For Operator 2, the capacities are 400, 500, and 120. Operator 3's vessels have capacities of 180, 50, and 195. For freight demand (d_{iv} , $v = 4$), the capacities are as follows: 175, 175, and 180 for Operator 1; 120, 120, and 160 for Operator 2; and 120, 90, and 180 for Operator 3.

The empirical configuration used in the computational experiments corresponds to a real-world case study of one of the busiest ferry ports in Western Europe, characterised by high-frequency short-sea services operated by multiple ferry operators. The number of vessels, berths, crossings, and demand volumes therefore reflect an intensive and operationally realistic ferry terminal environment rather than a stylised or hypothetical test instance.

Demand patterns and scenarios

At Port A, ferry ticket operations differ between freight vehicles and passenger cars. Freight vehicles typically have contracts with all three ferry operators, allowing them to book flexible tickets and board any available ferry from any operator to ensure efficiency and reduce waiting times. In contrast, passenger cars must book with a specific ferry operator and can only board that operator's ferry at their scheduled time.

Ferry schedules must accommodate both operator-specific car demand and non-operator-specific freight demand. Each demand type should be assigned to the appropriate ferries for shipping. Let $\mathcal{N}$ represent the set of all demand types. These demand types are categorised into four distinct groups with each type indexed by $v \in \mathcal{N}$:

- Cars with tickets from Operator 1 ($v = 1$)
- Cars with tickets from Operator 2 ($v = 2$)
- Cars with tickets from Operator 3 ($v = 3$)
- Freight with flexible tickets, which can be accommodated by any operator ($v = 4$)

To ensure the validity and robustness of the model, four demand scenarios were further defined based on historical vehicle arrival patterns at Port A. The analysis was conducted using eight years of data (2016–2023) to identify peak and off-peak periods across different years, weeks, and days. The findings indicate that certain days, such as those around Christmas, experience peak freight traffic, while school holidays correspond to peak car travel. Within each day, vehicle arrivals also exhibit temporal variations: daytime hours (8 AM–8 PM) are peak periods for both cars and freight, whereas nighttime hours (8 PM–8 AM) generally see lower traffic.

To evaluate the model's performance under different traffic conditions, four distinct demand scenarios were created, acting as boundary conditions for vehicle volumes at the port:

- **P/P** - Peak Cars / Peak Freight
- **P/O** - Peak Cars / Off-Peak Freight
- **O/P** - Off-Peak Cars / Peak Freight
- **O/O** - Off-Peak Cars / Off-Peak Freight

Fig. 4 illustrates the representative hourly arrival patterns of different vehicle types under each demand scenario derived from the service timetable. Passenger cars follow operator-specific ticketing schemes; therefore, car demand is recorded separately for each ferry operator. In contrast, freight vehicles operate under a flexible ticketing system that allows them to board any available ferry with sufficient capacity, regardless of operator. Consequently, freight demand is aggregated across operators, reflecting the operational flexibility typically observed in ferry terminals.

These patterns were used to fit Poisson distributions, which form the basis for the demand scenarios summarised in Table 4. The Poisson distribution was chosen to model vehicle arrivals at the port because it effectively represents the random and independent occurrence of events (vehicle arrivals) over fixed time intervals. This distribution is ideal for modelling vehicle demand, as it assumes that vehicles arrive at a constant average rate and independently of each other, which is typical of traffic patterns observed at ports.

In Table 4, the Poisson distribution parameters are provided for each demand scenario. The values represent the mean arrivals of vehicles (λ) per time unit, for both day and night periods, under different demand conditions for cars (separated by the ferry operator) and freight (combined between all operators). These parameters serve as the foundation for the demand patterns used to simulate vehicle arrivals in the model. These parameters were used to simulate vehicle arrivals in the model.

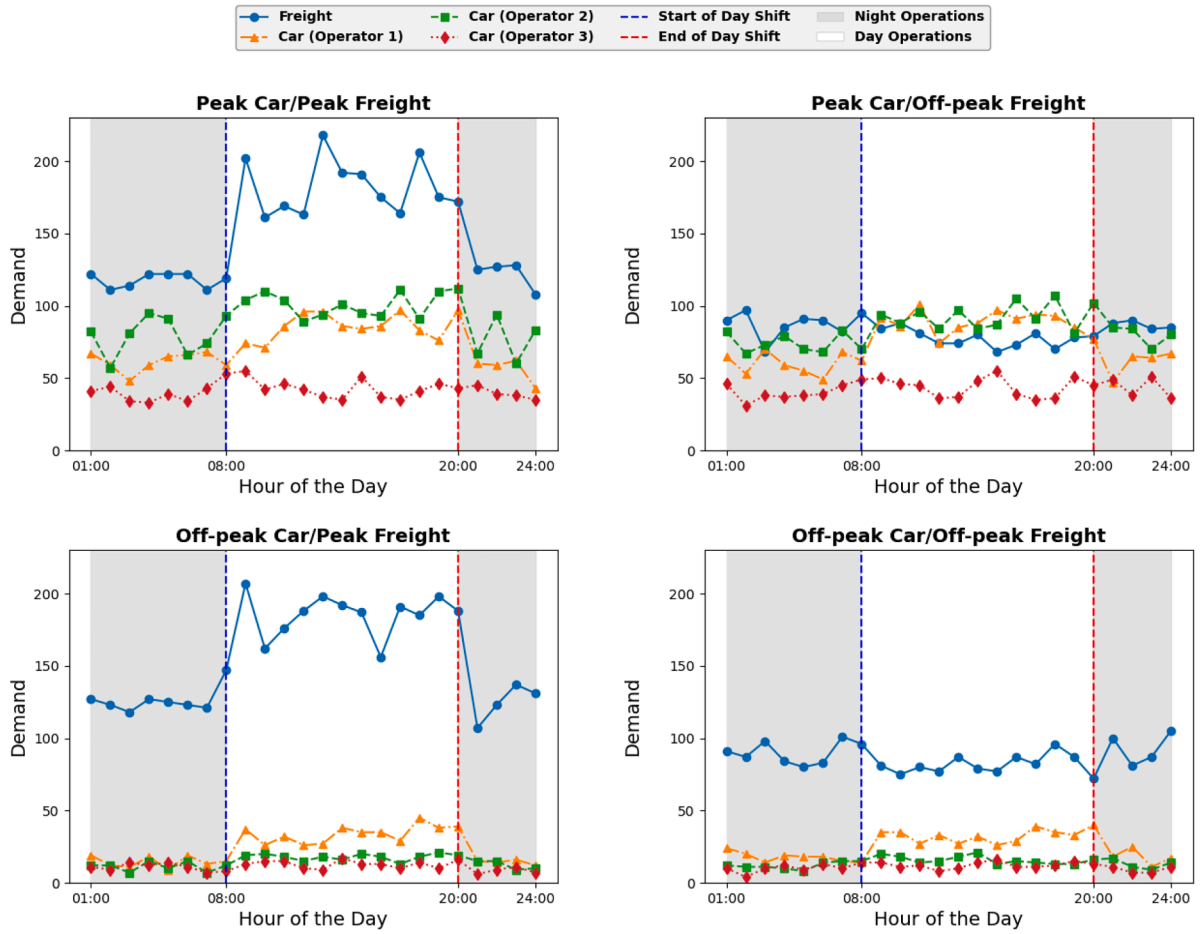


Fig. 4. Representative demand patterns for vehicle arrivals across four scenarios.

Table 4

Demand scenarios and poisson distribution parameters for vehicle arrivals.

Scenario	Car			Freights
	Operator 1	Operator 2	Operator 3	All Operators
P/P	94 (Day), 58 (Night)	96 (Day), 77 (Night)	44 (Day), 39 (Night)	184 (Day), 125 (Night)
P/O	94 (Day), 58 (Night)	96 (Day), 77 (Night)	44 (Day), 39 (Night)	77 (Day), 88 (Night)
O/P	33 (Day), 16 (Night)	16 (Day), 12 (Night)	11 (Day), 11 (Night)	184 (Day), 125 (Night)
O/O	33 (Day), 16 (Night)	16 (Day), 12 (Night)	11 (Day), 11 (Night)	77 (Day), 88 (Night)

Legend: P/P = Peak for both cars and freight, P/O = Peak for cars, Off-Peak for freight,

O/P = Off-Peak for cars, Peak for freight, O/O = Off-Peak for both cars and freight.

Operator 1, 2, 3 = Anonymised ferry operators. Cars: Operator-specific demand, Freight: Flexible tickets.

The model was tested under four defined scenarios to evaluate its ability to handle varying traffic conditions. By using peak and off-peak demand patterns as boundary conditions, which represent the upper and lower limits for vehicle volumes at the port, the analysis provides valuable insights into the model's performance. For each scenario, 50 random demand instances were generated, totalling 200 instances. This systematic approach ensures a thorough assessment of the model across diverse conditions, incorporating variations observed in historical data.

5.2. Experimental design

Three comparative experiments were conducted in this study. These experiments are designed to examine infrastructure feasibility, operational performance, and emission reduction outcomes under different stages of decarbonisation. Experiment 1 examines the sufficiency of planned infrastructure across transition phases. For each transition phase considered in the numerical experiments, an infrastructure sufficiency test is conducted to verify that the available cold-ironing berths, grid capacity, and Battery Energy Storage

Table 5
Computational performance summary over 200 demand instances.

Demand Scenario	Fastest (s)	Average (s)	Slowest (s)
P/P (Peak Cars / Peak Freight)	0.89	1.01	1.37
P/O (Peak Cars / Off-Peak Freight)	0.80	0.98	1.12
O/P (Off-Peak Cars / Peak Freight)	0.81	0.91	1.07
O/O (Off-Peak Cars / Off-Peak Freight)	0.74	0.86	0.94
All Instances (200)	0.74	0.94	1.37

System (BESS) capacity are adequate to support all scheduled hybrid ferry berthings without fallback to diesel operation. Experiments 2 and 3 focus on evaluating the operational and environmental performance of the proposed optimisation framework under different scheduling and transition scenarios.

- **Experiment 1: Infrastructure Sufficiency Assessment** — Assesses whether the planned grid and BESS capacities in each transition phase can support all hybrid ferries relying on onshore power during berthing, as scheduled by the proposed EAS model. Results are reported in [Appendix A](#).
- **Experiment 2: Operational Performance Benchmarking** — Compares the proposed EAS model with BAU scheduling to evaluate operational efficiency and associated emission reductions. Results are shown in [Section 5.4](#).
- **Experiment 3: Cold Ironing as a Technological Strategy** — Assesses emission reductions achieved by the proposed EAS model across transition phases, as reliance on cold ironing during berthing gradually increases, from both port authority and ferry operator perspectives. Results are discussed in [Section 5.5](#).

5.3. Solution approach and computational setup

To address the tri-objective nature of the problem, a lexicographic multi-objective optimisation approach was adopted, reflecting the port's decarbonisation priorities and operational constraints. The objectives, listed in order of precedence, are as follows:

1. Minimise CO₂ emissions — the primary environmental objective shared by the port authority and ferry operators, directly supporting the overarching goal of maritime decarbonisation.
2. Minimise grid capacity exceedance — a port-specific objective aimed at preventing excessive charge-discharge cycles of the BESS and ensuring the stable, reliable operation of both the grid and the BESS.
3. Minimise long-term maintenance and repair costs — achieved by reducing the number of berth activations within the considered scheduling horizon for both regular and cold ironing berths, with greater emphasis on the latter due to their higher maintenance demands and activation penalties. This objective aims to reduce wear, extend asset lifecycles, and lower overall expenditure.

These objectives are inherently conflicting. For example, prioritising the reduction of reliance on BESS to improve energy system reliability, or minimising berth activation to reduce long-term maintenance costs, over CO₂ emission minimisation may lead the schedule to favour non-hybrid ferries. Such vessels impose no electrical load and require no activation of cold-ironing-equipped berths, but fail to deliver emission reductions during berthing. The lexicographic approach addresses these trade-offs by optimising objectives sequentially in strict priority order, ensuring that a lower-priority objective is pursued only after the higher-priority objective has been achieved to its best attainable level, as improvements in lower-priority objectives cannot compensate for deterioration in higher-priority ones. To illustrate the conflicting nature of these objectives under alternative priority structures, selected sensitivity results are reported in [Appendix B](#).

The resulting mixed-integer programming (MIP) model for each phase of the lexicographic process was implemented in Python 3.12.7 and solved using Gurobi Optimiser 12.0.0 within Visual Studio Code 1.96. Computational experiments were executed on a workstation with an AMD Ryzen 7 PRO 7840U processor (3.30 GHz, 8 physical cores, 16 threads) and 32 GB of RAM.

The experimental setup corresponds to a real-world case study of one of the busiest short-sea ferry ports in Europe, characterised by high-frequency shuttle services, multiple operators, and dense daily sailing schedules. The instance size therefore reflects a realistic and operationally demanding ferry-port environment rather than a small-scale test case.

All problem instances were solved in under two seconds. [Table 5](#) reports the computational performance of the proposed optimisation model across all 200 demand instances and four demand scenarios.

The computational performance summary confirm that the model is computationally tractable for real-world ferry-port instances under all tested conditions, including simultaneous peak car and freight demand. All instances were solved to proven optimality within two seconds, with an average runtime of 0.94 s (i.e. around 940 ms). Only minor variation in runtime is observed across different demand scenarios, reflecting differences in demand intensity rather than numerical instability. This demonstrates that the model remains robust, efficient, and fully tractable even under the most operationally demanding conditions observed at the case study port, which is representative of busy ferry ports within Europe.

5.4. Comparison of energy-aware scheduling with business-as-usual approach

This subsection evaluates the benefits of the proposed Energy-Aware Scheduling (EAS) model compared to the Business-as-Usual (BAU) approach across the four decarbonisation transition phases. The primary goal is to demonstrate the real-world impact of oper-

Table 6
Comparison of BAU and EAS across hybridisation phases for busy and non-busy days.

Busy Days					
Phase	Crossings	Grid Exc.	Missed Elec.	CO ₂ Red.	Cap. Eff.
1. All Diesel	41 / 36*	0 / 0*	0 / 0*	12%	12%
2. Hybrid Start	41 / 36*	0 / 0*	0 / 0*	14%	12%
3. Hybrid Shift	41 / 36*	5 / 0*	0 / 0*	19%	12%
4. Full Hybrid	41 / 36*	10 / 12*	6 / 0*	35%	12%
Non-Busy Days					
Phase	Crossings	Grid Exc.	Missed Elec.	CO ₂ Red.	Cap. Eff.
1. All Diesel	40 / 24*	0 / 0*	0 / 0*	40%	40%
2. Hybrid Start	40 / 24*	0 / 0*	0 / 0*	42%	40%
3. Hybrid Shift	40 / 24*	5 / 0*	0 / 0*	48%	40%
4. Full Hybrid	40 / 24*	10 / 0*	4 / 0*	51%	40%

Legend: Asterisks (*) indicate EAS values.
Crossings = Total crossings (BAU/EAS); Grid Exc. = Grid exceedance events (BAU/EAS);
Missed Elec. = Missed electric berthing; CO₂ Red. = CO₂ reduction with EAS;
Cap. Eff. = Capacity usage efficiency improvement with EAS.

ational optimisation when combined with technological advancements. By comparing EAS with BAU under the same technological conditions, this example provides insights into how operational strategies influence the success of decarbonisation pathways.

In the BAU approach, real-world schedules established by ferry operators during the study period must be compared with the schedules generated by the proposed energy-aware model. To ensure a meaningful comparison, two representative days were selected based on historical data: a busy day, corresponding to the day in 2023 with the highest demand volume, and a non-busy day, representing the day in 2023 with the lowest demand volume. The results of the comparison between EAS and BAU for these two days are summarised in Table 6.

In the BAU approach, the number and timing of crossings remained fixed across all phases, based on the ferry scheduling data shared by Port A. Since no cold ironing usage was recorded in historical data, CO₂ emissions under BAU were estimated based on the planned number of hybrid ferries as outlined in Fig. 2. Based on the settings shown in Fig. 2, the BAU scenario assumes an equal number of ferries upgrades to hybrid vessels across four phases, with the same number of cold ironing berths allocated and specific berths designated for each operator. However, the intended benefits were only realised when the available cold ironing capacity, supplied by the grid and BESS, was sufficient to meet electricity demands during berthing. Otherwise, any shortfall in shore power led to missed opportunities for berthing and charging at cold ironing berths (called missed electric berthing), thereby undermining the environmental advantages of both hybrid ferries and cold ironing.

In contrast, EAS dynamically optimised the timing of crossings in each phase to balance the three optimisation objectives while ensuring all demand was met. As shown in Table 6, this approach adjusted operations to align with demand patterns, not only reducing missed electric berthing but also eliminating unnecessary crossings.

During the busy day, BAU required 41 crossings, whereas EAS reduced this to 36, eliminating five underutilised crossings and improving average capacity efficiency by 12%. This efficiency is calculated as the total number of cars or freight served on that day divided by the number of crossings in the BAU and EAS schedules, respectively. On the non-busy day, BAU recorded 40 crossings, while EAS reduced this to 24, achieving a 40% improvement in capacity resource efficiency.

The berthing schedules for BAU and EAS during Phase 4 (*Full Hybrid*) on both the representative busy and non-busy days are shown in Fig. 5. In each of the four subplots, the horizontal axis represents a 24-h time horizon, while the numbered blocks in black or grey denote the sequence of scheduled ferries for each operator. For instance, in Fig. 5(a), under the BAU scenario, the first ferry from Operator 1 is scheduled at hour 1, whereas under the EAS scenario, the first ferry from Operator 3 is scheduled at the same time. At hour 2, BAU schedules the second ferry from Operator 1 and the first from Operator 2, while EAS schedules the first ferries from both Operators 1 and 2. Over the full horizon, BAU allocates 15 sailings for Operator 1 compared with 12 under EAS. These differences illustrate how, under BAU, ferry operators independently schedule their services in a decentralised manner to meet their own ticketed car passenger and freight demand, while overlooking the flexibility of freight tickets that can be utilised across operators. This leads to operational inefficiencies, such as under-capacity crossings, overlapping schedules during peak hours, excessive ferry deployments, and higher berth usage. Consequently, energy consumption increases, creating challenges for electricity provision during cold ironing, especially in Phase 4 (*Full Hybrid*), where all ferries are hybrid vessels.

In contrast, under the EAS approach, a more centralised and dynamic scheduling method is implemented. Initial berthing times, service termination times and berth allocations are determined using the EAS models to meet the three defined objectives. Embarkation of vehicles is scheduled dynamically based on the acceptable time windows and the availability of scheduled ferry services. This approach minimises overlap among operators in serving flexible-ticket freight demand, while ensuring that each ferry operator's specific car passenger demand is fully satisfied. This collective coordination optimises ferry scheduling to guarantee sufficient capacity for both car passengers and freight vehicles, while reducing redundancy in the number of ferries deployed per time period.

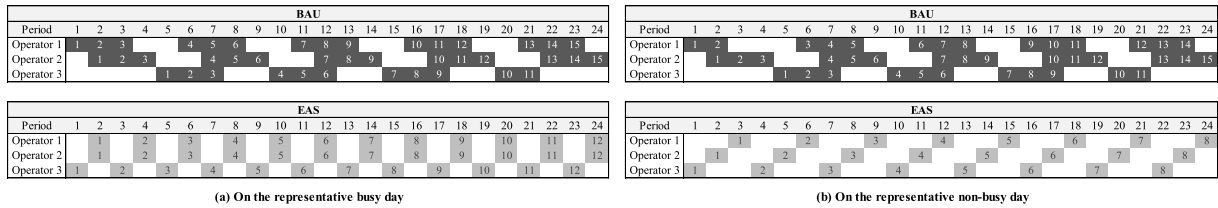


Fig. 5. Berthing schedules under the BAU and EAS approaches during Phase 4 (Full Hybrid).

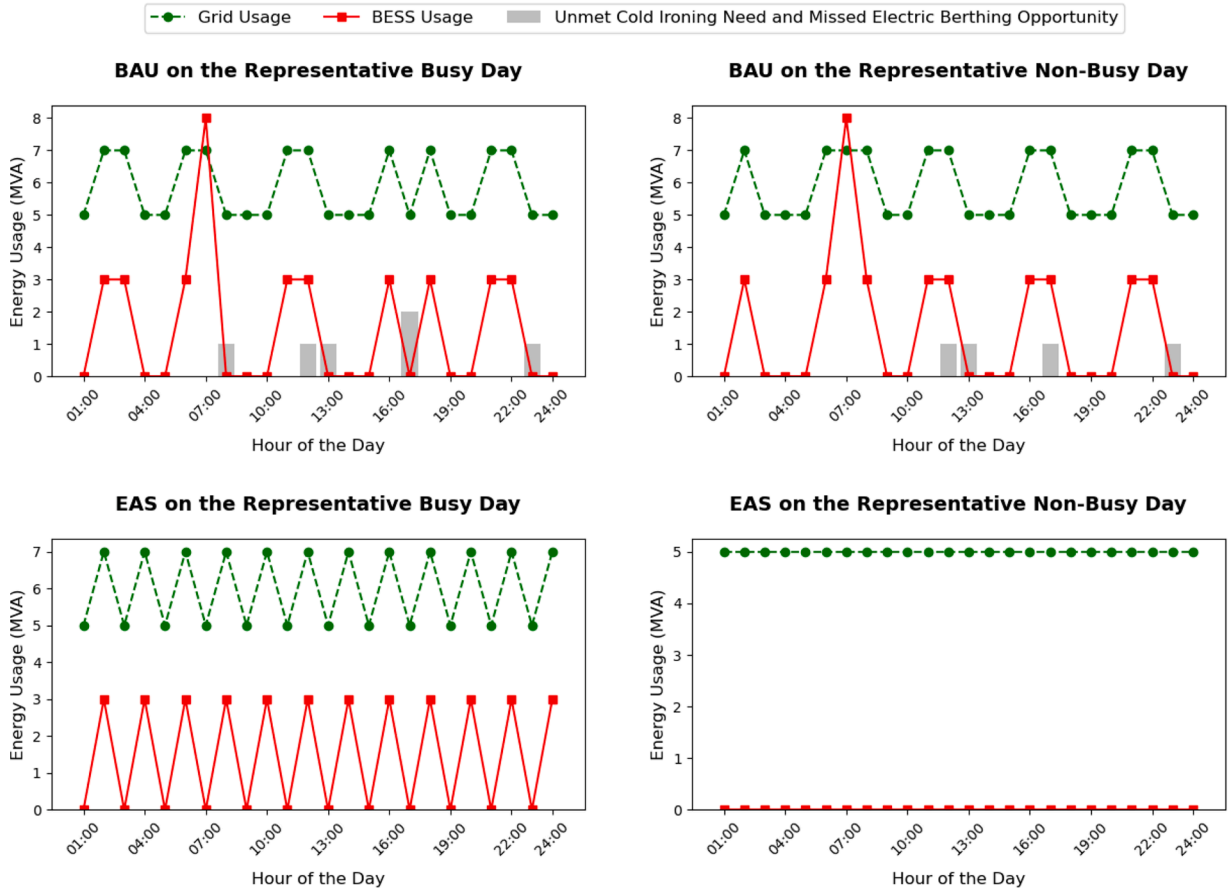


Fig. 6. Grid and BESS usage patterns under BAU and EAS approaches during Phase 4 (Full Hybrid).

The patterns of grid and BESS usage during berthing under the BAU and EAS approaches across these two days are compared in Fig. 6. The energy consumption pattern under EAS is significantly more balanced compared to BAU. The BAU approach results in substantial fluctuations in hourly energy consumption, drawing significant power from BESS during a short period, which could exceed discharge levels of BESS, cause system instability, require longer time to recharge and accelerate battery degradation.

Using the BAU approach in phase 4 (Full Hybrid), grid limitations frequently forced hybrid ferries to revert to diesel engines during berthing. For example, hybrid ferries relied on diesel power for one berthing in periods 8, 12, 13, and 23, and twice in period 17 on busy days, as well as in periods 12, 13, 17, and 23 on the non-busy day due to insufficient electricity availability. These occurrences significantly undermined the environmental benefits of hybridisation and exposed the inefficiencies of non-energy-aware strategies.

In contrast, the EAS model dynamically optimises ferry scheduling and electricity usage, enabling full reliance on cold ironing for all hybrid ferries. Even under the most electricity-intensive demand scenarios, EAS ensures that no hybrid ferry needs to revert to diesel engines while berthed. Although grid capacity exceedance events occur in the full-hybrid phase during busy days, coordinated use of grid supply and the Battery Energy Storage System (BESS) prevents operational disruption and excessive strain on energy resources.

Table 7

Aggregate performance results across diesel-to-hybrid transition phases.

Phase	P/P (Peak Car/Peak Freight)				P/O (Peak Car/Off-Peak Freight)			
	CO ₂ %	Grid Exc.	Elec. Berth%	Crossings	CO ₂ %	Grid Exc.	Elec. Berth%	Crossings
1. All Diesel	–	0	0%	36	–	0	0%	36
2. Hybrid Start	16%	0	22%	36	16%	0	22%	36
3. Hybrid Shift	39%	0	56%	36	39%	0	56%	36
4. Full Hybrid	70%	12	100%	36	70%	12	100%	36
Phase	O/P (Off-Peak Car/Peak Freight)				O/O (Off-Peak Car/Off-Peak Freight)			
	CO ₂ %	Grid Exc.	Elec. Berth%	Crossings	CO ₂ %	Grid Exc.	Elec. Berth%	Crossings
1. All Diesel	–	0	0%	24	–	0	0%	24
2. Hybrid Start	20%	0	29%	24	20%	0	29%	24
3. Hybrid Shift	44%	0	63%	24	44%	0	63%	24
4. Full Hybrid	70%	0	100%	24	70%	0	100%	24

Legend: CO₂% = Emission improvement (compared to phase 1 (*All Diesel*)), Grid Exc. = Grid capacity exceedances, Elec. Berth% = Percentage of berthing instances powered by electricity, Crossings = Total ferry crossings.

Importantly, reported grid capacity exceedance events do not indicate a failure of port operations. Each exceedance corresponds to a short time interval during which the BESS is deliberately activated to supply peak electricity demand beyond the grid import limit. These events therefore represent controlled and planned peak-shaving behaviour rather than power shortages or interruptions to ferry services.

The occurrence of 12 exceedance events per day arises only in the most extreme scenario considered, namely the full-hybrid phase combined with simultaneous peak car and peak freight demand. This configuration represents a worst-case stress test of the shore-power system rather than a typical operating condition. Even under the energy-aware schedule, exceedance events persist in this scenario because instantaneous peak demand temporarily exceeds the available grid capacity.

From an operational perspective, this frequency of exceedance remains feasible because the BESS has been sized to accommodate such peaks without compromising service continuity. However, frequent BESS discharge is undesirable in practice as it accelerates battery degradation and increases long-term maintenance requirements. This consideration directly motivates the second optimisation objective, which seeks to minimise the number of exceedance events rather than to eliminate them entirely.

If a port authority considers such exceedance frequencies unacceptable even under rare peak-demand conditions, the model clearly indicates that operational optimisation alone has reached its limit. In such cases, additional grid reinforcement or expansion of BESS capacity becomes necessary.

Overall, the results demonstrate that energy-aware scheduling substantially reduces the frequency of grid capacity exceedance events compared with the business-as-usual schedule. This outcome aligns with the operational objectives of the case-study port, where grid exceedance is acceptable only as an occasional contingency and not as a routine mode of operation.

5.5. CO₂ emission analysis across decarbonisation transition phases

To assess the potential CO₂ emission reductions achievable during each transition phase, the proposed energy-aware model was tested across the four demand scenarios described in Section 5.1: Peak Cars/Peak Freight (P/P), Peak Cars/Off-Peak Freight (P/O), Off-Peak Cars/Peak Freight (O/P), and Off-Peak Cars/Off-Peak Freight (O/O). These scenarios capture variations in cars and freight demand, allowing for a comprehensive evaluation of the model's performance under diverse operational conditions. Although the P/P scenario is not a common occurrence in this case study, it was included to stress-test the model's robustness under extreme demand conditions. By considering this scenario, the analysis ensures that the model remains effective even in high-demand situations that may push infrastructure and operational constraints to their limits.

Shoreside port emissions are commonly classified into three standard scopes, following frameworks established by the IMO and related studies (Zhang et al., 2025). Scope 1 includes direct emissions from owned or controlled sources. Scope 2 refers to indirect emissions from purchased electricity, heat, or steam, which are not directly relevant to ferry operations in this study. Scope 3 includes indirect emissions from activities not owned or directly controlled by the port. This research examines Scope 1 for ferry operators and Scope 3 emissions for Port A.

For each demand scenario, two types of CO₂ emission analyses were carried out: 1) Aggregate CO₂ emission reduction assesses total CO₂ reduction among the three operators, categorised as scope 3 emissions for Port A. 2) Operator-specific CO₂ emission reduction measures CO₂ reductions during berthing for each ferry operator, classified as scope 1 emissions for each operator.

5.5.1. Port-side CO₂ emission analysis

The results demonstrate the maximum emission reductions achievable in each decarbonisation phase, reflecting the effectiveness of the proposed approach in leveraging hybrid ferry technology and optimising energy usage. A detailed summary of the findings is provided in Table 7.

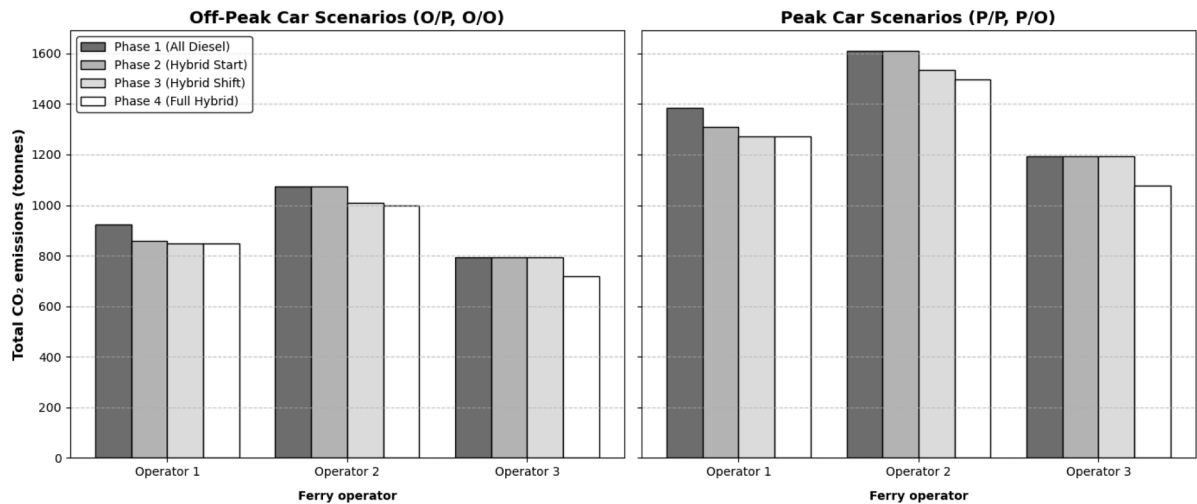


Fig. 7. Total daily CO₂ emissions from berthing and crossings for each operator across transition phases.

The findings reveal that peak and off-peak car demand significantly influences scheduling, while freight demand has minimal impact due to its flexible ticketing scheme and relatively lower variability compared to car demand. In scenarios with peak car demand, the total number of crossings consistently reaches 36, while off-peak car demand reduces this number to 24. Freight flexibility allows for optimised scheduling without altering the total number of crossings.

The analysis further shows that the gradual diesel-to-hybrid transition yields substantial emission reductions, ranging from 16% to 70%, depending on the phase. Meanwhile, the share of electricity-powered berthing increases progressively, from 22% in early phases to 100% in the final phase.

The adoption of hybrid ferries significantly reduces carbon emissions while maximising the use of electricity during berthing. Grid exceedances are observed only in the *Full Hybrid* phase, highlighting the need for strategic energy management in advanced phases of the transition.

5.5.2. Ferry operator-side CO₂ emission analysis

Fig. 7 illustrates the average CO₂ emissions from all ferry operations, including berthings and crossings, for each operator over a full day across the four diesel-to-hybrid transition phases. While all crossings remain diesel-powered, berthing operations can be powered by either electric or diesel, depending on the number of ferries converted to hybrid in each phase. In both peak and off-peak car demand scenarios, noticeable differences between operators emerge during the middle transition phases, i.e., phase 2 (*Hybrid Start*) and phase 3 (*Hybrid Shift*). However, by phase 4 (*Full Hybrid*), all operators achieve substantial CO₂ reductions, having fully transitioned to electric berthing.

Unlike the aggregate CO₂ emission analysis, which evaluates overall reductions within the port area, the operator-specific CO₂ emission analysis provides a more detailed assessment of each ferry operator's transition. This analysis highlights how individual operators benefit from hybrid adoption and their corresponding contributions to emission reductions. Table 8 summarises CO₂ reductions achieved as operators transition from diesel-powered to electricity-powered berthing.

The results show differences in the pace of each operator's transition from diesel to electricity and the resulting CO₂ reductions. Operator 1 transitions to hybrid ferries the fastest, significantly reducing diesel reliance from phase 2 (*Hybrid Start*) onwards. During this phase, it achieves a 5% CO₂ reduction in peak car scenarios and to 7% in off-peak scenarios. By phase 3 (*Hybrid Shift*), the reduction reaches 8% in both demand scenarios, marking the maximum achievable CO₂ reduction using cold ironing across all three ferries during berthing.

Operator 2 adopts hybrid ferries at a slower pace, remaining fully diesel-dependent until phase 3 (*Hybrid Shift*). With a one-phase delay compared to Operator 1, it achieves a 5% to 7% CO₂ reduction in phase 3 (*Hybrid Shift*) and further reaches a 7% reduction in phase 4 (*Full Hybrid*).

Operator 3 transitions the slowest, with no emission reductions until phase 4 (*Full Hybrid*). This delay is attributed to differences in fleet upgrade plans, investment strategies, and readiness to adopt hybrid technology.

By phase 4 (*Full Hybrid*), all operators successfully transition to 100% electricity-powered berthing operation, achieving CO₂ reduction of 8% for Operator 1, 7% for Operator 2, and 9% for Operator 3, compared to phase 1 (*All Diesel*). The extent of these reductions varies depending on vessel engine size and corresponding energy consumption. Operator 2 operates the largest ferries with the highest diesel consumption during crossings, whereas Operator 3 operates the smallest ferries with relatively lower fuel consumption. Since CO₂ reductions in these phases result solely from replacing diesel powered berthing with electricity powered berthing, the maximum achievable reduction is not that significant, as ferry crossings remain diesel-powered.

Table 8
Operator-specific performance results across diesel-to-hybrid transition phases.

Operator	Phase	Peak car scenarios (P/P, P/O)			Off-peak car scenarios (O/P, O/O)		
		CO ₂ %	Elec. berthing	Diesel berthing	CO ₂ %	Elec. berthing	Diesel berthing
Operator 1	phase 1 (<i>All Diesel</i>)	–	0	12	–	0	8
	phase 2 (<i>Hybrid Start</i>)	5%	8	4	7%	7	1
	phase 3 (<i>Hybrid Shift</i>)	8%	12	0	8%	8	0
	phase 4 (<i>Full Hybrid</i>)	8%	12	0	8%	8	0
Operator 2	phase 1 (<i>All Diesel</i>)	–	0	12	–	0	8
	phase 2 (<i>Hybrid Start</i>)	0%	0	12	0%	0	8
	phase 3 (<i>Hybrid Shift</i>)	5%	8	4	6%	7	1
	phase 4 (<i>Full Hybrid</i>)	7%	12	0	7%	8	0
Operator 3	phase 1 (<i>All Diesel</i>)	–	0	12	–	0	8
	phase 2 (<i>Hybrid Start</i>)	0%	0	12	0%	0	8
	phase 3 (<i>Hybrid Shift</i>)	0%	0	12	0%	0	8
	phase 4 (<i>Full Hybrid</i>)	9%	12	0	9%	8	0

Legend:
CO₂% = CO₂ emission reduction in each phase compared to phase 1 (*All Diesel*), evaluated per operator.
Elec. berthing = Number of berthing instances powered by electricity, evaluated per operator.
Diesel berthing = Number of berthing instances powered by diesel, evaluated per operator.

6. Conclusions

This paper presents a comprehensive methodology to support the gradual transition from diesel ferries to hybrid ferries at a European port, aligning with global maritime decarbonisation goals. The study incorporates an innovative mixed-integer programming (MIP) model to optimise berth allocation and ferry scheduling, addressing key operational, environmental, and economic objectives.

6.1. Findings and managerial insights

The computational experiments and analysis reveal the following key findings and insights:

- Transitioning to hybrid ferries, as part of a broader technological advancement strategy, combined with an energy-aware operational optimisation approach, reduces CO₂ emissions from 16% in phase 2 (*Hybrid Start*) to 70% in phase 4 (*Full Hybrid*), with zero missed electric berthing opportunities. These results are achieved by stabilising energy demand, avoiding the demand surge during berthing overlapping that can occur under non-energy-aware scheduling.
- All demand scenarios can be accommodated using the proposed EAS model, with fewer crossings compared to BAU. Car demand follows a fixed single-operator ferry ticketing scheme, directly influencing scheduling and the number of crossings. In contrast, freight demand operates under a flexible multi-operator ticketing scheme, allowing greater scheduling flexibility with no effect on the number of crossings in this case.
- The transition roadmap examined in this case study shows that the existing infrastructure is sufficient to meet electricity demand in Phase 2 (*Hybrid Start*) and Phase 3 (*Hybrid Shift*), while only limited reinforcement is required in Phase 4 (*Full Hybrid*). In particular, a modest increase of 1 MVA in grid capacity or the addition of 6 MW of Battery Energy Storage System (BESS) capacity is sufficient to preserve feasibility. Under the most demanding combination of peak car and peak freight demand, a small number of grid capacity exceedance events still occur despite energy-aware scheduling. These events reflect controlled use of stored energy in the BESS to accommodate short-lived demand peaks rather than operational disruption. Their occurrence under this extreme scenario indicates the point at which energy-aware scheduling optimisation has reached its practical limit and where incremental grid reinforcement becomes the appropriate policy response.
- The results show that, under coordinated energy-aware scheduling, regular ferry demand can be served without waiting by actively using only three cold-ironing-equipped berths across all analysed scenarios. This represents the minimum number of berths that need to be operationally activated during the scheduling horizon, rather than the total number of berths a port should maintain. In practice, additional berths remain essential to ensure operational resilience, accommodate maintenance activities, manage disruptions, and support future demand growth as ferry traffic increases over time. The finding should therefore be interpreted as an efficiency benchmark for berth activation that can help ports reduce unnecessary maintenance and operating costs, rather than as a recommendation to idle or decommission existing berth infrastructure.
- The EAS model achieved CO₂ emission reductions of 12% to 51% compared to the BAU approach, with benefits increasing as more diesel ferries transition to hybrids. These findings demonstrate that coupling technological advancements with cost-effective operational strategies can significantly enhance environmental performance. The EAS approach reduces dependence on diesel engines during berthing. By optimising electricity usage and evenly distributing grid loads, the EAS model not only maximises CO₂ savings but also reduces BESS charge-discharge cycles, extending its lifespan and ensuring that the BESS remains fully charged most of the time.

- In the absence of hybrid upgrades or decarbonisation efforts—such as in Phase 1 (*All Diesel*), where hybridisation has not yet commenced—the EAS approach still demonstrates notable environmental benefits by eliminating unnecessary crossings without requiring additional investment. Compared to BAU scheduling, EAS achieves CO₂ emission reductions of 12% on a representative busy day and 40% on a representative non-busy day. These results show the potential of cost-effective and immediately implementable operational strategies to reduce emissions. EAS thus offers a practical, cost-effective pathway for ports to improve their environmental performance while laying the groundwork for future decarbonisation.

An important property of the proposed model is the fixed and synchronised nature of ferry schedules on short-sea routes. Optimising berthing decisions at one port automatically determines the arrival and berthing pattern at the opposite port, allowing the benefits of energy-aware scheduling, such as reduced simultaneity of hybrid ferry berthings and avoidance of peak cold-ironing demand, to propagate across the entire corridor. This feature enhances the generalisability of the proposed model and supports its application to ferry routes where ports are at different stages of transition towards shore power adoption.

Overall, the proposed approach demonstrates that a gradual diesel-to-hybrid transition can deliver substantial operational, environmental, and economic benefits when supported by energy-aware scheduling and berth allocation. Rather than relying solely on infrastructure-heavy investments, the model emphasises the value of smart operational planning and electricity load management as enabling mechanisms for a financially sustainable transition. The empirical results provide decision support for port authorities, ferry operators, and policy makers seeking both short-term and long-term pathways towards low-carbon ferry operations. By prioritising optimisation-based planning tools before committing to capital-intensive grid or BESS expansions, ports can achieve early emissions reductions while preserving investment flexibility. The model further offers evidence to inform targeted policy instruments, including time-of-use incentives, emission-based berth prioritisation, and differentiated access rules based on energy efficiency and scheduling flexibility. By explicitly accounting for the high-frequency and tightly coupled nature of ferry services, this study also supports the development of coordinated, energy-aware scheduling systems underpinned by contractual arrangements between ports and ferry operators. Such coordination can play a critical role in aligning operational decisions with decarbonisation objectives across ferry corridors.

6.2. Limitations and suggestions for future studies

A key methodological insight of this study is that ferry scheduling and berth allocation cannot be meaningfully separated in short-sea ferry terminals, and must instead be optimised within a single integrated framework. This stems from the fixed and highly synchronised nature of ferry services, where berthing decisions directly determine feasible schedules, energy usage patterns, and the ability to exploit shore power effectively.

Building on this insight, future studies should investigate more ambitious decarbonisation strategies involving fully electric ferries. In particular, extending shore power usage beyond auxiliary engines during berthing to also support main propulsion during crossings would substantially alter energy demand profiles. Such a transition would introduce additional challenges related to grid capacity, BESS sizing, and charging coordination, thereby requiring further technical, operational, and economic analysis.

In addition to technological evolution, future research should examine commercial and institutional dynamics. The formation of alliances among ferry operators, for example, may enable coordinated service planning and reductions in the total number of crossings during both peak and off-peak periods. Such collaboration could further enhance emissions reductions while improving utilisation of shared berth and energy infrastructure.

While the present case study assumes sufficient cold-ironing infrastructure in each transition phase, other ferry ports may experience temporary shortfalls due to demand growth, delays in infrastructure deployment, or unplanned outages. A natural extension of the proposed framework would therefore be to incorporate a diesel fallback option, allowing the optimisation to identify when fallback becomes unavoidable and how its environmental impacts can be minimised.

The present study employs Gurobi as a standard commercial optimisation solver, which proved sufficient for the case study port, one of the busiest ferry ports in Europe, where all demand instances were solved to proven optimality within two seconds. However, in view of potential future traffic growth, larger fleets, or real-time operational requirements, future research may explore more scalable solution strategies such as rolling-horizon optimisation, decomposition-based methods, or tailored heuristics.

Finally, future ferry scheduling models should explicitly account for landside traffic interactions. Neglecting the impact of ferry arrivals and departures on landside congestion, particularly in busy ports, may limit the effectiveness of otherwise well-designed decarbonisation strategies. Addressing landside traffic dynamics is therefore essential to ensure the practicality and overall success of sustainable maritime transport strategies.

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Asefe Forghani: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization; **Ying Xie:** Writing – review & editing, Validation, Supervision, Investigation, Funding acquisition, Conceptualization; **Mahdi Jahangard:** Writing – original draft, Investigation, Data curation; **Dongping Song:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization; **Yuanjun Feng:** Writing – review & editing, Validation, Methodology, Formal analysis.

Data availability

This study uses empirical data from a ferry port in Western Europe, referred to as Port A. An anonymised summary of the data, including infrastructure configuration, vessel characteristics, and demand patterns, is provided in [Section 5.1](#). Full access to the original dataset is restricted by confidentiality agreements with the port authority and ferry operators.

Declaration of competing interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Appendix A. Evaluation of infrastructure sufficiency in port A's transition plan

To evaluate the adequacy of Port A's planned infrastructure for the phased transition from diesel to hybrid ferries, all demand instances were tested under two scenarios: (1) a constrained cold ironing infrastructure, where grid and BESS capacities are limited to those planned in each of the four decarbonisation transition phases ([Fig. 2](#)); and (2) an unconstrained scenario, assuming all berths at Port A have unlimited cold ironing capacity. This analysis examines whether the planned infrastructure in each phase can meet the electricity demands of all vessels and maximise environmental benefits, or if expansions to grid capacity, BESS, or further conversions of regular berths to cold ironing-equipped berths are required. [Table A.1](#) summarises the findings.

Table A.1
Infrastructure requirements and adjustments for the four transition phases.

Phase	Planned (G/B, Berths)	MaxEUse, CI/N-CI Used	Required Adjustments
1. All Diesel	0/0, 0 CI/9 N-CI	0, 0 CI/3 N-CI	None
2. Hybrid Start	5/0, 1 CI/8 N-CI	5, 1 CI/2 N-CI	None
3. Hybrid Shift	5/5, 5 CI/4 N-CI	5, 2 CI/1 N-CI	None
4. Full Hybrid	7/8, 9 CI/0 N-CI	10, 3 CI/0 N-CI	Grid (+1) or BESS (+6)

Legend: G/B = Grid/BESS capacity; CI/N-CI = Cold Ironing/Non-Cold Ironing berths;
 MaxEUse = Maximum energy usage in each phase;
 CI/N-CI Used = Number of Cold Ironing (CI) and Non-Cold Ironing (N-CI) berths used;
 Adjustments = Additional capacity required to ensure feasibility.

The results indicate that the number of cold ironing berths specified in the planned phases is sufficient for all operations. While a maximum of three cold ironing berths is theoretically required, maintaining the additional berths planned for each phase provides operational flexibility during unexpected disruptions or maintenance.

For phases 1–3, the planned grid and BESS capacities are sufficient to achieve maximum decarbonisation by operating all the hybrid ferries. Expanding infrastructure during these phases provides no additional benefits and does not increase reliance on hybrid crossings, making further cold ironing investments unnecessary.

In phase 4 (*Full Hybrid*), the planned grid and BEE capacities are insufficient to meet certain demand instances. This can be resolved by increasing the grid capacity to 10 MVA if relying entirely on grid power, thereby eliminating the need for BESS. Alternatively, feasibility can be achieved with minimal adjustments by either adding 6 MW to the BESS or increasing the grid capacity by 1MVA, thus preserving most of the planned infrastructure. Phase 3 (*Hybrid Shift*) demonstrates no grid exceedance, with the 5 MVA BESS included in the planned infrastructure effectively serving as a backup resource. This confirms that the capacity established in phase 2 (*Hybrid Start*) is sufficient for phase 3 (*Hybrid Shift*) without requiring further expansion.

For the computational experiments in [Section 5](#), the planned infrastructure shown in [Fig. 2](#) is applied consistently. In rare instances where cold ironing capacity results in infeasibility, an additional 6 MW of BESS is introduced as a contingency measure. This adjustment is applied only in Phase 4 (*Full Hybrid*) to maintain feasibility.

Appendix B. Sensitivity analysis on objective prioritisation

This appendix presents selected sensitivity analyses to support interpretation of the adopted lexicographic objective structure. The optimisation results reported in [Section 5](#) are obtained using a lexicographic multi-objective order that reflects the decision hierarchy of the case study port authority. In the proposed lexicographic order, denoted as P_0 , objectives are prioritised as follows: (i) minimisation of CO₂ emissions, thereby improving environmental quality in and around the port area; (ii) minimisation of grid capacity exceedance events, thereby reducing reliance on the Battery Energy Storage System (BESS) and enhancing overall energy system reliability; and (iii) minimisation of berth activation, thereby limiting long-term maintenance and repair costs associated with berth infrastructure.

To examine how alternative decision hierarchies influence operational outcomes, the objective order was modified and compared against P_0 . Two alternative lexicographic sequences were considered:

- P_1 (**Grid–Emission swap**): grid capacity exceedance minimisation → CO₂ emissions minimisation → berth activation minimisation, representing a context in which energy system reliability is prioritised ahead of environmental performance;

- **P₂ (Berth–Emission swap):** berth activation minimisation → CO₂ emissions minimisation → grid capacity exceedance minimisation, representing a context in which infrastructure utilisation and maintenance considerations dominate environmental objectives.

Under the original infrastructure configuration and demand scenarios considered in the main case study, as presented in Fig. 2 and Section 5.1, the optimisation yields identical solutions under P₀, P₁, and P₂. This outcome is consistent with the results reported in Section 5.5. Grid capacity exceedance events occur only in Phase 4 (*Full Hybrid*), while in earlier phases the grid constraint remains non-binding under the proposed energy-aware model. Moreover, across all demand scenarios defined in Table 4, including the Off-Peak Cars / Off-Peak Freight (O/O) case, all available ferries are required to meet demand. As a result, for any operator with at least one hybrid ferry, at least one cold-ironing-equipped berth must be activated, leaving no opportunity to reduce berth activation penalties through alternative scheduling. In Phase 4 (*Full Hybrid*), although grid capacity exceedance occurs, all ferries are hybrid, leaving no operational flexibility to mitigate exceedance through vessel substitution. Consequently, reordering the grid or berth objectives does not alter scheduling decisions under the original demand conditions.

To further examine the robustness of the proposed lexicographic order, the sensitivity analysis was extended by introducing controlled binding grid constraints in earlier transition phases. With the parameters reported in Fig. 2, as discussed in Section 5.5, grid capacity exceedance under the energy-aware schedule occurs only in Phase 4 (*Full Hybrid*). To enable meaningful sensitivity insights for the middle phases, a targeted hypothetical adjustment was therefore applied.

For this purpose, in Phase 2 (*Hybrid Start*) and Phase 3 (*Hybrid Shift*), grid capacity was reduced by 1 MVA and BESS capacity increased by 5 MW relative to Fig. 2. These adjustments create binding grid conditions in phases where hybrid and diesel ferries coexist, thereby enabling observation of how objective reordering affects grid exceedance behaviour. No adjustments are made in Phase 1 (*All Diesel*) or Phase 4 (*Full Hybrid*) in order to preserve consistency with the main analysis.

Under these modified infrastructure conditions, no differences are observed between P₀, P₁, and P₂ for either the Peak Cars and Peak Freight (P/P) or Off-Peak Cars and Off-Peak Freight (O/O) demand scenarios. In both cases, demand remains sufficiently high that all ferries assigned to each operator are required. As a result, there is no scope to idle vessels or substitute between diesel and hybrid ferries in order to trade emissions against grid readability, or berth activation decisions, such as reallocating services from cold ironing equipped berths to regular berths.

To explicitly illustrate the conflicting nature of the objectives, a hypothetical scenario was constructed in which demand is substantially reduced. In this reduced-demand case, both car and freight arrival rates are set to half of the O/O values based on the Poisson parameters in Table 4. In addition, the acceptable embarkation time windows ℓ_v are extended by two periods for each demand type relative to the case study settings, allowing greater aggregation of demand over time and increased scheduling flexibility. This demand scenario, denoted as (0.50/0.50), represents an unusually low-demand day, reduces the number of required ferry crossings, and introduces operational slack that enables discretionary vessel idling.

To amplify objective conflicts, fleet composition was also modified by slightly slowing the hybrid upgrade of ferries in the intermediate phases. In Phase 2 (*Hybrid Start*), Operator 1 operates one hybrid ferry instead of two, while the other operators remain unchanged. Similarly, in Phase 3 (*Hybrid Shift*), Operator 2 operates one hybrid ferry instead of two, with the other operators unchanged. As in the previous sensitivity setup, grid capacity in these phases is reduced by 1 MVA and BESS capacity is increased by 5 MW to ensure binding grid constraints.

Under these conditions, objective conflicts become evident. In the reduced-demand setting, fewer ferry crossings are sufficient to serve demand, allowing the optimisation model to idle one ferry per operator. Under P₀, where emission minimisation is the highest-priority objective, diesel ferries are preferentially idled whenever possible. This ensures that hybrid ferries remain in service, preserves cold-ironing usage, and maximises emission reductions.

In Phase 2 (*Hybrid Start*), P₁ and P₂ yield identical outcomes. In this phase, only one hybrid ferry exists in the entire fleet under the hypothetical configuration, belonging to Operator 1. By idling this hybrid ferry, both grid capacity exceedance and the activation of cold-ironing-equipped berths can be completely avoided. This decision leads to identical reductions in grid exceedance events and cold-ironing berth activation under P₁ and P₂, but at the cost of an identical increase in emissions of approximately 15% relative to P₀, where a diesel ferry is idled instead.

In Phase 3 (*Hybrid Shift*), P₀ and P₁ produce identical solutions. In this phase, all ferries of Operator 1 are hybrid, and the available grid capacity without reliance on BESS is insufficient even for a single electrically powered berthing. As a result, grid capacity exceedance cannot be reduced through alternative scheduling, regardless of whether grid reliability is prioritised ahead of emissions. Consequently, reordering the grid and emission objectives does not alter scheduling decisions, and P₀ and P₁ yield identical outcomes.

In contrast, under P₃, where berth activation cost is prioritised ahead of emissions, the optimisation idles the newly upgraded hybrid ferry of Operator 3 instead of a diesel ferry. This reduces the number of activated cold-ironing-equipped berths by one relative to P₀, but results in a substantial increase in emissions of approximately 21%, while grid exceedance remains unchanged.

In Phase 1 (*All Diesel*), where all ferries are diesel, and Phase 4 (*Full Hybrid*), where all ferries are hybrid, idling decisions are identical across all priority structures, as no substitution between vessel types is possible. Consequently, sensitivity to objective ordering disappears in these phases, and P₀, P₁, and P₃ yield identical outcomes.

Table B.1 reports selected quantitative results for the hypothetical reduced-demand scenario (0.50/0.50), expressed relative to P₀. Results are shown for all four transition phases and confirm that differences arise only in the intermediate phases, where both technological heterogeneity and operational slack are present.

Table B.1Sensitivity results for the reduced-demand scenario (0.50/0.50), reported relative to P_0 .

Priority	Phase	$\Delta CO_2\%$	Δ Grid Exc. (events)	Δ CI Berths Activated
P_1	Phase 1 (<i>All Diesel</i>)	0	0	0
	Phase 2 (<i>Hybrid Start</i>)	+15	−4	−1
	Phase 3 (<i>Hybrid Shift</i>)	0	0	0
	Phase 4 (<i>Full Hybrid</i>)	0	0	0
P_2	Phase 1 (<i>All Diesel</i>)	0	0	0
	Phase 2 (<i>Hybrid Start</i>)	+15	−4	−1
	Phase 3 (<i>Hybrid Shift</i>)	+21	0	−1
	Phase 4 (<i>Full Hybrid</i>)	0	0	0

Legend: $\Delta CO_2\%$ = change in emission reduction relative to P_0 ; Δ Grid Exc. (events) = change in the number of grid capacity exceedance events relative to P_0 ; Δ CI Berths Activated = change in the number of cold-ironing-equipped berths activated relative to P_0 .

Overall, these results indicate that objective prioritisation becomes consequential primarily under unusually low-demand conditions, where the optimisation model has sufficient flexibility to idle vessels. In such settings, prioritising grid reliability or berth utilisation ahead of emission minimisation can undermine decarbonisation outcomes by favouring the idling of hybrid ferries and increased reliance on diesel operation. Under realistic demand levels at the case study port, however, all ferries are required to meet demand, operational flexibility is limited, and the proposed lexicographic order P_0 yields stable, robust, and policy-consistent outcomes across all transition phases.

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