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Cost-effective planning and abatement costs of battery electric passenger vessel services

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ABSTRACT

This paper analyzes the energy replacement potential for high-speed passenger vessels. Emphasis is on whether better planning of services can mitigate technical and economic barriers to zero emission transport. A novel Mixed-Integer Programming problem for battery electric vessel services that jointly minimizes operator and passenger costs subject to strategic (fleet selection and land-based infrastructure location), tactical (frequency), and operational decisions (sailing pattern) is proposed. The planning problem is utilized to estimate technology replacement potential and associated costs for two existing services/routes in Norway and based on four hypothetical demand scenarios derived from the same two services. The results showcase that constraints related to battery range and charging limit the replacement potential and make energy conservation more pertinent. Abatement cost estimates range between 3 000 and 18 000 NOK per ton CO_2, placing them well above the social cost of carbon calculated at 2 000 NOK per ton by 2030.

1. Introduction

The transport sector is among the most polluting sectors worldwide, accounting for about 25 percent of greenhouse gas (GHG) emissions from energy in 2019 (IEA, 2022). It is consequently expected to deliver substantial emission cuts to meet emission targets set the by the Paris agreement. Norway's current targets under the agreement are to reduce its GHG emissions by at least 50 to 55 percent relative to 1990 levels by 2030 and to become a low-emission society by 2050. Ambitious climate policies have already made it a front-runner in the diffusion of low and zero emission technologies for private cars (Wangsness et al., 2020). In 2021, the Norwegian Government launched its Climate Plan 2021–2030 to also halve domestic maritime transport emissions by 2030 relative to 2005 emissions. This is ahead of International Maritime Organization's (IMO's) initial strategy to halve GHG emissions from ships by 2050 relative to 2008 levels. Among key measures launched by the Climate Plan are low and zero emission requirements – where feasible – for ferries from 2023 and high-speed ferries from 2025. Moreover, more weight is placed on the Polluter-Pays Principle by signaling increases in the carbon tax from 590 Norwegian Kroner (NOK = approx. 0.11 USD) per ton today to 2 000 NOK per ton in 2030.

Although Norway is among the countries with the longest coastline, it is small and many coastal communities are sparsely populated. Passenger vessels such as high-speed ferries are a common part of the country's coastal transport system, with around 100 diverse passenger vessel services currently in operation. Due to low demand with around 70 percent of services transporting

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less than 100 passengers per day (Tveter et al., 2020), they are among the costliest (Aarhaug et al., 2017) and most emission intensive (Eide et al., 2018) of public transport modes. Replacing the existing fleet of conventional diesel-fueled vessels by zero emission technologies can therefore contribute to Norway's GHG target, but can also carry abatement costs that substantially surpass the planned carbon tax trajectory. This paper aims to provide new insights regarding technical and economic feasibilities of replacing diesel by zero emission passenger vessels, considering both costs related to upholding existing services and changes in optimal frequencies with change in energy technology.

Currently, there are 52 battery electric ferries in operation in Norway,[1] but no zero emission high-speed vessel. However, the initiative, *Transport: Advanced and Modular* (TrAM) is in its final stages and aims to launch an electrical high-speed ferry in 2022. This initiative is coordinated by the Public Transit agency Kolumbus AS in the county of Rogaland, and has resulted in the construction of the world's first battery electric high-speed vessel named *Medstraum*. The vessel will accommodate 150 passengers and 20 bicycles, with a battery capacity of 1 500 kilowatt hour (kWh) and a maximum charging power of 2 000 kW. The vessel is designed for an operating speed of 23 knots (Rogaland Fylkeskommune, 2021). Zero emission high-speed vessels are currently also being considered for other connections, and several feasibility studies for technology replacement exist (see Sundvor et al. (2021) for an overview).

The energy replacement potential for high-speed passenger vessels is confined due to their demanding usage profile and limited time for charging/bunkering. Using Automatic Identification System (AIS) data to calculate energy use of the existing Norwegian fleet, Sundvor et al. (2021) estimate that 51 out of 73 vessels are suitable for hydrogen propulsion, while only 12 are also suitable for battery electric propulsion. This is a hurdle because energy carriers such as hydrogen and ammonia are in their infancies, and current uptake of zero emission technology in the maritime sector is primarily due to battery electric propulsion (Sundvor et al., 2021). With the introduction of zero emission criteria for passenger vessels just a few years away, this paper focuses on battery electric vessels under the overarching hypothesis that the replacement potential is excelled with better planning of services.

This paper advances the pioneering study of Sundvor et al. (2021) using *optimization* to strike the balance between costs and benefits of transport provision. Key research questions examined herein concern to what extent new constraints related to charging affect optimal scheduling of battery electric vessels (compared to conventional vessels) and the size of economic gains from adapting timetables. To study this, we define the *Zero Emission Vessel Route Planning Problem* (ZEVRPP), which deals with the optimal planning of a route to be serviced by battery electric vessels. The ZEVRPP is a planning problem that is relevant for all coastal areas offering a passenger vessel service to their inhabitants. We develop a novel Mixed-Integer Programming (MIP) model for the ZEVRPP. The model includes *strategic decisions* regarding vessel characteristics and fleet size alongside charging infrastructure location, a *tactical decision* in terms of determining service frequency, and *operational decisions* regarding the sailing speeds at different legs along the route. The objective of the planning problem is minimization of system costs, comprising both operator costs and passenger waiting and travel time costs.

The ZEVRPP is studied to estimate technology replacement potential and associated costs for two existing services in Norway, as well as for four hypothetical and increased demand scenarios for these two services. The latter generalize the analysis to services that are operated in more densely populated areas. The results showcase that constraints related to battery range and charging limit the replacement potential and make energy conservation more pertinent with adoption of battery electric vessels. In most cases analyzed, optimal frequency entails increasing the fleet size to uphold existing schedules, while in some cases it is optimal to reduce frequency with battery electric propulsion. In latter cases, there are substantial costs savings from changing current timetables, which in our experience is an abatement strategy that is overlooked by Norwegian decision makers. Cost estimates range between 3 000 and 18 000 NOK per ton of abated CO_2, placing them well above the social cost of carbon calculated at 2 000 NOK per ton by 2030.

The literature on optimization-based decision support for planning of zero emission passenger vessel services is scarce, and the role that tactical decisions play in facilitating battery electric vessel services has received limited attention in service planning. This paper contributes to filling these research voids, hence providing important new knowledge and decision support to steer the desired sustainable transformation of the transport sector.

This paper is organized as follows. Section 2 provides a stylized characterization of key economic trade-offs in the diffusion of zero emission vessels alongside the paper's placement in the literature. Section 3 provides a general description of the optimization problem, while Section 4 outlines the mathematical model. Section 5 presents the case studies, while Section 6 presents the numerical results. Finally, Section 7 summarizes the study and provides recommendations for policy and further research.

2. Background and literature review

In the following, we provide a background and review of relevant literature.

Optimal frequency of zero emission public transport

Our personal communication with County Councils in charge of public transport in Norway reveals that emphasis is on replacing vessels whilst upholding existing routes and schedules. This approach disregards that the cost structure can be fundamentally changed with the introduction of new technologies, thereby leading to suboptimal allocation that makes technology swapping excessively costly and hence limits transition. This can be illustrated by a simple model for optimal public transport supply, inspired

[1] See https://energiogklima.no/elektriske-bilferger-i-norge/ (in Norwegian)

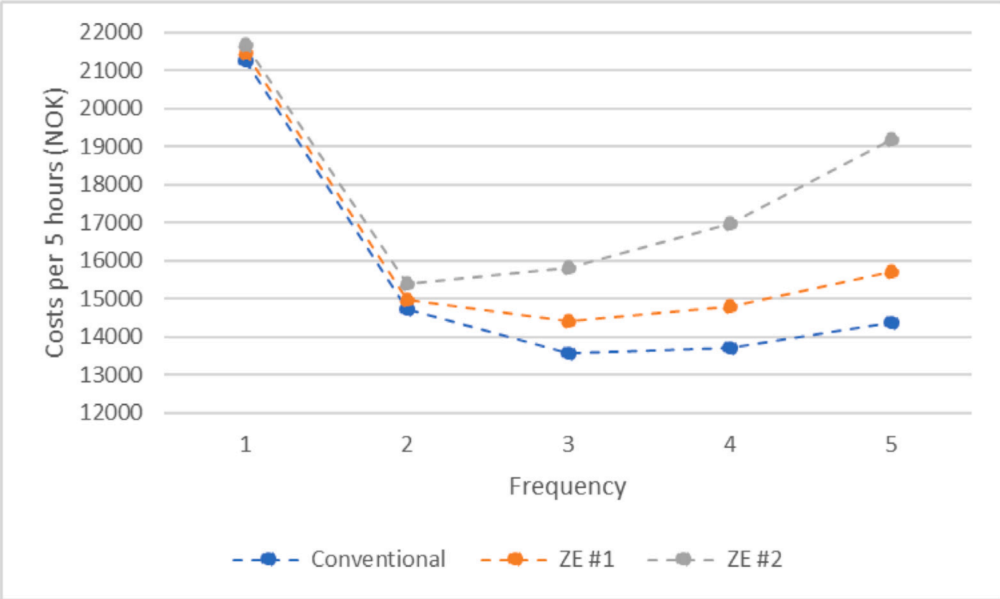

Fig. 1. Optimal frequency for a hypothetical vessel service.

by Mohring (1972). Note that this section presents an independent stylized numerical example to convey the intuition behind key results from the main optimization study. The simple model presented herein does not coincide with the complex optimization problem developed in Section 4, but encompasses key elements of the complex problem. The stylized example in this section further approximates the main results presented in Section 6 for consistency.

Let the stylized operator cost function be $C = a + bf$, where a denotes fixed and b denotes variable costs associated with providing a passenger vessel service. f denotes service frequency within a given planning horizon. In general, it can be assumed that the cost of operation increases with the transition from diesel to battery electric propulsion because of added infrastructure costs and range requirements.

Similar to the main optimization study, we assume a planning horizon of five hours for the stylized numerical example. Let $(5C^{PW}/2f)D$ denote expected waiting time costs for the passengers, where 5 is the length of the planning horizon, C^{PW} denotes the passengers' value of time and D denotes demand during the planning horizon (i.e., number of passengers per five hours). For the stylized example, we assume 38 passengers to be transported within the planning horizon and a value of waiting time of 168 NOK per hour. Operator cost functions mimic main results from Table 6, and assume as numeraire fixed costs of NOK 3992 and 3798 and variable costs of NOK 1500 and 1476 for battery electric and conventional vessels, respectively. We generate two numerical examples for the zero emission case (i.e., ZE #1 and #2) that are distinguished by higher hypothetical operator cost increases in frequency relative to base values for numerical example ZE #2 compared to #1. For transparency, costs related to transit time and transport by alternative modes are ignored in this section.

Unlike public transport models based on Mohring (1972), we assume throughout that frequency within the planning period is defined by an integer. In this case, small changes in the cost of frequency can amount to increases in system costs without affecting service frequency. This is seen in Fig. 1, where the shift from conventional to ZE #1 leaves the optimal frequency (i.e., the frequency that minimizes total costs) unchanged at three. More radical changes – e.g., with the shift from conventional to ZE #2 in Fig. 1 – on the other hand can also affect optimal frequency (in the figure it goes from three to only two).

If the current optimal level of service (i.e., for conventional vessels) is three, maintaining this also for scenario ZE #2 leads to economic losses because operator costs outweigh passenger benefits in terms of reduced waiting time costs. In the context of the numerical example, total costs can be reduced by about three percent by reducing frequency from three to two in scenario ZE #2. Furthermore, it is not only the frequency that impacts passenger costs—the transit time, and hence the passenger transit costs, is affected by the selected sailing speed along the route. This is in contrast to a bus service where the buses must follow the traffic and/or the speed limits. Thus, better planning of services can be a cost-effective strategy to curb emission, and should consequently be considered in tandem with technical measures when applying the least-cost principle to reducing emissions from passenger vessel services.

Literature review

There are not many papers in the literature, if any, providing optimization-based decision support models for zero emission passenger vessel services. The optimization problem subsequently defined is positioned in the literature on public transport problems, but encompasses several sub-problems that have been sparsely studied in public transport planning. We are unaware of other studies that jointly consider these sub-problems. Moreover, the literature on zero emission transport problems is currently scarce, and this study makes advances by jointly considering technical and operational measures to lower costs of energy transitions.

There are, in general, two types of objective functions applied for comparable planning problems: Multi-objectives minimizing both operator and passenger costs, and the sole minimization of operator costs. Public transit problems typically consider the former, which is aligned with the planning problem proposed in this study. According to Lai and Lo (2004), it is typical to consider both operator costs and passenger disutility in public transit network design studies because competing transport modes become more attractive when the passenger costs increase. Shang et al. (2019) consider both passenger waiting and transit time as part of the objective function. Arbex and da Cunha (2015) add to previous work by considering a transit penalty, penalizing the number of transits in their network in addition to the waiting and travel times. Aslaksen et al. (2020), on the other hand, seek to maximize customer service quality through rapid departures while minimizing excess transit time. The latter is operationalized by the difference between actual transit time and the transit time on a direct link. The current study adds to these public transport problems by considering the cost of passenger transport by a substitute mode in addition to passenger vessel operator and disutility costs.

Prominent studies on optimization of passenger vessel services include Lai and Lo (2004) and Aslaksen et al. (2020, 2021), none of which focuses on zero emission vessels. Lai and Lo (2004) study the Ferry Network Design Problem considering the optimal fleet size, routing, and scheduling of two ferry services whilst minimizing operator and passenger waiting and transit time costs. The model is formulated as a Mixed-Integer multiple Origin-Destination Network Flow Problem with ferry capacity constraints. It incorporates two types of networks: a network describing the flow of passengers and a network describing the movement of vessels. Aslaksen et al. (2020) present a Ferry Service Network Design Problem for schedule generation for autonomous ferries. They study a set of homogeneous ferries, where each vessel repeats a cyclical sequence of port visits. To solve the problem, the authors propose a two-step approach, where they first generate routes and corresponding frequencies using a construction heuristic. In the second step, the model determines the combination of routes and frequencies that maximizes perceived customer satisfaction. The model by Aslaksen et al. (2020) requires a minimum frequency between ports, which is adopted in this study. In a proceeding paper, Aslaksen et al. (2021) consider the Combined Dial-a-Ride and Fixed Schedule problem, seeking to determine the optimal assignment mix of vessels to dynamic and fixed schedules. Our paper focuses solely on scheduled transport.

A majority of comparable problems, including those presented in Lai and Lo (2004) and Aslaksen et al. (2020, 2021), assume demand to be predetermined, thereby disregarding the impact the level of service can have on ridership. One exception is Klier and Haase (2015), who study a public transit network problem with flexible or endogenous demand. Their study predicts the expected travel time along the different paths in the networks and thereby the expected demand, which is subsequently used to maximize the total number of expected public transit passengers subject to a budget constraint. The modeling approach proposed herein accommodates flexible demand, both by enabling endogenous demand among nodes and by joint optimization of maritime and road passenger transports.

The model subsequently developed advances planning problems on zero emission transport by jointly optimizing energy use and infrastructure location. Rinaldi et al. (2018) consider a Vehicle Scheduling Problem for electric and hybrid buses in a single depot case, where the charging infrastructure is installed at the depot. This study considers charging constraints as a part of the scheduling problem. Moreover, in contrast to our model, the problem by Rinaldi et al. (2018) does not capture the relationship between the time spent charging and the battery level. Sassi and Oulamara (2017) outline the Electric Vehicle Scheduling and Optimal Charging Problem, in which the aim is to optimize the allocation of fixed tours to electric vehicles while minimizing charging costs. Similar to our study, Sassi and Oulamara (2017) consider vessel range and battery capacity. However, Sassi and Oulamara (2017) do not model the interaction among speed and energy consumption, and infrastructure location is assumed exogenous. Zhang et al. (2021) consider assignment of electric buses to predefined routes and decide on the charging technology that should be installed at terminal stations. In their study, the charging schedule depends on the charging technology installed at the terminal stations, which could either be fast or slow. In contrast to this study, Zhang et al. (2021) adopt discrete time periods rather than continuous time. The use of discrete time periods is predominant when new aspects are introduced in the literature, whereas continuous time is used for providing more realistic models. Zhang et al. (2021) further diverge from our approach by not considering the relationship among power prices and costs of vessel operations. Villa et al. (2020) introduce the Electric Riverboat Charging Station Location Problem for rural areas with no electric grid connections, and where charging stations are supplied with solar power. Similar to this paper, Villa et al. (2020) allow choosing different battery sizes, where larger batteries store more energy but are heavier and result in a higher energy consumption. However, boats are assumed to sail at a constant speed, meaning that energy consumption between nodes depends solely on battery size. Rogge et al. (2018) study the replacement of combustion engines with electric buses, addressing scheduling of bus routes using electrical buses while at the same time accounting for their range limitations, charging times, and charging infrastructure. Rogge et al. (2018) assume that charging only occurs in a given depot, while herein, the location of charging facilities is a decision variable.

In contrast to the preceding studies on zero emission technology, we explicitly model interactions among speed choices and energy use. Similar approaches for conventional vessels include Fagerholt et al. (2010) and Andersson et al. (2015). Ritari et al. (2021) study the adoption of batteries as an energy carrier in hybrid vessels to explore how large-capacity batteries affect operational measures such as routing, speed, and fleet deployment, compared to conventional vessels. This is thematically aligned with our study on zero emission vessels.

While our paper advances the literature on planning problems for zero emission transport, it also leaves out some aspects previously considered by comparable studies. First, it does not consider uncertainties in energy demands. This is examined by Liu et al. (2018), who develop a model for the planning of charging stations for a bus service subject to energy demand uncertainty due to traffic conditions and demand uncertainties. We consider in particular energy uncertainty related to traffic conditions less relevant for passenger vessel transport. Second, our study focuses only on a short planning horizon (i.e., the peak period for a given day), and does therefore not consider time-of-use electricity pricing as e.g., in He et al. (2019, 2020).

3. Problem description

This section formally defines the ZEVRPP, which is a relevant problem for all coastal areas offering a passenger vessel service to their inhabitants. The problem is typically encountered by an operator, either already operating a connection served by conventional vessels, or designing a new one to be served by zero emission vessels. Even though the problem is relevant for most alternative energy carriers (e.g., conventional fuels, battery electric or hydrogen), we present it from a battery electric perspective. Section 3.1 describes the assumptions made before a formal definition of the ZEVRPP is given in Section 3.2. Finally, Section 3.3 provides a numerical example to highlight some important aspects of the problem.

3.1. Assumptions

We consider a given cyclical high-speed vessel route visiting a given set of ports in a specific sequence, where each pair of ports has a known demand for transportation. Moreover, each sailing leg between two ports has a known distance, enabling a calculation of sailing times for different sailing speeds.

The given route is to be serviced by a number of high-speed vessels to be chosen among a set of candidate vessel types given as input to the problem. We assume that each vessel of a given type has a known investment cost, passenger capacity, speed range and speed-dependent energy consumption. In the case of battery electric technology, which is our main focus in this paper, the size of the battery is also given as input for each vessel type. Similar parameters could also be included for other (zero emission) energy carriers, e.g., hydrogen, capturing the vessels' ability to store energy on board. We assume that only one type of high-speed vessels can be chosen for a given route in order to ensure that a realistic route plan where each departure from a port is serviced by similar vessels with the same capacity. This assumption is also reasonable because vessels are today often designed for a specific route.

For all relevant zero emission technologies, some onshore infrastructure must be installed. In the case of battery electric passenger vessels, infrastructure to charge the chosen vessels' batteries must be installed in at least one port. We assume that an estimate of the infrastructure investment cost in each port within the route is given as input, together with the available rate of energy transfer (i.e., charging speed) in the area.

Although we assume a fixed total, or upper bound for, demand for transportation between a port pair, we assume that the number of passengers choosing the passenger vessel as their desired mode of transportation is influenced by the frequency of service. This gives a *frequency-dependent* demand, similar to Klier and Haase (2015), who state that a higher frequency results in shorter waiting time, which yields a higher demand. Here, we define the frequency of service as the number of roundtrips the route is sailed within the given planning horizon. Passengers that do not choose the passenger vessel service due to too low frequency are assumed to use alternative modes of transportation to satisfy their demands. Additionally, the capacities of the vessels used along the route may restrict the number of passengers that can be transported. We assume there is a given cost per passenger for this unmet demand, which may vary among different port pairs due to differences in the options for alternative transportation. For example, if the passenger vessel service is the only means of transportation between two ports, the cost of unmet demand is set significantly higher than if there also exists a bus service.

We assume that passengers have a *value of time*, both concerning time spent waiting prior to boarding a vessel (i.e., between departures) and the transit spent on board. Even though, as discussed by Wardman (2001), the value of time may depend on many factors and vary among different passengers, we assume there is a given conversion factor from passenger waiting time to a monetary cost that enables a direct comparison of passenger and operator costs.

Finally, we assume Well-to-Tank emissions related to electricity consumption to be zero. Statistics from the Norwegian Energy Regulator shows that close to all electricity consumed in Norway stems from renewable sources, and only less than two percent of the electricity consumption stems from fossil fuels. Since we focus on the Norwegian case, we maintain the assumption of zero emission vessel operations, albeit this may not hold in the global context.

3.2. Problem definition

The ZEVRPP considers decisions at the strategic, tactical and operational planning level. The strategic decisions include determining how many vessels of which type to acquire and in which port(s) to install charging infrastructure. The tactical decision of the problem is to determine the route's service frequency. Within the given planning horizon, which can be a representative period of a day, only one frequency can be selected to ensure predictable timetables for passengers. The decisions on the operational level are the number of passengers to serve between any port-pairs along the route, as well as vessel speeds on each leg and time usage, i.e., time spent sailing, charging and waiting in ports. The decisions of where and for how long to charge affect both the time the vessels spend on a roundtrip and the vessels' battery levels. If the vessels spend longer time charging, they will experience an increased battery level on the roundtrip, but also a direct increase in roundtrip time. On the other hand, a greater battery level enables sailing at higher speeds, since a greater speed necessitates a higher energy usage per distance unit. This makes the operational decisions highly inter-dependent.

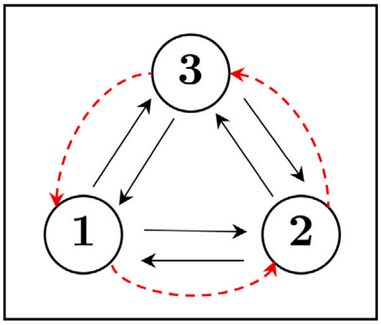

Fig. 2. Input 1 – cyclical route (red arcs) with frequency-dependent demand (black arcs). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Frequency-dependent demand over the planning horizon for the example problem (f represents the candidate frequencies)

	1-2	**1-3**	**2-3**	**2-1**	**3-1**	**3-2**
$f = 1$	40	50	50	60	40	45
$f = 2$	50	52	52	68	43	46
$f = 3$	55	63	55	72	44	58
$f = 4$	62	70	57	73	55	63

These decisions must be made while ensuring that the number of passengers transported is restricted by the chosen vessels' capacities and the (frequency-dependent) demand for transportation, and that the operation of the chosen vessels is restricted by their battery capacities. Furthermore, a vessel's battery level must at all times stay below a maximum and above a minimum level to ensure safe operations and to prolong the lifetime of the battery. This is an important restriction to ensure that appropriate vessels with a suitable battery capacity are chosen. Finally, the schedule of the route, given by the number of vessels, the service frequency and the sailing speeds along the route, must respect the length of the given planning horizon.

The objective of the ZEVRPP is to minimize the total system cost. The system cost is defined as the sum of the operator and passenger costs. The *operator* cost is the sum of 1) fixed cost related to acquiring (or chartering) the chosen vessel fleet, 2) investment cost of the onshore charging infrastructure, 3) and variable energy cost related to the operations. The variable energy cost, which amounts to the cost of electricity for battery electric vessels (and fuel cost for conventional ones), depends non-linearly on the chosen sailing speed, where higher sailing speeds give higher energy consumption per distance unit. The *passenger cost* also comprises three terms: 1) the cost of unmet demand, corresponding to the alternative cost of travel when demand is not met by the passenger vessels, 2) the cost of waiting between departures, and 3) the cost of excessive waiting on board the vessel in transit (e.g., if the vessels sail at a low speed or spend long time in ports due to charging).

Even though the main focus of the ZEVRPP is to support the strategic and most important decisions, the tactical and operational decisions may also play an important role. Strategic choices limit the solution space for the tactical and operational decisions, and feedback from this limitation's impact can be important to consider. Therefore, optimizing the decisions at all planning levels simultaneously could lead to better overall solutions.

3.3. Numerical example

To further illustrate some aspects of the ZEVRPP, we present a simplified toy-sized numerical example. In order not to make the example too extensive and complex, we do not show the operational decisions regarding sailing speeds and the number of passengers transported along the route, and focus instead on the strategic and tactical ones. Similar to the stylized numerical example in Section 2, the simple model presented here does not coincide with the complex optimization problem developed in Section 4, but showcases key elements of the complex problem.

We consider a cyclical route with three ports to be visited in the sequence 1 – 2 – 3 – 1, as shown in Fig. 2, with a corresponding frequency-dependent demand over a given planning horizon (e.g., five hours, as used in our case study presented in Section 6) as given in Table 1. The numbers for the dependency between frequency and demand are arbitrarily chosen for illustrational purposes. In this example, each port has a given potential rate of energy transfer as shown in Fig. 3. Furthermore, there is a set of different types of candidate battery electric passenger vessels, each vessel type with given battery and passenger capacities, as well as cost and (speed-dependent) energy consumption function.

A possible solution to this problem is illustrated in Fig. 4, where the light blue color of port 1 indicates that charging infrastructure is installed here, implying that this is the only port where the vessels can charge. Furthermore, the solution consists of two vessels of type v_1, where each vessel sails the route's roundtrip twice during the planning horizon, which means that the passengers experience a service frequency of four.

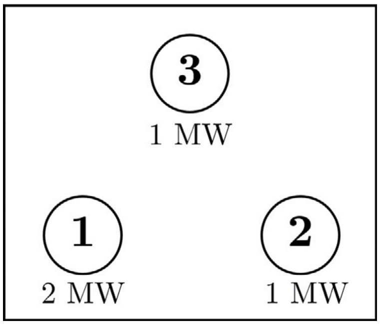

Fig. 3. Input 2 – charging power that is available in each port.

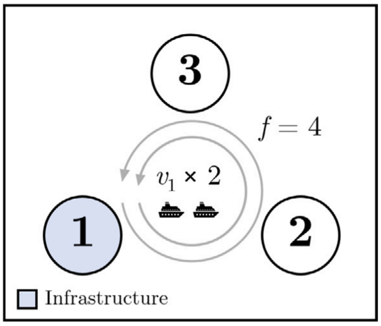

Fig. 4. Solution – charging infrastructure, vessel fleet and service frequency.

4. Mathematical formulations

This section presents the mathematical formulation of the *zero emission vessel model* in Section 4.3. However, we begin in Section 4.1 by describing some modeling assumptions and choices, before we in Section 4.2 introduce the notation used. We also develop a *conventional vessel model* which we use for comparing the solutions among zero emission and conventional vessels. Appendix C explains how the zero emission model is adapted to conventional vessels.

4.1. Modeling approach and assumptions

As explained in Section 3, a predefined cyclical route is given as input to the problem. This route is described by the set $\mathcal{K}$, which contains the ports in the route in the order they are visited. As each port is visited every roundtrip, the number of visits within the planning horizon is the same for all ports and equal to the frequency of the route, which is, as explained in Section 3, a decision in our model. The set of ports $\mathcal{K}$ also implicitly gives the set of sailing legs between the ports along the route. The modeling of sailing time and speeds is important in the ZEVRPP, which follows the approach proposed by Andersson et al. (2015). The sailing time along each leg is computed in advance for a discrete number of speeds. A vessel can then be assigned a speed which is a linear combination of the discrete speed levels. Accordingly, a vessel may choose any speed level between its lowest and highest discrete speed options. The energy consumption also depends on the speed. We introduce a parameter that defines the energy consumption on each leg at each of the discrete speed levels. Hence, the option of choosing linear combinations of the speed levels, therefore, also applies to the energy consumption.

The vessel's battery must be charged in at least one of the ports along the given route. We assume for simplicity that the charging occurs at constant power, i.e., there is a linear relationship between the time spent charging and the battery level. Furthermore, as explained in Section 3, we assume that the passenger demand depends on the frequency of the service. We model frequency-dependent demand through a parameter, D_{ijf}, which is the demand from port i to port j with a service frequency of f. This demand parameter is bounded by a total demand, D^T_{ij}, which equals the demand at the maximum frequency. The difference in demand for varying frequencies is assumed to be caused by some passengers preferring alternative transportation due to a lower quality vessel service. These passengers, along with the number of passengers inhibited from travel due to insufficient vessel capacity, result in *unmet demand* in the model. We assume that the unmet demand is covered by alternative modes of transportation, and we include a cost for this in the objective function.

Another frequency-dependent parameter is the passengers' average waiting time in port. In general, from public transport literature, e.g., Shang et al. (2019), the average waiting time is defined as half the length of the planning horizon divided by the frequency. This approach is also adopted in our model.

Table 2
Summary of decision variables.

α_k	1 if charging infrastructure is built in port k, 0 otherwise
δ_v	1 if vessel type v is chosen, 0 otherwise
z_f	1 if frequency f is chosen, 0 otherwise
y_v	Number of vessels of type v used
x_{kvs}	Weight variable for speed s for vessels of type v on leg k
l_{kjv}	Number of passengers traversing leg k with destination port j with a vessels of type v
q_{kj}	Number of passengers picked up in port k with destination port j
u_{ij}	Unmet demand between port i and port j
t_v^{RT}	Total roundtrip time for a vessel of type v
t_{kv}^C	Charging time before traversing leg k with a vessel of type v
w_{kv}^T	Time spent in port k per roundtrip excluding charging time for a vessel of type v
t_{ij}	Sailing time from port i to port j
b_{kv}	Battery level when leaving port k for vessels of type v

4.2. Notation

Let each sailing leg along the route be represented by index $k \in \mathcal{K}$, following the order of the legs along the route. Furthermore, port k corresponds to the origin of leg k. Let $\mathcal{V}$ be the set of available vessel types and let a set of discrete speed levels, $\mathcal{S}_v$, be associated with every vessel type v. Let $\mathcal{F}$ be the set of candidate service frequencies.

The length of the considered planning horizon is denoted $\overline{T}$. For each sailing leg k, vessel type v and speed level s, let T_{kvs} be the corresponding sailing time. In addition to the sailing time, the parameter $\underline{T}_k^W$ represents the minimum waiting time in port k for docking, embarking and disembarking. We define the parameter T_{ij}^U as the sailing time from port i to port j with the fastest vessel type sailing at its maximum speed level, with no waiting or charging time except from the minimum requirement $\underline{T}_k^W$ along the route. This parameter is later used to calculate the passenger cost of excessive transit times. Moreover, let W_f be the average passenger waiting time at frequency f, calculated as explained in Section 4.1.

The passenger capacity of a vessel of type v is given by Q_v, while E_{kvs} represents the energy consumption on leg k with a vessel of type v sailing at speed level s. Now, let $\overline{B}_v$ and $\underline{B}_v$ be the maximum and minimum battery levels of a vessel of type v, respectively. Furthermore, let P_k be the available charging power in port k.

The costs are represented by the following parameters: Let C_v^{FC} represent the fixed cost of using a vessel of type v. This parameter includes the investment cost. In addition, let C_k^{INF} be the fixed cost of investing in charging infrastructure in port k. Both these fixed costs are annualized and scaled to the length of the planning horizon, $\overline{T}$. Let C_k^{VC} be the energy cost per unit charged in port k. The cost per unit of unmet demand from port i to j is denoted C_{ij}^{ALT} and reflects the passengers' ability to choose different modes of transportation between the port pairs. The cost parameter C^{PW} represents the passenger cost per time unit of waiting in a port, whereas C^{SW} represents the cost per time unit of excessive sailing time.

The strategic and tactical decisions are given by the following variables: Let α_k be a binary variable, which is equal to 1 if charging infrastructure is built in port k, and 0 otherwise. Let δ_v be another binary variable, which takes the value 1 if vessels of type v are chosen, and 0 otherwise. Let the integer variable y_v be the number of vessels of type v used. Finally, let z_f denote yet another binary variable, which is equal to 1 if departure frequency f is chosen, and 0 otherwise.

The operational decisions are given by the following: Let x_{kvs} be a weight variable for the speed level s for a vessel of type v on sailing leg k, such that a linear combination of the speed levels can be determined independently on each leg for each vessel type. Let l_{kjv} be the number of passengers traversing leg k destined for port j on vessels of type v. Furthermore, let q_{ij} be the number of passengers picked up in port i with destination j throughout the entire planning period, thus differing from l_{kjv} by only considering flow between port pairs and not passengers merely passing over a leg. The unmet demand, u_{ij}, is calculated as the difference between the total demand over the planning period, D_{ij}^T, and the number of passengers served between port i and j, q_{ij}. Let t_v^{RT} be the total roundtrip time for a vessel of type v. This variable includes sailing, charging, and waiting times along the route. Moreover, let t_{kv}^C be the charging time in port k for each vessel of type v per roundtrip. Let w_{kv}^T be the time spent in port k per roundtrip for a vessel of type v. In addition to possible idling, this variable captures the time spent on docking, embarkment and disembarkment. To consider the cost of passengers in transit, we define t_{ij} as the total transit time between ports i and j. Finally, let b_{kv} be the battery level of a vessel of type v when leaving port k.

All decision variables are summarized in Table 2, while Appendix A provides a complete account of the notation of the model, including sets and parameters.

4.3. Zero emission vessel model

In the following we present the *zero emission vessel model*, i.e., the model where we assume that battery electric vessels are used. It should be noted that we have chosen to present the model including some non-linear terms, both in the objective function and some of the constraints, as this presentation is more intuitive and easier to understand. However, in order to later solve the model by a commercial mixed-integer programming solver, we linearize these non-linear expressions as explained in Appendix B.

Objective function

We define the following objective function.

$$\begin{aligned} \min \quad z = & \sum_{v\in\mathcal{V}} C_v^{FC} y_v + \sum_{k\in\mathcal{K}} C_k^{INF} \alpha_k + \sum_{v\in\mathcal{V}} \sum_{k\in\mathcal{K}} \sum_{f\in\mathcal{F}} C_k^{VC} P_k t_{kv}^C f z_f \\ & + \sum_{i\in\mathcal{K}} \sum_{j\in\mathcal{K}} C_{ij}^{ALT} u_{ij} + C^{PW} \sum_{f\in\mathcal{F}} W_f z_f (\sum_{i\in\mathcal{K}} \sum_{j\in\mathcal{K}} q_{ij}) \\ & + C^{SW} \sum_{f\in\mathcal{F}} \sum_{i\in\mathcal{K}} \sum_{j\in\mathcal{K}} (t_{ij} - T_{ij}^U) D_{ijf} z_f \end{aligned} \tag{1}$$

The objective function (1) minimizes the total system costs of the high-speed vessel service. The first two terms represent the investment cost of the vessels and the onshore charging infrastructure, respectively. The third term represents the variable sailing cost based on the energy consumption. Together, the three first terms constitute the operator costs. The fourth term calculates the total cost of passengers using alternative modes of transportation, i.e., the cost of unmet demand. The last two terms are time costs for the passengers, i.e., the passenger waiting costs in port and the cost of excessive transit time beyond what is minimum for all passengers, respectively. Note that terms three, five and six are non-linear.

Constraints related to strategic and tactical decisions

Constraints (2) ensure that only the selected vessel type may be used, by connecting the δ_v and y_v variables. M_v^1 in Constraints (2) is a big-M parameter that should be assigned a sufficiently large number. Constraints (3) and (4) guarantee that only one vessel type and frequency is chosen, respectively.

$$y_v \leq M_v^1 \delta_v, \qquad v \in \mathcal{V} \tag{2}$$

$$\sum_{v\in\mathcal{V}} \delta_v = 1 \tag{3}$$

$$\sum_{f\in\mathcal{F}} z_f = 1 \tag{4}$$

Time constraints

The following time constraints handle the relationships between roundtrip time, sailing speeds and frequency. Constraints (5) define the total roundtrip time as the sum of the time spent traversing all the legs along the route and the total time spent charging and waiting in each port. The non-linear Constraint (6) ensures that the chosen frequency multiplied with the sum of roundtrip times is equal to the total available vessel time. Constraints (7) enable a minimum time in each port for docking, embarkment and disembarkment of passengers. Constraints (8) force the time in port to be zero if the vessel type is not chosen. M_v^2 is another big-M parameter. Constraints (9) ensure that the sum of the speed weights is equal to one if the vessel type is chosen, and zero otherwise.

$$t_v^{RT} = \sum_{k\in\mathcal{K}} \sum_{s\in\mathcal{S}_v} T_{kvs} x_{kvs} + \sum_{k\in\mathcal{K}} (t_{kv}^C + w_{kv}^T), \qquad v \in \mathcal{V} \tag{5}$$

$$\sum_{f\in\mathcal{F}} \sum_{v\in\mathcal{V}} f z_f t_v^{RT} = \overline{T} \sum_{v\in\mathcal{V}} y_v \tag{6}$$

$$w_{kv}^T \geq \underline{T}_k^W \delta_v, \qquad k \in \mathcal{K},\ v \in \mathcal{V} \tag{7}$$

$$\sum_{k\in\mathcal{K}} w_{kv}^T \leq M_v^2 \delta_v, \qquad v \in \mathcal{V} \tag{8}$$

$$\sum_{s\in\mathcal{S}_v} x_{kvs} = \delta_v, \qquad v \in \mathcal{V},\ k \in \mathcal{K} \tag{9}$$

Furthermore, Constraints (10) and (11) define the time passengers spend on board the vessel. The constraints are split in two due to the route's cyclical nature.

$$t_{ij} = \sum_{v\in\mathcal{V}} \left[\sum_{k=i}^{j-1} \sum_{s\in\mathcal{S}_v} T_{kvs} x_{kvs} + \sum_{k=i-1}^{j-1} (t_{kv}^C + w_{kv}^T) \right], \qquad i \in \mathcal{K},\ j \in \mathcal{K} \mid j > i \tag{10}$$

$$t_{ij} = \sum_{v\in\mathcal{V}} \left[\sum_{k=i}^{|\mathcal{K}|} \sum_{s\in\mathcal{S}_v} T_{kvs} x_{kvs} + \sum_{\tilde{k}}^{|\mathcal{K}|} (t_{\tilde{k}v}^C + w_{\tilde{k}v}^T) + \sum_{k'}^{j-1} \left(\sum_{s\in\mathcal{S}_v} T_{k'vs} x_{k'vs} + t_{k'v}^C + w_{k'v}^T \right) \right], \qquad i \in \mathcal{K},\ j \in \mathcal{K} \mid j > i \tag{11}$$

where

$$\tilde{k} = argmin\{|\mathcal{K}|, i+1\}$$

$$k' = argmax\{1, j-1\}$$

Battery constraints

The battery constraints handle the battery level of the vessels and enforce the relationships between energy consumption, charging power and charging time. Constraints (12) and (13) are balance constraints. They ensure that the battery level before traversing a leg is consistent with the battery level before the previous leg, adjusted by the energy consumption of the previous leg and any charging in the port of departure. The constraints are again split in two due to the route's cyclical nature. Constraints (14) and (15) ensure that the battery level of a vessel never exceeds its predefined minimum and maximum limits. Lastly, Constraints (16) make sure that charging only occurs at ports where charging infrastructure is installed, where M_v^3 is another big-M parameter.

$$b_{kv} = b_{k-1,v} - \sum_{s \in S_v} E_{k-1,vs} x_{k-1,vs} + P_k t^C_{kv}, \quad k \in \mathcal{K} \setminus \{1\},\ v \in \mathcal{V} \tag{12}$$

$$b_{1,v} = b_{|\mathcal{K}|,v} - \sum_{s \in S_v} E_{|\mathcal{K}|,vs} x_{|\mathcal{K}|,vs} + P_1 t^C_{1,v}, \quad v \in \mathcal{V} \tag{13}$$

$$b_{kv} \le \overline{B}_v \delta_v, \quad k \in \mathcal{K},\ v \in \mathcal{V} \tag{14}$$

$$b_{kv} - \sum_{s \in S_v} E_{kvs} x_{kvs} \ge \underline{B}_v \delta_v, \quad k \in \mathcal{K},\ v \in \mathcal{V} \tag{15}$$

$$t^C_{kv} \le M^3_{kv} \alpha_k, \quad k \in \mathcal{K},\ v \in \mathcal{V} \tag{16}$$

Passenger flow constraints

Constraints (17) force all load variables to become zero for the vessel types that are not chosen, where M_v^4 is a big-M parameter. Constraints (18) ensure that the vessels' passenger load does not exceed the vessel type capacity multiplied with the departure frequency.

$$l_{kjv} \le M^4_{kjv} \delta_v, \quad k \in \mathcal{K},\ j \in \mathcal{K},\ v \in \mathcal{V} \tag{17}$$

$$\sum_{j \in \mathcal{K}} l_{kjv} \le Q_v \sum_{f \in \mathcal{F}} f z_f, \quad v \in \mathcal{V},\ k \in \mathcal{K} \tag{18}$$

Constraints (19) and (20) ensure an appropriate conservation of passenger flow. They state that the number of passengers entering the vessel in a port with a specific destination, is the difference between the previous and current load with the same destination. The constraints are again split in two to account for the cyclical routes. Constraints (21) ensure that the number of embarking passengers does not exceed the frequency-dependent demand.

$$q_{kj} = \sum_{v \in \mathcal{V}} (l_{kjv} - l_{k-1,jv}), \quad k \in \mathcal{K} \setminus \{1\},\ j \in \mathcal{K} \,|\, j \ne k \tag{19}$$

$$q_{1,j} = \sum_{v \in \mathcal{V}} (l_{1,jv} - l_{|\mathcal{K}|,jv}), \quad j \in \mathcal{K} \setminus \{1\} \tag{20}$$

$$q_{ij} \le \sum_{f \in \mathcal{F}} D_{ijf} z_f, \quad i \in \mathcal{K},\ j \in \mathcal{K} \,|\, j \ne i \tag{21}$$

Constraints (22) calculate the unmet demand as the total demand minus the transported passengers. Consequently, the variable u_{ij} covers both the unmet demand due to a too low frequency and the unmet demand stemming from insufficient vessel passenger capacity. The two last passenger flow Constraints (23) and (24), split in two due to the cyclical route, make sure that passengers leave the vessel at the correct ports.

$$q_{ij} + u_{ij} = D^T_{ij}, \quad i \in \mathcal{K},\ j \in \mathcal{K} \,|\, j \ne i \tag{22}$$

$$l_{k-1,jv} \le l_{kjv}, \quad v \in \mathcal{V},\ k \in \mathcal{K},\ j \in \mathcal{K} \,|\, j \ne k \tag{23}$$

$$l_{|\mathcal{K}|,jv} \le l_{1,jv}, \quad v \in \mathcal{V},\ j \in \mathcal{K} \setminus \{1\} \tag{24}$$

Non-negativity, binary, and integer requirements

The variable domains are given by Constraints (25)–(35).

$$\delta_v \in \{0,1\}, \quad v \in \mathcal{V} \tag{25}$$

$$\alpha_k \in \{0,1\}, \quad k \in \mathcal{K} \tag{26}$$

$$z_f \in \{0,1\}, \quad f \in \mathcal{F} \tag{27}$$

$$y_v \in \mathbb{Z}^+, \quad v \in \mathcal{V} \tag{28}$$

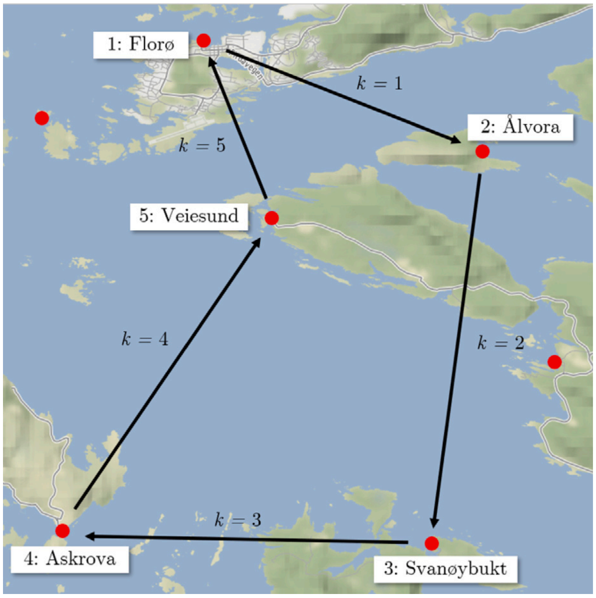

Fig. 5. The Florø route (FL).

$$l_{kjv} \in \mathbb{R}^+, \qquad k \in \mathcal{K},\ j \in \mathcal{K} \mid j \neq k,\ v \in \mathcal{V} \qquad (29)$$

$$q_{kj} \in \mathbb{R}^+, \qquad k \in \mathcal{K},\ j \in \mathcal{K} \mid j \neq k \qquad (30)$$

$$u_{ij} \in \mathbb{R}^+, \qquad i \in \mathcal{K},\ j \in \mathcal{K} \mid j \neq i \qquad (31)$$

$$x_{kvs} \in \mathbb{R}^+, \qquad k \in \mathcal{K},\ v \in \mathcal{V},\ s \in \mathcal{S}_v \qquad (32)$$

$$b_{kv}, t^C_{kv}, w^T_{kv} \in \mathbb{R}^+, \qquad k \in \mathcal{K},\ v \in \mathcal{V} \qquad (33)$$

$$t^{RT}_v \in \mathbb{R}^+, \qquad v \in \mathcal{V} \qquad (34)$$

$$t_{ij} \in \mathbb{R}^+, \qquad i, j \in \mathcal{K} \qquad (35)$$

It should be noted that the model does not keep track of the exact timing of different vessel activities (i.e., sailing, berthing and charging). This means that when the number of vessels is large, there might be a potential conflict at the charging station(s) which we do not consider. However, we argue that for our real case study, this does not become a practical problem due to the low number of vessels selected for operation.

5. Case study

We consider two real high-speed vessel services or routes in the Florø and Stavanger areas, located on the west coast of Norway. The routes are shown in Figs. 5 and 6. Both these routes are currently operated with conventional vessels, but there are plans for introducing battery electric vessels in the next years. The total lengths of the Florø and Stavanger routes are 24.2 and 16.5 nautical miles, respectively. Section 5.1 presents the data used to generate the test instances, which are summarized in Section 5.2.

5.1. Input data

Vessel data

The data for the relevant battery electric vessels was provided by a maritime consultancy company involved in this project. Based on this we defined 21 realistic vessel types ranging in passenger capacity (PAX) from 50 to 300, in line with existing passenger vessels currently in operation in Norway. Table 3 summarizes these vessel types with their costs, lengths, passenger capacities, battery capacities, sets of speed levels, as well as power demands for different speed levels. It should be noted that power demands

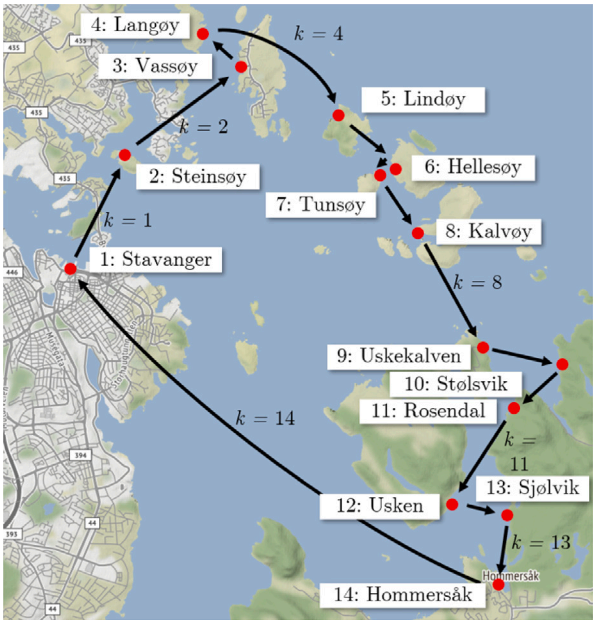

Fig. 6. The Stavanger route (SV).

in practice depend on weather conditions, but since we are considering a strategic planning problem (i.e., determining vessel fleet and charging infrastructure), we omit these operational aspects and use power demands under "normal" weather conditions. The name of each vessel type referred to in the table consists of a number and a letter. The numbers, given in the range from 1 to 7, indicate the size of the vessel, where larger numbers mean larger vessels. The letters in the vessel type name divide the vessels with respect to battery size, where S, M and L correspond to Small, Medium and Large batteries, respectively. To remain within the scope of realistic vessel types, the vessels of 30 m are combined with battery capacities of 1 000, 2 000 and 3 000 kWh, while the vessels of 40 m are combined with batteries of 2 000, 3 500 and 5 000 kWh.

To ensure that the battery is used in a way preserving its lifetime, lower and upper limits of 40% and 90% of the battery capacity, respectively, are set for the operational range the battery levels for all vessels. This follows the guidelines of the public transport company Kolombus related to their new vessel Medstraum—the world's first all-electric passenger vessel. There are two main reasons for using such a high lower battery limit for high-speed passenger vessels: 1) it will contribute to preserving the battery's lifetime, and 2) since weather conditions will vary, such a high value makes the route operable also in bad weather where the vessel needs more energy to maintain the schedule. A set of candidate speed levels of 10, 15, 20, 25 and 30 knots is set, similar for all vessel types, each associated with a given power demand as shown in the table.

For the conventional vessels, we assume they have the same seven sizes and speeds as the zero emission vessels and that each conventional vessel requires the same amount of power as the corresponding zero emission vessel with the same dimensions and medium battery size. Based on this we obtain the same type of input data for the seven conventional as for the zero emission vessel types shown in Table 3. In the following we denote a conventional vessel type by nC, where n refers to one of the same seven vessel sizes, while C just refers to 'Conventional'.

Demand data

As described in Section 4, the model includes two different parameters as input for the demand, D^T_{ij} and D_{ijf}, i.e., the total and frequency-dependent demand, respectively. In our test cases we assume $D^T_{ij} = D_{ij|\mathcal{F}|}$, thus basing the maximum demand on the demand corresponding to the highest frequency allowed. We consider a length of the planning horizon of five hours for all tests, corresponding to the time period 05:00 to 10:00 in the morning. For the Florø route, which has a current frequency of only two within the given five hour planning horizon, the demand was calculated based on ticket sales during the weekdays. For the Stavanger route, which has a frequency of five in the same period (i.e., one per hour), the demand was obtained from actual passenger counts including all departures in August and September of 2021. We use the demand of the morning operation since this time of the day has high demand, and will as such be best for determining the strategic decisions (i.e., fleet and charging infrastructure). Obviously, the tactical (i.e., frequency) and operational decisions (e.g., sailing speeds) might be different in other periods of the day when the demand is different/lower. This approach of using the peak period to set the strategic investment decisions also follows the suggestions by the counties in Norway that operate the two routes used for our case study.

The demand described above is obtained based on the actual frequency. To make the demand dependent on the frequency, given by the parameter D_{ijf}, we generate the available frequencies and scale the demand as follows. For the Florø case with a current frequency of two, we introduce the available frequencies given by $\mathcal{F} = \{1, 2, 3\}$ and scale the demand based on the actual

Table 3
Zero emission vessel types (VT) used in the test instances. NOK = Norwegian Kroner.

VT	Length (m)	PAX	Cost (mill. NOK)	Battery (kWh)	Speed levels (nm)	Power demand (kW)
1S	30	50	92.9	1000	(10, 15, 20, 25, 30)	(115, 405, 703, 1079, 1637)
1M	30	50	99.8	2000	(10, 15, 20, 25, 30)	(116, 447, 766, 1159, 1737)
1L	30	50	106.7	3000	(10, 15, 20, 25, 30)	(121, 490, 833, 1239, 1841)
2S	30	100	93.9	1000	(10, 15, 20, 25, 30)	(119, 472, 805, 1205, 1798)
2M	30	100	100.8	2000	(10, 15, 20, 25, 30)	(125, 517, 873, 1287, 1904)
2L	30	100	107.7	3000	(10, 15, 20, 25, 30)	(133, 564, 946, 1369, 2013)
3S	30	150	94.9	1000	(10, 15, 20, 25, 30)	(129, 544, 915, 1335, 1967)
3M	30	150	101.8	2000	(10, 15, 20, 25, 30)	(140, 593, 990, 1418, 2078)
3L	30	150	108.7	3000	(10, 15, 20, 25, 30)	(153, 644, 1068, 1503, 2193)
4S	30	200	95.9	1000	(10, 15, 20, 25, 30)	(147, 622, 1035, 1467, 2145)
4M	30	200	102.8	2000	(10, 15, 20, 25, 30)	(162, 674, 1115, 1553, 2261)
4L	30	200	109.7	3000	(10, 15, 20, 25, 30)	(179, 729, 1199, 1640, 2381)
5S	40	200	117.8	2000	(10, 15, 20, 25, 30)	(104, 347, 954, 1416, 2225)
5M	40	200	128.2	3500	(10, 15, 20, 25, 30)	(114, 374, 1019, 1513, 2350)
5L	40	200	138.5	5000	(10, 15, 20, 25, 30)	(124, 404, 1087, 1613, 2477)
6S	40	250	118.8	2000	(10, 15, 20, 25, 30)	(114, 376, 1023, 1518, 2357)
6M	40	250	129.2	3500	(10, 15, 20, 25, 30)	(124, 406, 1091, 1618, 2484)
6L	40	250	139.5	5000	(10, 15, 20, 25, 30)	(135, 438, 1163, 1721, 2614)
7S	40	300	119.8	2000	(10, 15, 20, 25, 30)	(125, 408, 1095, 1624, 2491)
7M	40	300	130.2	3500	(10, 15, 20, 25, 30)	(135, 440, 1167, 1727, 2621)
7L	40	300	140.5	5000	(10, 15, 20, 25, 30)	(147, 474, 1241, 1833, 2752)

frequency to 80%, 100% and 120% for the three different frequencies, respectively. Similarly, for the Stavanger case, which has a current frequency of five, we introduce the seven available frequencies given by $\mathcal{F} = \{1, 2, 3, 4, 5, 6, 7\}$ and scale the demand to 20% to 140% with steps of 20 percentage points.

Costs and other relevant data

The model takes several other cost parameters as input. For the fixed cost of acquiring a vessel of type v, C_v^{FC}, we use the investment costs shown in Table 3 and scale it to the length of the planning horizon of five hours, assuming a yearly interest rate of 5% and 18 h of usage per day. Based on data from an energy company, the port charging infrastructure investment cost is 12 million NOK, and we assume it to be the same for all ports. We calculate the cost of installing charging infrastructure in a port scaled down to our planning horizon, C_k^{INF}, following the same procedure as for the vessels. For all ports, both in the Florø and the Stavanger cases, we assign an available charging power of 2 000 kW, which is a reasonable approximation based on the electricity grid in these areas. The energy cost per kWh for the zero emission vessels, C_k^{VC}, is set to 3.1 NOK/kWh based on data obtained from the energy company. For the conventional vessels, the energy cost per outputted kWh is estimated to 1.7 NOK, based on an MGO price of 700 USD/ton (Bergen Bunkers, 2021), a conversion rate of 8.93 NOK/USD, an MGO heating value of 42.7 kJ/g and a thermodynamic efficiency of 30% (Wild, 2005).

The alternative cost of transportation between ports can be challenging to set appropriately. We consider the different pair of ports and assign a high value of 10 000 NOK if the high speed passenger vessel service is the only realistic public transportation option (e.g., on islands), and a lower value of 100 NOK if there exists alternatives (e.g., a bus connection).

Regarding the value of passenger time, we distinguish between time spent waiting between departures (i.e., due to low frequency) and excess travel time spent on board the vessel. For the excess travel time cost, C^{SW}, we use the value of 112 NOK/hour as estimated by Flügel et al. (2020). For the value of time spent waiting for a departure, Wardman et al. (2016) state that this cost should be 1.5 times higher than the cost of time spent on board. Hence, we set $C^{PW} = 168$ NOK/hour. The minimum time spent in each port for docking and (dis-)embarking, $\underline{T}_k^W$, is set to three minutes based on today's timetable.

5.2. Test instances

Based on the two routes for Florø and Stavanger and the data described in Section 5.1, we define the test instances FL1 and SV1 as our base case instances which describe the real demand for the two routes. Since both instances have low passenger demand, which is the case for most coastal areas in Norway, we also generate two additional instances based on the same routes, but with significantly increased demand. This is to imitate services or routes in more densely populated areas. We do this by using the two base case instances, FL1 and SV1, and multiply the demand between each pair of ports with a given number. For the Florø case, we multiply the demand by 10 and 100 and obtain the additional test instances FL10 and FL100, respectively. For the Stavanger case, which has somewhat larger real demand than the Florø case, we multiply by 7 and 12 and obtain the new test instances SV7 and SV12, respectively. To obtain more reasonable frequencies to choose among for the new instances, we also increase these. The frequency-dependent demand is scaled as described in Section 5.1, i.e., 80%–120% for the FL instances and 20%–140% for the SV instances, all in steps of 20 percent points.

Table 4
Overview of the test instances, where the frequencies represent the alternative number of departures over the five-hour planning horizon.

Name	Geographical area	Demand multiplier	Frequencies
FL1	Florø	1	{1, 2, 3}
FL10	Florø	10	{5, 10, 15}
FL100	Florø	100	{20, 25, 30}
SV1	Stavanger	1	{1, 2, 3, 4, 5, 6, 7}
SV7	Stavanger	7	{5, 10, 15, 20, 25, 30, 60}
SV12	Stavanger	12	{5, 10, 15, 20, 25, 30, 60}

Table 5
Overview of the solutions for all instances with optimal objective value (z^*), vessel type (VT), number of vessels (#) and frequency (f)

Instance	Zero Emission Solution				Conventional Solution			
	z^* [NOK]	VT	#	f	z^* [NOK]	VT	#	f
FL1	17 869	1S	1	2	15 691	1C	1	3
FL10	72 738	1S	4	10	58 026	1C	3	10
FL100	277 352	5S	13	30	189 333	3C	7	30
SV1	45 851	1S	3	7	37 025	1C	2	7
SV7	158 266	2M	6	15	123 709	2C	8	30
SV12	464 142	7S	24	60	347 687	7C	15	60

Table 4 summarizes all six test instances along with the set of available frequencies. While the alternative cost for traveling between a given port pair is either set to 10 000 or 100 NOK for the two base case instances, the alternative cost for traveling between a port pair is set randomly between 50 and 200 NOK for the instances FL10, FL100, SV7 and SV12.

6. Computational results

In this section, we present the computational study and analyzes. Section 6.1 presents the results for the different test instances. We compare the zero emission solutions to the conventional ones in all the instances in order to estimate the abatement costs. In Sections 6.2–6.4, we discuss key takeaways and insights from the results. The models were solved using the MIP-solver Gurobi version 9.1.2 on a computer with Intel Core i7-10700 2.90 GHz processor. All instances were solved to optimality within a few seconds.

6.1. Optimal results

When solving the six test instances using both the zero emission and conventional vessel models, we obtain the results summarized in Table 5. We observe that the cost of operating zero emission vessels is higher than that of conventional vessels in all of the cases. It can be noted that both models' solutions include the same vessel types with respect to length and passenger capacity for any given instance, except for instance FL100. The optimal number of vessels vary between the zero emission and conventional solutions for most instances, especially those with high demand. This is mainly due to the zero emission vessels' limited reach and the time needed for charging. Therefore, a higher number of vessels is needed to operate with the same frequency. For the same reason, we also see that the optimal frequency is higher in the conventional than the zero emission solution in two of the six instances. It should be noted that the percentage increase in costs for all artificial (high demand) scenarios relative to their base scenarios fall short of the corresponding increases in demand, suggesting increasing returns to scale in passenger vessel service production.

Table 6 shows the cost breakdown for instance FL1, while Table 7 presents the load factors (i.e., vessel capacity utilization) and sailing speeds along the route for the same instance. We see in Table 6 that the zero emission solution has a lower vessel investment cost than the conventional solution. This is because the chosen zero emission vessel has the smallest battery available. The cost of energy, i.e., electricity or fuel, is also substantially lower in the zero emission case, mostly due to the lower sailing speeds. However, due to the lower frequency and sailing speeds, the passengers' costs of waiting and transit time, which is a substantial part of the total cost, is significantly higher in the zero emission solution. The varying speed along the route, as shown in Table 7, is a seemingly surprising result given that using an even speed along the route would have resulted in lower energy consumption and cost. However, this result can be explained by that the vessel sails at a high speed when there are many passengers onboard to reduce the transit cost, while sailing at a lower speed when there are few passengers onboard to reduce energy cost. We believe these results are quite interesting, especially since they suggest a change in planning and management of vessel operations that currently involve using an even speed.

Note that the cost of alternative transportation is the same in both solutions. The only customers choosing alternative modes of transportation, independently of the frequency, are the customers traveling between ports 1 and 5, due to a low alternative cost of transportation (i.e., 100 NOK). This means that the same number of passengers is served in total in both solutions. However, as shown in Table 7, a larger number of passengers are served per roundtrip (i.e., higher load factor) in the zero emission case, due to the lower frequency.

Table 6
Cost breakdown of the FL1 instance (ZE = Zero Emission solution)

Cost Term	Zero Emission Solution		Conventional Solution		
	Value [NOK]	% of Total	Value [NOK]	% of Total	% of ZE
Vessel Investment	3535	19.8%	3798	24.2%	107%
Infrastructure Investment	457	2.6%	*NA*	*NA*	*NA*
Energy Cost	3001	16.8%	4428	28.2%	147%
Cost of Alt. Transport	1542	8.6%	1542	9.8%	100%
Cost of Waiting at Port	7827	43.8%	5218	33.3%	66.7%
Transit Cost	1507	8.4%	706	4.5%	46.8%
Total Cost	17869	100.0%	15691	100.0%	87.7%

Table 7
Number of passengers (# of Pax), load factor and sailing speed on each leg per roundtrip for the FL1 instance.

Leg	Zero Emission Solution			Conventional Solution		
	# of Pax	Load Factor	Speed [kn]	# of Pax	Load Factor	Speed [kn]
1	3.83	7.67%	10	2.56	5.11%	10
2	3.83	7.67%	10	2.56	5.11%	19.2
3	4.86	9.73%	10	3.24	6.48%	20
4	14.83	29.67%	20	9.89	19.78%	25
5	14.88	29.76%	20	9.92	19.84%	25

Similar results are obtained also for the other five test instances. However, the passenger costs are less substantial while the operator costs become more important for these other five instances. This is especially the case for the instances with increased demand. As an example, for instance FL100, the passenger costs constitute only 15.8% of the total costs compared to 60.9% for FL1. It should also be noted that whereas we see low vessel capacity utilization in FL1 (the load factor in Table 7) since this route is servicing a sparsely populated rural area, these numbers are significantly higher for the five other instances with larger demand.

As mentioned in Section 4.3, we do not consider the potential conflict at charging stations, which can become a practical constraint when the number of vessels gets large, as for the artificial instances with the highest demand (i.e., FL100 and SV12). Therefore, the charging infrastructure costs might be too optimistic for these instances as there might be a need to have more charging stations available to avoid a conflict among the vessels. However, as we can see from the cost breakdown in Table 6, this cost component only constitutes 2.6% of the total cost for FL1, and actually much less than this for high-demand instances (i.e., 0.2% and 0.1% for instances FL100 and SV12, respectively). Therefore, investing in more charging infrastructure to avoid this conflict would not change the results much and certainly not the main conclusions from our analyses.

The subsequent sections focus primarily on cases FL1 and SV1, which are based on real data and therefore most relevant for Norwegian stakeholders. Comparable results for the artificial cases are available from the authors upon request.

6.2. Analyses of the abatement costs and value of optimizing frequency and sailing speeds

To analyze the value of optimizing frequency and sailing speeds, as well as further analyzing the abatement costs of introducing zero emission vessels, we run the real world instances, FL1 and SV1, with fixed frequencies and sailing speeds. These variables are fixed to their currently observed frequencies and speed levels in the corresponding geographical areas. By doing this, we can compare the abatement cost of introducing zero emission vessels when alterations to the current operations and service level are allowed versus when this is assumed fixed. The observed speed is 25 knots for all legs in both Florø and Stavanger and the service frequencies are, as previously mentioned, two and five, respectively.

First, we study the impact on the abatement cost of going from conventional to zero emission vessels, both when the service level (i.e., frequency and sailing speed) is fixed and when it is optimized. The results are summarized in Fig. 7. For the FL1 test instance, the abatement cost of choosing zero emission over conventional vessels is 14% (2 178 NOK) when the service level is optimized and 21% (3 744 NOK) when today's service level is kept or fixed. For the SV1 instance, the corresponding abatement costs are 24% (8 826 NOK) and 13% (5 594 NOK), respectively, thus yielding no clear indication whether the cost of choosing zero emission vessels is higher or lower when the service level is kept fixed or optimized. Note that the absolute numbers of the absolute costs referred to above are scaled down to the length of the planning horizons in the test instances, amounting to five hours both for FL1 and SV1.

If we rather consider the abatement cost from a situation with the fixed service level as of today to an optimized service level, as shown in Fig. 8, we obtain a more interesting result. While the additional cost of choosing zero emission vessels for the FL1 instance when the service level remains constant is 21% (3 744 NOK), the corresponding cost is only 2% (414 NOK) when we also optimize the service level. For the SV1 case, the abatement cost decreases from 13% to 7% (2 932 NOK) when going from fixed to optimized service level. These results indicate a clear advantage of optimizing the service frequency and sailing speeds when transitioning from conventional to zero emission vessels.

To analyze the true value of optimizing the strategic, tactical and operational decisions at the same time, we extend our analysis further and evaluate the extra cost incurred by fixing the current service level. The results for the FL1 and SV1 instances are presented

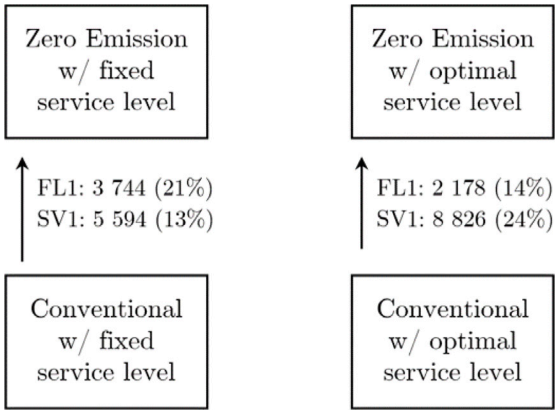

Fig. 7. Abatement cost (NOK) and relative increase when fixing service level to current level.

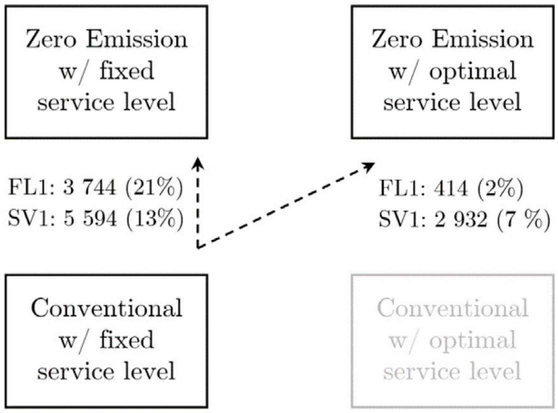

Fig. 8. Abatement cost (NOK) and relative increase when optimizing the service level.

in Fig. 9 and show that the value of optimizing the service level is substantial. One may still argue that complicating the model with operational and tactical decisions is not necessary if the strategic decision variables take the same values when solving these separately. To quantify this value, we follow the approach described in the paragraph above; solving the model again, fixing the strategic decisions from the first solution. This is in fact the case for the conventional solutions of both the FL1 and the SV1 instance, as shown in Fig. 10. Both the vessel type and the number of acquired vessels are equal when solving the model with fixed frequency and sailing speeds, and when they are these decisions are optimized. For the zero emission solutions of the two instances, we do, however, observe different strategic decisions when fixing the service level, compared to the optimized model. In other words, there exists a significant gain in simultaneously optimizing the operational, tactical and strategic decisions. As seen in Fig. 10, these gains are 17% (2 957 NOK) and 4% (1 827 NOK) for the FL1 and SV1 instances, respectively.

To summarize this analysis, we have presented three key results in relation to maintaining the current service level. Firstly, we observe that the abatement cost when transitioning from a conventional passenger vessel service with a fixed service level to a zero emission solution is significantly lower when the frequency and the sailing speeds also are optimized. This result is, as previously mentioned, illustrated in Fig. 8. Secondly, we conclude there is a significant value of including tactical and operational decisions when considering the zero emission solutions, even though we are primarily interested in the strategic investment decisions. This was shown in Fig. 10. Thirdly, despite this, we see that the abatement cost is always positive and significant.

6.3. Impact of CO_2tax

Market-based instruments to mitigate carbon dioxide emissions from maritime transports is high on the agenda of decision makers. IMO's initial strategy to reduce GHG emissions considers market-based measures as an intermediate-term measure, while the European Union's Green Deal proposes to extend the Union's Emission Trading System to maritime transport. In this section, we study the impact of carbon pricing for the transition to battery electric vessels.

A tax per ton CO_2 emitted is an important political instrument for reducing emissions (The World Bank, 2014). Fig. 11 shows the impact of an increasing CO_2 tax on the abatement cost scaled by the length of the planning horizon (five hours) of changing

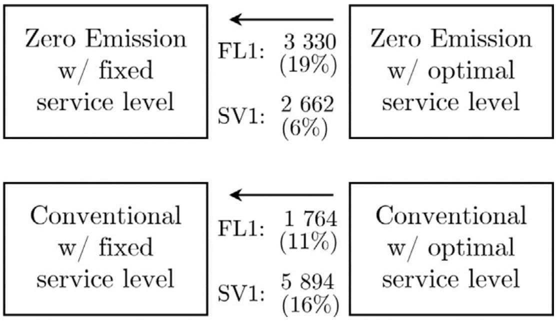

Fig. 9. Difference in total system cost (NOK) and relative difference when comparing fixed service levels with optimal solutions for zero emission and conventional vessels, respectively.

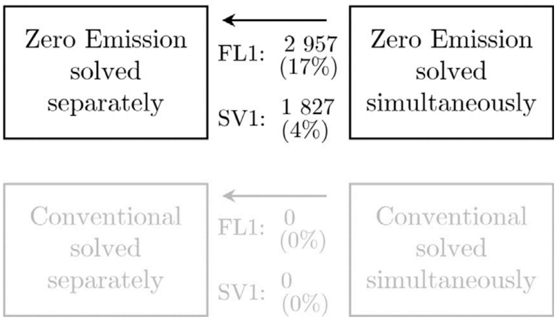

Fig. 10. Value (NOK) and relative difference when solving the operational, tactical and strategic decisions simultaneously.

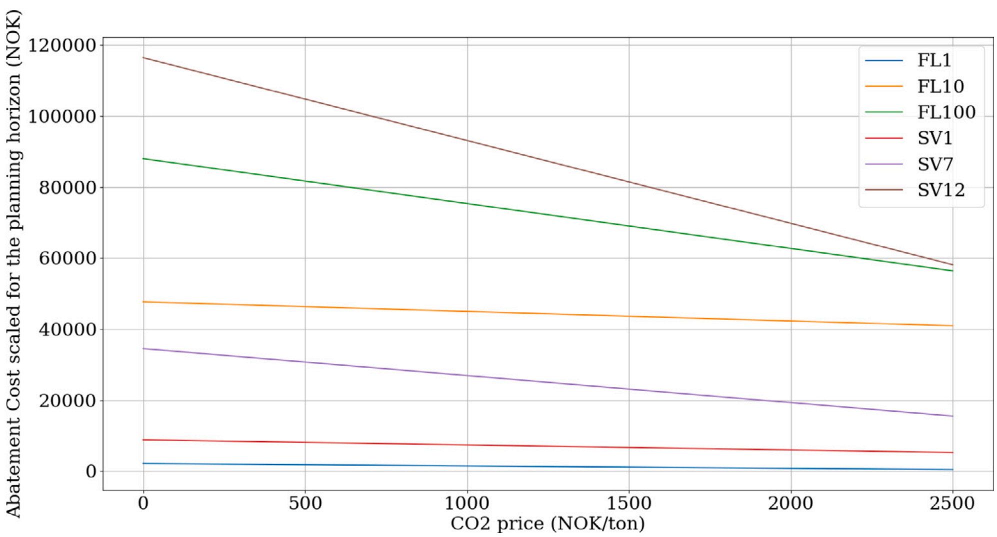

Fig. 11. The abatement cost as a function of a CO_2 tax.

to zero emission vessels for different CO_2 tax levels for the six test instances. Here, the service level is also optimized. The CO_2 tax is not included directly in the fuel cost of the model, but the emission costs when using conventional vessels are computed ex post based on the emissions from the optimal solutions, yielding a linear relationship between the CO_2 tax and the cost of choosing zero emission vessels. The emissions for the conventional vessels are calculated based on their fuel consumption, where each kilogram of fuel equals an emission of 3.2 kilograms of CO_2 (Statistics Norway, 2017).

Note that in Fig. 11, the abatement cost of the instances with the highest demand and therefore the most substantial CO_2 emissions has steeper reductions compared to the instances with lower emissions. A more detailed analysis of the results from the graph is listed in Table 8. The required break even tax is listed in the first row. For politicians and experts, a pronounced goal for

Table 8
An overview of the effect of CO_2 tax levels on the abatement costs of the different instances.

Instances	FL1	FL10	FL100	SV1	SV7	SV12
Break even CO_2 tax	3 198	17 710	6 956	6 172	4 537	4 991
Abatement Cost at 2000 NOK/ton	816	42 324	62 713	5 960	19 325	69 787
% Reduction in Abatement Cost	62.5%	11.3%	28.8%	32.4%	44.1%	40.1%

Table 9
Solutions for in the different values of C^{PW}, showing the optimal vessel type (VT), the number of vessels (#) and the frequency (f).

Instance	C^{PW}	VT	#	f	Total cost	Cost of Alt. Transport	% of Total
FL1	5	1S	1	1	8 454	514	6.1%
	50	1S	1	2	13 456	257	1.9%
	100	1S	1	2	17 030	1 542	9.1%
	168	1S	1	2	17 869	1,542	8.6%
	225	1S	2	3	25 178	1 542	6.1%
SV1	5	2M	1	2	23 997	11 570	48.2%
	50	1S	2	5	34 734	4 628	13.3%
	100	1S	3	7	43 847	0	0.0%
	168	1S	3	7	45 851	0	0.0%
	200	1S	2	5	58 805	16 199	27.5%
	250	1S	3	7	63 396	16 199	25.6%

the CO_2 tax is 2000 NOK per ton by 2030 (Energi og Klima, 2021). Hence, the abatement cost for each test instance when the CO_2 tax equals 2000 NOK/ton is shown in the second row of Table 8. The third row shows the reduction in abatement cost relative to a tax rate of zero. The table clearly shows that a CO_2 tax of 2000 NOK/ton is insufficient for the zero emission solutions to be cost-competitive compared to the conventional ones.

6.4. Impact of passenger waiting cost

The cost of waiting in port, represented by the parameter C^{PW}, was, as described in Section 5.1 and based on (Flügel et al., 2020) and Wardman et al. (2016), set to 168 NOK/hour. However, it can be argued that this value is more suited for high-frequent services where passengers do not plan their arrivals based on the schedule. Even though the solutions for the increased demand instances, i.e., FL10, FL100, SV7 and SV12, can be considered high-frequent services, this is hardly the case for the real instances FL1 and SV1, which have optimal frequencies of two and seven over a five hour planning horizon, respectively (shown in Table 5). Because of this, the costs of waiting in port also constitute as much as 43.8% (Table 5) and 40.8% of the total costs for the FL1 and SV1 instances, respectively. However, in these instances it can be assumed that the passengers will schedule their arrivals closer to the time of departure, reducing the inconvenience of the low frequency. Therefore, it is of interest to perform a sensitivity analysis for different values of the cost of waiting in port.

The results of this sensitivity analysis are presented in Table 9. The table includes both strategic and tactical solutions for each instance, i.e., the chosen vessel type, the number of vessels and the service frequency, along with the total cost, as well as the cost of alternative transportation in both absolute terms and as a percentage of the total costs.

We observe from Table 9 that for increasing values of C^{PW}, the optimal frequency for the FL1 instance increases. This can be expected as with increased values of C^{PW}, the optimal frequency should be increased to reduce average waiting time, which again avoids that the waiting cost becomes too dominant. We observe a similar trend for instance SV1, except for when $C^{PW} = 200$ NOK. A notable result from the FL1 instance is that it is not optimal to satisfy all the demand for any value of C^{PW}. For the SV1 instance on the other hand, all demand is met when C^{PW} is equal to 100 and 168 NOK. We also observe that both the strategic and tactical decisions are highly sensitive to the perceived waiting cost of the passengers. If the passengers find the cost of waiting too high compared to the cost of alternative transportation, they will not use the vessel service.

7. Conclusions

Climate and environmental policies target substantial emission cuts from transport. While road transports play a leading role, other modes including maritime transports are now receiving more attention. In Norway, the Government aims to halve domestic maritime emissions by 2030 and to adopt zero emission standards for high-speed passenger vessels by 2025. This is by no means an easy transition, and knowledge-based decision support is paramount to meet policy objectives in a cost-effective manner and to ensure politically feasible transition. In this paper, we consequently study the Zero Emission Vessel Route Planning Problem, which deals with the optimal planning of a route to be serviced by battery electric vessels. To provide decision support, we propose a novel

Mixed-Integer Programming optimization model for the ZEVRPP, which jointly minimizes operator and passenger costs subject to strategic, tactical, and operational decisions.

The planning problem is utilized to estimate technology replacement potential and associated costs for two existing services in Norway, as well as four hypothetical increased demand scenarios derived from these two services. The latter generalizes the analysis to services that are operated in more densely populated areas, which also makes the study transferable to other countries. In all cases considered, the total costs of operation increase with the adoption of zero emission technology. This is attributed to battery range and charging time that combined require a higher number of vessels compared to the number of diesel ferries to uphold frequency. Because of these constraints, the optimal frequency is reduced with adoption of zero emission technologies in some of the cases considered, and the transition is generally accompanied by passenger discomfort from increased travel and waiting time. These are key trade-offs in the diffusion of battery electric vessels, which our paper presents in a clear way to decision makers.

In our experience, decision makers seek to replace existing vessels by zero emission technologies whilst upholding existing services. This approach contradicts the least cost principle in abatement cost estimation, and our advice is consequently to seek the optimal combination of technical and operational measures to reach emission targets. The results show economic advantage of optimizing frequency and sailing speeds with adoption of zero emission technology. While changing existing schedules can be unpopular among the general public, making no alternations can conflict with welfare maximization subject to scarce public funds. We believe the results presented herein provide important insights to decision makers and constituencies alike to facilitate a broader understanding of the economic trade-offs involved in the diffusion of zero emission vessels.

Wangsness et al. (2020) identify a conflict among efficiency and effectiveness of Norway's policies for electrifying road transport. Our paper shows that the gap is further increased with policies to promote zero emission high-speed vessels. Estimated abatement costs range between 3000 and 18 000 NOK/ton in the cases considered, thereby surpassing the Government's estimate of the social cost of carbon of 2000 NOK/ton in 2030. This might suggest that there is a potential for reducing emissions at a lower cost elsewhere. The Norwegian Government's investigation into measures for meeting emission targets set by the Paris agreement (Norwegian Environment Agency, 2020) applies abatement cost estimates ranging from 500 to 1500 NOK/ton for battery electric high-speed vessels. Our study suggests that these are substantially undervalued.

Our personal communication with County Councils in charge of service planning reveals that regional governments are motivated to adopt zero emission technologies for their connections. However, major concerns are uncertainties related to the added costs of service provision and the degree to which they will be compensated. Regional governments in Norway do not have the discretion to extract tax revenues and are consequently dependent on transfers from the central government. Currently, the key source of regional government income known as the general grant scheme has no mechanisms implemented to offset costs related to adoption of zero emission technology. Developing sound financing models will thus be a vital step towards diffusion of zero emission public transport.

While this study has provided novel insights into technical, economic and political feasibilities of zero emission technologies, we acknowledge that some of the conclusions can change with subsequent analysis. First, maritime battery technology may improve – as seen from the rapid development of automotive applications – and other energy carriers such as hydrogen or ammonia that offer longer range can become viable. Second, we have not considered possibilities to alter or optimize routes to accommodate new energy systems. Indeed, omitting ports where substitute modes are readily available and where grid capacity is scarce can be an unpopular yet welfare enhancing measure to diffuse battery electric vessels. Because of anticipated political constraints to implement major changes to the public transport system, we have considered route optimization out of scope for the current paper that aims to provide decision support for energy transitions in the short and intermediate terms. Third, extensions of the model to multiple planning horizons, e.g., by differencing among peak and off-peak, can provide further insights. Among others, this will enable consideration of time-of-use electricity pricing for zero emission vessel services. We welcome additional contributions on these topics.

CRediT authorship contribution statement

Håkon Furnes Havre: Methodology, Software, Formal analysis, Investigation, Visualization, Writing – original draft. **Ulrik Lien:** Methodology, Software, Formal analysis, Investigation, Visualization, Writing – original draft. **Mattias Myklebust Ness:** Methodology, Software, Formal analysis, Investigation, Visualization, Writing – original draft. **Kjetil Fagerholt:** Supervision, Methodology, Validation, Writing – review & editing. **Kenneth Løvold Rødseth:** Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

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Appendix A. Notation for the zero emission model

Sets	
$\mathcal{K}$	Set of legs in route
$\mathcal{V}$	Set of available vessel types
$\mathcal{S}_v$	Set of discrete speed levels for vessel type v
$\mathcal{F}$	Set of frequencies
Parameters	
$\overline{T}$	Length of planning period
T_{kvs}	Sailing time of leg k with speed s and vessel type v
$\underline{T}_k^W$	Minimum waiting time in port k to allow passengers to enter and exit the vessel
T_{ij}^U	Travel time from port i to port j with the fastest vessel type available, sailing at its fastest speed level, following the route with no charging or waiting time beyond the minimum requirements
W_f	Average waiting time at frequency f
D_{ij}^T	Maximum demand from port i to port j
D_{ijf}	Frequency dependent demand from port i to port j, at frequency f
Q_v	Passenger capacity of vessel type v
E_{kvs}	Energy consumption on arc k with vessel type v sailing at speed s
$\overline{B}_v$	Maximum battery level of vessel type v
$\underline{B}_v$	Minimum battery level of vessel type v
P_k	Available charging power in port k
C_v^{FC}	Fixed cost per vessel of type v
C_k^{INF}	Fixed cost of investing in charging infrastructure in port k
C_k^{VC}	Cost per unit of energy charged in port k
C_{ij}^{ALT}	Alternative cost per passenger not transported between port i and j
C^{PW}	Value of passenger time while waiting at port
C^{SW}	Value of passenger time while sailing
Variables	
α_k	1 if charging infrastructure is built in port k, 0 otherwise
δ_v	1 if vessel type v is chosen, 0 otherwise
z_f	1 if frequency f is chosen, 0 otherwise
y_v	Number of vessels of type v used
x_{kvs}	Weight variable for speed s for vessels of type v on leg k
l_{kjv}	Number of passengers traversing leg k with destination port j with a vessels of type v
q_{kj}	Number of passengers picked up in port k with destination port j
u_{ij}	Unmet demand between port i and port j
t_v^{RT}	Total roundtrip time for a vessel of type v
t_{kv}^C	Charging time before traversing leg k with a vessel of type v
w_{kv}^T	Time spent in port k per roundtrip excluding charging time for a vessel of type v
t_{ij}	Sailing time from port i to port j
b_{kv}	Battery level when leaving port k for vessels of type v

Appendix B. Linearizing the non-linear terms of the zero emission model

In the objective function (1), the third, fifth and sixth term are non-linear since a continuous variable is multiplied with the binary variable z_f. This also applies to Constraints (6). Here, we explain how these terms can be linearized to obtain a mixed-integer programming (MIP) model which can be solved by a commercial MIP-solver (e.g., Gurobi).

To linearize the third term in the objective function, which is the variable cost of charging, we introduce an auxiliary variable, v_f, and the following additional constraints to be included in the model:

$$v_f \geq \sum_{v \in \mathcal{V}} \sum_{k \in \mathcal{K}} C_k^{VK} P_k t_{kv}^C - M_f^5 (1 - z_f), \qquad f \in \mathcal{F} \tag{36}$$

where M_f^5 is a big-M parameter. The third term in the objective function (1) then becomes

$$\sum_{f \in \mathcal{F}} f v_f. \tag{37}$$

Constraints (36) ensure that for the chosen frequency f where $z_f = 1$, the auxiliary variable will take the value of the first term of the right-hand side since the objective function aims at minimizing v_f. For the other frequencies (i.e., where $z_f = 0$), the auxiliary variable v_f will take the value 0 due to non-negativity requirement.

The same approach as above is used to linearize the other non-linear terms of the objective function, which we do not show here.

To linearize Constraints (6), another auxiliary variable s_f is introduced. The s_f-variable represents the product of z_f and the sum of t_v^{RT}. It is equal to zero if z_f equals zero, and equal to the sum of the roundtrip times when z_f is one. Accordingly, the following constraints are included in the problem:

$$s_f \geq \sum_{v \in \mathcal{V}} t_v^{RT} - M_f^8 (1 - z_f), \qquad v \in \mathcal{V},\ f \in \mathcal{F} \tag{38}$$

After introducing (38), Constraints (6) from the original formulation in Section 4.3 can be replaced with Constraint (39) below.

$$\sum_{f \in \mathcal{F}} f s_f = \overline{T} \sum_{v \in \mathcal{V}} y_v \tag{39}$$

A problem with the linearization of Constraints (6) is that Constraints (38) allow the roundtrip time, t_v^{RT}, to be less than the value of s_f. This is caused by the fact that the definition of roundtrip time, i.e., the right-hand side of Constraints (5), also define the transit time, t_{ij}, in Constraints (10) and (11). Since the transit time is minimized as a part of the sixth term in the objective function (1), the roundtrip time, t_v^{RT}, is minimized. We want t_v^{RT} to exactly represent the roundtrip time, because we seek to distribute the waiting time in the ports, w_{kv}^T, in an economically efficient manner. To alleviate the issue described above, we reformulate the definition of the transit time, t_{ij}, in Constraints (10) and (11) as follows:

$$\begin{aligned} t_{ij} = \sum_{f \in \mathcal{F}} s_f - \sum_{v \in \mathcal{V}} \Bigg[\sum_{k=j}^{|\mathcal{K}|} \Bigg(\sum_{s \in \mathcal{S}_v} T_{kvs} x_{kvs} + t_{kv}^C + w_{kv}^T \Bigg) + \sum_{k''}^{i-1} \sum_{s \in \mathcal{S}_v} T_{kvs} x_{kvs} \\ + \sum_{k=1}^{i} (t_{kv}^C + w_{kv}^T) \Bigg], \quad i \in \mathcal{K},\ j \in \mathcal{K} \,|\, i < j \end{aligned} \tag{40}$$

where,

$$k = argmin\{1, i-1\}$$

$$t_{ij} = \sum_{f \in \mathcal{F}} s_f - \sum_{v \in \mathcal{V}} \Bigg[\sum_{k=j}^{i-1} \sum_{s \in \mathcal{S}_v} T_{kvs} x_{kvs} + \sum_{k=j}^{i} (t_{kv}^C + w_{kv}^T) \Bigg], \qquad i \in \mathcal{K},\ j \in \mathcal{K} \,|\, j < i \tag{41}$$

As stated above, the actual roundtrip time is s_f for the chosen frequency f, and zero for all the other frequencies. Thus, we find the transit time between ports i and j by subtracting the terms that do not define the time between the ports from the sum of s_f. Hence, the variable representing the waiting time in a port, w_{kv}^T, will take the actual waiting time, since Constraints (38) must be satisfied.

Appendix C. Conventional vessel model

Here, we show how the model in Section 4.3 is adapted to the situation with fossil-fueled conventional (diesel) vessels. This model is used for comparison so that we can evaluate the abatement cost of introducing zero emission solutions. The conventional vessel model shares most of the characteristics with the zero emission model, so we therefore focus only on the differences in the following.

Additional notation

The sets remain the same as in Section 4.2 (summarized in Appendix A), but the vessel types included in the set $\mathcal{V}$ are now all conventional ones. Most of the parameters also remain the same as in Section 4.2, except some that become redundant. There is no longer a need for charging infrastructure, which means that all parameters, variables and constraints related to this can be removed from the zero emission model. Furthermore, the variables related to vessel battery level and time spent charging in port are also no longer needed. The conventional model has one new variable compared to the zero emission model. The new variable e_v^{RT} represents the fuel consumption on one roundtrip of the route for a vessel of type v and depends on the chosen sailing speed.

Mathematical model

The can now define the following new objective function for the conventional vessel model:

$$\begin{aligned} \min \quad & z = \sum_{v\in\mathcal{V}} C_v^{FC} y_v + \sum_{v\in\mathcal{V}}\sum_{f\in\mathcal{F}} C^{VC} e_v^{RT} F_f z_f \\ & + \sum_{i\in\mathcal{K}}\sum_{j\in\mathcal{K}} C_{ij}^{ALT} u_{ij} + C^{PW} \sum_{f\in\mathcal{F}} W_f z_f (\sum_{i\in\mathcal{K}}\sum_{j\in\mathcal{K}} q_{ij}) \\ & + C^{SW} \sum_{f\in\mathcal{F}}\sum_{i\in\mathcal{K}}\sum_{j\in\mathcal{K}} (t_{ij} - T_{ij}^{U}) D_{ijf} z_f \end{aligned} \tag{42}$$

The roundtrip time does no longer include the charging time and the following Constraints (43) replace Constraints (5). For the same reason, Constraints (10) and (11) are replaced by Constraints (44) and (45), respectively.

$$t_v^{RT} = \sum_{k\in\mathcal{K}}\sum_{s\in\mathcal{S}_v} T_{kvs} x_{kvs} + \sum_{k\in\mathcal{K}} w_{kv}^T, \qquad v\in\mathcal{V} \tag{43}$$

$$t_{ij} = \sum_{v\in\mathcal{V}} \left[\sum_{k=i}^{j-1}\sum_{s\in\mathcal{S}_v} T_{kvs} x_{kvs} + \sum_{k=i-1}^{j-1} w_{kv}^T \right], \qquad i\in\mathcal{K},\ j\in\mathcal{K} \mid j>i \tag{44}$$

$$t_{ij} = \sum_{v\in\mathcal{V}} \left[\sum_{k=i}^{|\mathcal{K}|}\sum_{s\in\mathcal{S}_v} T_{kvs} x_{kvs} + \sum_{\tilde{k}}^{|\mathcal{K}|} w_{\tilde{k}v}^T + \sum_{k'}^{j-1} \left(\sum_{s\in\mathcal{S}_v} T_{k'vs} x_{k'vs} + w_{k'v}^T \right) \right] \qquad i\in\mathcal{K},\ j\in\mathcal{K} \mid j<i \tag{45}$$

where,

$$\tilde{k} = argmin\{|\mathcal{K}|, i+1\}$$
$$k' = argmax\{1, j-1\}$$

Since all constraints related to battery level and charging are redundant, Constraints (12), (13), (14), (15) and (16) of the zero emission model are removed. The fuel consumption depends on the vessels' sailing speeds, as it did for the energy consumption in the zero emission model, and is calculated according to Constraints (46). Finally, we require non-negativity for the fuel consumption variable in (47).

$$e_v^{RT} = \sum_{k\in\mathcal{K}}\sum_{s\in\mathcal{S}_v} E_{kvs} x_{kvs}, \qquad v\in\mathcal{V} \tag{46}$$

$$e_v^{RT} \in \mathbb{R}^+, \qquad v\in\mathcal{V} \tag{47}$$

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