

Article

Impact of Weather Variability on the Operational Costs of a Maritime Ferry

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Abstract

Maritime ferries increasingly operate under non-stationary hydro-meteorological conditions that complicate cost planning. This study investigates how short-term weather variability affects expenditures for a ferry on the Gdynia–Karlskrona route. We combine a state-based operational framework (18 discrete states) with a subsystem-level cost model covering navigation, propulsion/steering, loading/unloading, stability control, and mooring/anchoring. Direct and indirect costs are linked to subsystem activity and state duration, while weather is incorporated through hazard categories that scale hourly costs. Expert-elicited rates and observed monthly state durations provide the basis for baseline estimates and hazard scenario simulations. Results reveal a disproportionate cost structure: two open-sea states constitute over 97% of the baseline monthly cost (19,490.19 PLN). Weather hazards further amplify costs, with moderate (1st-degree) and severe (2nd-degree) scenarios producing increases of ~8% and ~20%, respectively, compared to normal conditions. By embedding weather as an endogenous factor in a probabilistic cost model based on a semi-Markov process, the approach enhances predictive fidelity and supports decision-making for climate-resilient planning. These findings suggest that adaptive routing, speed management, and targeted maintenance of the propulsion and steering subsystems during open-sea navigation offer the highest potential for cost resilience. The study provides operators and policymakers with a transparent framework for climate-resilient planning and investment in semi-enclosed maritime corridors.

Keywords: Baltic Sea; ferry operations; weather variability; operational costs; stochastic modeling; semi-Markov process; hydro-meteorological hazards; decision support; cost resilience



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1. Introduction

The maritime transportation sector is entering a phase of unprecedented operational complexity, driven by aging infrastructure, stricter environmental regulations, and increasing meteorological volatility [1,2]. As vessels and port systems exceed their original design life, they are exposed to intensified hydro-meteorological regimes that accelerate material degradation and undermine traditional cost-optimization frameworks [3–7]. These challenges are particularly evident in semi-enclosed maritime domains such as the Southern Baltic Sea, where limited fetch and shallow bathymetry amplify wave action, storm frequency, and fatigue processes [2,8].

Furthermore, from a broader economic perspective, it is important to note that in addition to the supply-side costs analyzed in this study, the demand side is also a critical

factor for the overall economic viability of shipping. For instance, in the Baltic Dry Index (BDI)-related literature, freight rate volatility is shown to be influenced by the time inconsistency of shipbuilding cycles and fluctuating global demand [9,10]. During economic downturns, a decrease in demand leads to falling freight rates and underutilized capacity. Conversely, during periods of expansionary growth, the sector often cannot rapidly increase supply, leading to shipping bottlenecks and surging freight costs. While these demand-side dynamics are fundamental to the shipping industry's financial health, our model deliberately focuses on the technical, supply-side cost structures. This allows for a clear and quantifiable analysis of the base operational cost sensitivity to weather variability, which constitutes a fundamental and persistent underlying cost driver irrespective of the market cycle.

Conventional lifecycle cost models, developed under assumptions of environmental stationarity and regular maintenance cycles, are increasingly inadequate in this dynamic context [11,12]. Their reliance on historical averages and fixed degradation curves fails to capture the nonlinear, path-dependent nature of environmental damage mechanisms such as stress-corrosion cracking or fatigue induced by clustered, high-energy wave events [13,14]. As shown by Wang et al. (2024), after examining an inland passenger barge using an integrated lifecycle assessment, systematic underestimation of maintenance frequency and lifecycle costs is evident when environmental data are excluded from operational planning [15]. Accordingly, the level of underestimation varies between 30–50% for maintenance and 18–25% for total lifecycle costs in high-variability regions. In contrast, earlier deterministic cost models that assumed more stable environmental baselines reported lower deviations, typically within the 20–30% range, underscoring the increased financial risk associated with contemporary climate variability.

These effects are especially pronounced in the Southern Baltic, where warming trends of approximately 0.6 °C per decade exceed global oceanic averages, reducing seasonal ice cover and amplifying autumnal storm energy [1,16,17]. Such conditions impose conflicting operational constraints: ice-avoidance routing may mitigate hull abrasion but increase exposure to slamming loads, while fuel-optimized speed profiles may become counterproductive under persistent head seas [18]. Recent analyses, drawing on UNCTAD (United Nations Conference on Trade and Development) maritime transport statistics and regional operational data, suggest that weather-related disruptions already account for up to 42% of total operating costs in Baltic ferry operations, surpassing expenditures on crew, port fees, and even fuel [19].

The significant financial impact of weather variability is not limited to ferry operations. Studies on bulk shipping have quantitatively demonstrated that weather delays constitute a major cost component [20], while comprehensive evaluations confirm that ship performance and fuel efficiency are predominantly determined by the interplay of chosen route and encountered weather conditions [21]. This underscores that accurately modeling the weather-cost relationship is a universal challenge in maritime economics. Although advanced weather routing systems are being developed to mitigate these impacts [22,23], their optimization potential remains limited without high-fidelity cost models capable of translating real-time meteorological data into operational expenditures. Our study addresses this precise gap by developing a subsystem-level cost model that can serve as a critical input for such decision-support tools.

Emerging stochastic frameworks, including semi-Markov models and probabilistic maintenance scheduling, provide a partial remedy by incorporating degradation uncertainty [24–28]. However, these models often treat environmental influences as exogenous inputs rather than integrated drivers of system behavior [13,29]. This limitation prevents

them from accurately representing transitions between operational states driven by short-term weather variability.

From a methodological standpoint, the application of Markov and semi-Markov processes is well-established in maritime risk and safety science. Recent research has successfully employed these stochastic methods for long-term risk estimation of maritime accidents [30], safety assessment of multi-state maritime systems [22], and determining navigational safety criteria [23]. These applications demonstrate the power of this approach in modeling complex, state-dependent systems under uncertainty. Our study innovatively transfers this robust methodological framework from the traditional domain of safety and risk analysis to the field of operational cost forecasting, creating a direct and quantifiable link between weather-induced operational states and financial performance.

To address this gap, this study develops a novel modeling framework where short-term weather variability is treated not as an external disturbance, but as an endogenous, probabilistic driver of costs. The proposed methodology is built on the tight coupling of two core components: a semi-Markov process modeling the dynamics of weather hazards, and a state-dependent cost model for the ferry's technical subsystems. This integration allows the model to move beyond static averages and explicitly capture the path-dependent and clustered nature of weather-driven costs, quantifying how sequences of meteorological conditions such as wind regimes, wave energy spectra, and storm clustering directly impact operational expenditures.

By embedding environmental data directly into the cost-optimization process, the model enhances predictive adaptability: rather than minimizing average expenditures, it minimizes conditional costs under changing environmental regimes. The framework provides ferry operators with a decision-support tool for real-time routing, speed control, and maintenance prioritization under uncertainty, while offering policymakers a quantitative basis for climate-aligned infrastructure investment strategies.

The primary objective of this study is to develop and demonstrate a novel modeling framework that integrates short-term weather variability as an endogenous, probabilistic driver of ferry operational costs. Our specific aims are: (1) to define the ferry's operational cycle through discrete states and associated subsystem costs; (2) to incorporate high-resolution weather data via hazard categories and probabilistic state residence times; and (3) to quantify the impact of this variability on the total operational cost structure. The novelty of our approach lies in the tight coupling of a semi-Markov weather process with a state-dependent cost model, moving beyond static averages to capture the path-dependent and clustered nature of weather-driven costs.

The remainder of this paper is structured as follows. Section 2 (Materials and Methods) details the study area, vessel description, the developed cost model, and the integration of the semi-Markov weather process. Section 3 (Results and Discussion) presents the outcomes of the cost simulations, including the baseline and weather-adjusted costs, and discusses their practical implications for ferry operators. Finally, Section 4 (Conclusions) summarizes the key findings, highlights the study's contributions and limitations, and suggests directions for future research.

2. Materials and Methods

2.1. Study Area and Vessel Description

2.1.1. Study Area

This study focuses on the ferry service operating across the Southern Baltic Sea, specifically along the route connecting the ports of Gdynia (Poland) and Karlskrona (Sweden). This maritime corridor represents a vital transport link within the Baltic region, character-

ized by moderate open-sea exposure, constrained port access, and dynamically varying hydro-meteorological conditions.

The Gdynia–Karlskrona route traverses several navigational zones, including port areas, restricted coastal waters, and the open Baltic Sea. The voyage typically involves 18 distinct operational states, ranging from cargo loading, undocking, and maneuvering, to open-sea navigation and docking at the destination port. The route exposes the vessel to a range of environmental stressors, including wind gusts, variable wave heights, seasonal icing, and salinity fluctuations, all of which can significantly impact system degradation, fuel consumption, and operational reliability.

Thanks to its high service frequency daily round trips the route provides an extensive dataset for analyzing the relationships between environmental variability and technical system performance under real-world conditions. Data from this operational corridor serve as the basis for modeling ferry subsystem behavior, degradation trajectories, and associated cost structures.

2.1.2. Vessel Description

The subject vessel is a large ferry designed for daily passenger and freight transport across the Baltic Sea [24,31,32]. In total, seven subsystems are distinguished in its architecture:

S_1 : Navigation Subsystem—Comprises core navigational equipment, including GPS, AIS, radar, gyrocompass, echo sounders, ECDIS, ARPA, and communication systems. It plays a critical role throughout all operational states, both at sea and in port areas.

S_2 : Propulsion and Steering Subsystem—Includes four main engines, three bow thrusters, two fixed-pitch propellers, and two rudders. This system governs all propulsion and maneuvering activities and is particularly active during transit and port maneuvers.

S_3 : Loading and Unloading Subsystem—Consists of upper and front vehicle decks and passenger boarding bridges in both Gdynia and Karlskrona. It operates primarily during port turnaround phases.

S_4 : Stability Control Subsystem—Comprises port and sea-based anti-heeling mechanisms used during cargo operations and in dynamic sea conditions, respectively.

S_5 : Mooring and Anchoring Subsystem—Includes winches and anchoring equipment located both at the stern and the bow. It is utilized during berthing and unberthing operations.

S_6 : Protection Subsystem—Comprises fire detection and firefighting systems, monitoring devices, and access control equipment in compliance with international safety standards. It safeguards the vessel, crew, and cargo against onboard hazards and external threats.

S_7 : Rescue Subsystem—Consists of lifeboats, life rafts, marine evacuation systems (MES), lifejackets, and emergency beacons such as EPIRB and SART. It ensures safe evacuation of passengers and crew and supports emergency operations at sea.

The subsystems are illustrated in Figure 1.

While the ferry's complete architecture comprises multiple functional domains, the focus of this study is restricted to its technical system, which includes five of the operational subsystems— S_1 – S_5 —while the protection and rescue subsystem (S_6), the social subsystem (S_7) are omitted. This restriction allows the analysis to focus on the technical domains most directly related to the vessel's operational performance and cost structure.

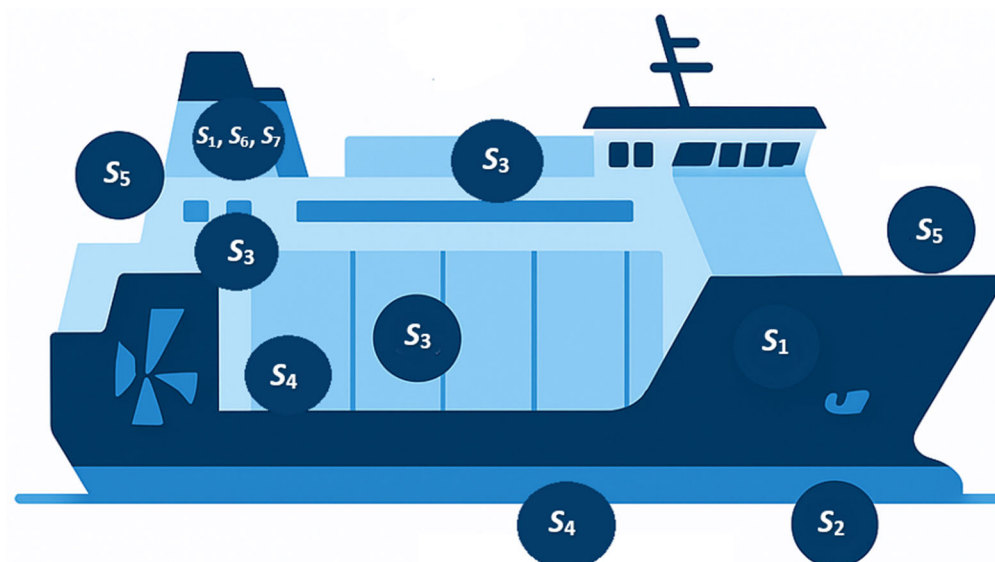


Figure 1. Technical subsystems of the analyzed ferry highlighted in the vessel's schematic layout.

The vessel's operational cycle includes 18 discrete states ranging from loading and departure in Gdynia to docking, unloading, and return transit from Karlskrona. The 18-state operational framework presented in Table 1 and Figure 2 is based on the actual operational procedures of the Gdynia-Karlskrona ferry service as provided by the operator. It accurately reflects the vessel's navigation patterns, port operations, and the specific geographical constraints of the route. The average monthly durations represent planned operational times derived from the operator's schedules. In this study, we apply our cost modeling and weather impact analysis within this real-world operational framework to quantify how weather variability affects expenditures across these predefined states. The characteristic times for each operational state, which are crucial for understanding the cost calculations, are provided in the 'Average monthly duration [h]' column in Table 1. Each state is associated with specific subsystem utilization profiles and varying cost rates, which depend on the subsystem's active or standby status. The complete operational cycle is quasi-deterministic and repetitive, making it amenable to probabilistic modeling. Operating states are presented in Table 1 and in Figure 2.

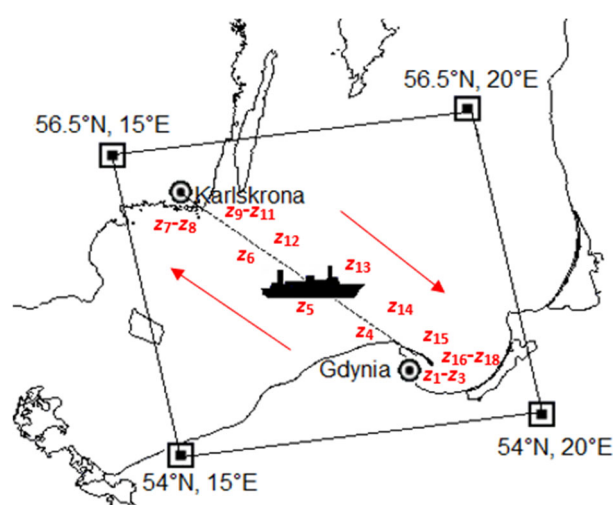


Figure 2. Spatial distribution of the ferry operating states (z_1 – z_{18}) along the voyage cycle, including port maneuvers, loading/unloading, coastal navigation, and open sea navigation.

Table 1. Operating states of the maritime ferry.

State Number	Description of Operating States	Average Monthly Duration [h]
z_1	loading at the Port of Gdynia data	27.36
z_2	unberthing operation at the Port of Gdynia	1.44
z_3	departure from the Port of Gdynia and sailing to buoy “GD”	18.72
z_4	sailing in Polish restricted waters (from buoy “GD” to the boundary of the traffic separation scheme)	25.92
z_5	sailing in open waters (from the boundary of the traffic separation scheme within Polish maritime areas to buoy “Angoering”)	261.36
z_6	sailing in Swedish restricted waters (from buoy “Angoering” to the “Verko” quay in Karlskrona)	18.72
z_7	berthing operation at the Port of Karlskrona	3.6
z_8	unloading at the Port of Karlskrona	11.52
z_9	loading at the Port of Karlskrona	26.64
z_{10}	unberthing operation at the Port of Karlskrona	1.44
z_{11}	ferry crossing within the Port of Karlskrona	2.16
z_{12}	departure from the Port of Karlskrona and sailing through Swedish restricted waters to buoy “Angoering”	11.52
z_{13}	sailing in open waters (from buoy “Angoering” to the boundary of the traffic separation scheme within Polish maritime areas)	252.72
z_{14}	sailing in restricted waters (from the boundary of the traffic separation scheme within Polish maritime areas to buoy “GD”)	24.48
z_{15}	sailing from buoy “GD” to the maneuvering area in the Port of Gdynia	17.28
z_{16}	maneuvering in the Port of Gdynia	2.16
z_{17}	berthing operation at the Port of Gdynia	3.6
z_{18}	unloading at the Port of Gdynia	9.36

2.2. Cost Model

The choice of a semi-Markov process to model weather variability is justified by its capability to capture two critical characteristics of the Baltic Sea’s meteorological environment that are essential for accurate cost modeling. First, it accounts for duration-dependent transition probabilities, meaning the likelihood of a weather change depends on how long the system has already been in its current state. This is a more realistic representation than memoryless Markov chains, as it models the persistence of weather regimes. Second, it inherently captures the clustered nature of storm events, where severe weather conditions tend to occur in successive days. This clustering leads to cumulative, non-linear impacts on subsystem degradation and costs, which cannot be accurately represented by models relying on average or independent weather events [8,25].

Model represents a mathematical formulation of the total costs associated with the maintenance and operation of a technical system within a defined time horizon. The

model incorporates both direct and indirect expenditures incurred during the system's lifecycle [33–35].

Direct costs are strictly linked to the operation and upkeep of the system within a given interval. These include, for instance, expenses related to servicing and repairs, consumable materials, or training of operational personnel. Indirect costs, by contrast, are not directly tied to the operation of the system itself but emerge as secondary consequences of its exploitation. Examples include energy consumption, expenses associated with data protection or security, as well as potential costs resulting from delays or disruptions in system performance.

A fundamental assumption of the model is that the operational state of the system influences its functional structure, safety configuration, and consequently the cost of exploitation. This implies that the system's structure may adapt dynamically depending on the state it currently occupies. The functional structure encompasses the organization and interactions among components, subsystems, or modules working together toward specific operational goals. In practice, as operational states shift, the system may reorganize its functionality in order to sustain or enhance efficiency, safety, or other key performance parameters.

A fundamental assumption of the model is that the operational state of the system directly influences its functional structure, safety configuration, and consequently, the cost of exploitation. To operationalize this and assign credible monetary values to subsystem usage, the approximate hourly cost coefficients for the ferry's technical subsystems were established through a structured expert elicitation process. This process was conducted as a dedicated workshop involving five key system operators and marine engineers, each possessing over 15 years of operational experience on the Gdynia-Karlskrona route. The elicitation followed a modified Delphi method to ensure robustness and consensus:

- **Independent Proposal:** Experts were first presented with detailed technical definitions of the subsystems (S_1 – S_5) and the 18 operational states. They then independently proposed hourly cost coefficients based on their knowledge of subsystem-specific factors such as energy consumption, component wear-and-tear, maintenance intensity, and required crew attention during different maneuvers.
- **Facilitated Consensus Building:** The initial, anonymized proposals were collected and then discussed in a moderated plenary session. The discussion focused on reconciling divergent estimates by examining the underlying operational rationale—for instance, why propulsion costs during open-water navigation (55c) are distinct from those during complex maneuvering (75c). This step ensured that the final values were not arbitrary but reflected a shared, justified understanding of resource allocation.
- **Final Consensus Values:** The iterative process led to a final set of consensus values, which are presented in Table 2. This methodology is an established approach for synthesizing expert judgment where empirical data is scarce, ensuring the cost parameters are defensible and grounded in consolidated operational experience [36,37].

The resulting cost structure is directly linked to the actual utilization and workload of each subsystem, providing a transparent and justified basis for the model. For illustrative purposes, assuming a scaling coefficient $c = 1$ PLN, the total baseline monthly cost amounts to 19,490.19 PLN. In practical applications, this coefficient should be calibrated against actual accounting data to reflect real operational expenditures. It is crucial to note that these costs represent direct operational expenditures attributable to the functioning of the technical subsystems themselves (e.g., energy for thrusters, wear on loading equipment, operation of stability systems). They were explicitly separated from the vessel's overall operational balance (which includes fuel for main propulsion, crew salaries, insurance, and port fees) to isolate and analyze the cost impacts of the technical system's operational

profile. The scaling coefficient ‘ c ’ provides a flexible basis for further calibration with actual accounting data.

Table 2. Hourly operational costs of technical subsystems across ferry operational states.

Operating State	S_1 Navigation	S_2 Propulsion & Steering	S_3 Loading /Unloading	S_4 Stability Control	S_5 Mooring /Anchoring
z_1	20c (active)	25c (inactive)	30c (loading Gdynia)	13c (active)	5c (inactive)
z_2	20c (active)	75c (maneuvering)	10c (inactive)	10c (inactive)	30c (active)
z_3	20c (active)	75c (maneuvering)	10c (inactive)	10c (inactive)	5c (inactive)
z_4	20c (active)	55c (open water)	10c (inactive)	13c (active)	5c (inactive)
z_5	20c (active)	55c (open water)	10c (inactive)	13c (active)	5c (inactive)
z_6	20c (active)	75c (maneuvering)	10c (inactive)	13c (active)	5c (inactive)
z_7	20c (active)	75c (maneuvering)	10c (inactive)	10c (inactive)	30c (active)
z_8	20c (active)	25c (inactive)	20c (loading Karlskrona)	13c (active)	5c (inactive)
z_9	20c (active)	25c (inactive)	20c (loading Karlskrona)	13c (active)	5c (inactive)
z_{10}	20c (active)	75c (maneuvering)	10c (inactive)	10c (inactive)	30c (active)
z_{11}	20c (active)	75c (maneuvering)	10c (inactive)	10c (inactive)	5c (inactive)
z_{12}	20c (active)	55c (open water)	10c (inactive)	13c (active)	5c (inactive)
z_{13}	20c (active)	55c (open water)	10c (inactive)	13c (active)	5c (inactive)
z_{14}	20c (active)	55c (open water)	10c (inactive)	13c (active)	5c (inactive)
z_{15}	20c (active)	75c (maneuvering)	10c (inactive)	10c (inactive)	5c (inactive)
z_{16}	20c (active)	75c (maneuvering)	10c (inactive)	10c (inactive)	5c (inactive)
z_{17}	20c (active)	75c (maneuvering)	10c (inactive)	10c (inactive)	30c (active)
z_{18}	20c (active)	25c (inactive)	30c (loading Gdynia)	13c (active)	5c (inactive)

The navigation subsystem (S_1) operates across all operational states of the ferry. Its cost is constant at 20c when active, and 10c when inactive.

The propulsion and steering subsystem (S_2) is characterized by differentiated costs depending on the type of operation. During intensive maneuvers, such as unberthing, berthing, or restricted-water navigation (states $z_2, z_3, z_6, z_7, z_{10}, z_{11}, z_{15}, z_{16}, z_{17}$), the hourly cost is 75c. In open-water navigation (states $z_4, z_5, z_{12}, z_{13}, z_{14}$), the cost is lower at 55c. When inactive, this subsystem generates a residual cost of 25c.

The loading and unloading subsystem (S_3) contributes to costs mainly during port operations. During cargo handling in Gdynia (states z_1, z_{18}), the hourly cost is 30c, while in Karlskrona (states z_8, z_9) it is 20c. Outside these phases, its idle cost is 10c.

The stability control subsystem (S_4) is engaged in multiple operational states, especially those involving cargo operations and dynamic sea conditions (states $z_1, z_4, z_5, z_6, z_8, z_9, z_{12}, z_{13}, z_{14}, z_{18}$). Its active cost is 13c, while the standby cost is 10c.

Finally, the mooring and anchoring subsystem (S_5) is activated during berthing and unberthing operations (states z_2, z_7, z_{10}, z_{17}), generating a cost of 30c. When not in use, the subsystem still incurs a minimal standby cost of 5c.

In all cases, c denotes a scaling coefficient that serves as a reference for subsystem cost determination. It constitutes a reference scale and may be calibrated in the future based on empirical data. This framework highlights how the variation in operational states directly

shapes the functional and safety structures of the ferry and, consequently, the overall cost of its operation. Table 2 summarizes the activity levels of the ferry's technical subsystems (S_1 – S_5) across individual operational states, indicating whether each subsystem is active or in standby mode and the corresponding hourly cost assigned to its operation.

These values, derived from the structured expert elicitation process, serve as the input parameters for the subsequent stochastic cost modeling and allow for simulation of different operational scenarios. While these cost coefficients are based on consolidated expert judgment rather than direct empirical measurements, the rigorous methodology ensures they provide a credible and defensible basis for demonstrating the functionality of the proposed framework. In applied studies, these values should be calibrated using real operational or accounting data provided by ferry operators. It is also important to note that the present model focuses exclusively on the ferry's technical subsystems (S_1 – S_5), omitting other significant cost categories such as fuel consumption, crew wages, insurance, or port fees. This simplification is deliberate, as the primary objective is to establish a methodological basis for linking subsystem activity with operational states. These assumptions provide a transparent foundation for the stochastic cost modeling and scenario analyses developed in the subsequent sections of the paper.

2.3. Weather

2.3.1. Weather Conditions

Weather constitutes one of the most influential external factors affecting the cost structure of ferry operations. Hydro-meteorological processes such as wind gusts, wave height variability, and seasonal icing alter subsystem workloads and reshape the duration of operational states. In stochastic terms, weather may be represented as a semi-Markov process with discrete hazard categories, each defined by a set of environmental parameters and associated with characteristic transition probabilities and sojourn times. This probabilistic approach captures the inherently dynamic and clustered nature of Baltic weather, where short sequences of storms may exert more influence on costs than prolonged periods of moderate operation.

In this study, three categories of weather impact are distinguished:

- 0os-degree hazard (no hazard): conditions corresponding to normal weather, with no significant impact on operations or costs;
- 1st-degree hazard (moderate hazard): conditions of increased weather-related stress, leading to moderate operational disruptions and elevated costs;
- 2nd-degree hazard (severe hazard): conditions of extreme weather, producing substantial operational risks, downtime, and significantly higher costs.

Following consultations with experts and practitioners, weather conditions that affect operating costs in specific operating states were identified. Based on the analysis of data collected from available measurement points, four weather processes along the Gdynia–Karlskrona route were subsequently distinguished:

- The weather process related to Gdynia Port;
- The weather process related to the Baltic Sea open waters;
- The weather process related to Karlskrona Port.

The meteorological data for wind speed, wind direction, and wave height for the respective operational areas were obtained from the ERA5 reanalysis dataset and validated against coastal measurement stations operated by the Institute of Meteorology and Water Management (IMGW, Gdynia, Poland) in Poland and the Swedish Meteorological and Hydrological Institute (SMHI, Norrköping, Sweden) over a 6-year period, with a 3 h interval between consecutive measurements (a total of 105,602 meteorological data records gathered

from seven measurement stations along the Gdynia–Karlskrona corridor). More detailed information on the meteorological dataset, including the number and exact location of measurement points as well as the seasonally disaggregated state residence probabilities, can be found in [8]. These data were used to classify the weather states according to the criteria in Tables 3–5 and to estimate the state residence probabilities. The specific thresholds for wind speed, direction, and wave height that define each weather state and its associated hazard category were established in consultation with maritime operations experts to ensure their practical relevance to ferry operations on the Gdynia–Karlskrona route. In the ports of Gdynia and Karlskrona, the main weather factors negatively affecting operating costs are wind speed and wind direction, whereas in Puck Bay and in open waters the key factors are wave height and wind speed.

Table 3. Classification of weather states for the Gdynia Port operating area.

Weather State	Wind Speed	Wind Direction	Category
c_1	[0, 17) m/s	$[0^\circ, 22.5^\circ) \cup [67.5^\circ, 112.5^\circ) \cup [337.5^\circ, 360^\circ)$	1st
c_2	[17, 33) m/s	$[0^\circ, 22.5^\circ) \cup [67.5^\circ, 112.5^\circ) \cup [337.5^\circ, 360^\circ)$	2nd
c_3	[0, 17) m/s	$[22.5^\circ, 67.5^\circ) \cup [112.5^\circ, 247.5^\circ)$	0os
c_4	[17, 33) m/s	$[22.5^\circ, 67.5^\circ) \cup [112.5^\circ, 247.5^\circ)$	1st
c_5	[0, 17) m/s	$[247.5^\circ, 337.5^\circ)$	1st
c_6	[17, 33) m/s	$[247.5^\circ, 337.5^\circ)$	2nd

Note: Hazard categories: 0os (no hazard)—normal conditions with no significant impact; 1st (moderate hazard)—conditions of increased weather-related stress; 2nd (severe hazard)—extreme conditions producing substantial operational risks and higher costs.

Table 4. Classification of weather states for the Karlskrona Port operating area.

Weather State	Wind Speed	Wind Direction	Category
c_1	[0, 17) m/s	$[0^\circ, 67.5^\circ) \cup [292.5^\circ, 360^\circ)$	0os
c_2	[17, 33) m/s	$[0^\circ, 67.5^\circ) \cup [292.5^\circ, 360^\circ)$	1st
c_3	[0, 17) m/s	$[67.5^\circ, 157.5^\circ)$	1st
c_4	[17, 33) m/s	$[67.5^\circ, 157.5^\circ)$	2nd
c_5	[0, 17) m/s	$[157.5^\circ, 292.5^\circ)$	0os
c_6	[17, 33) m/s	$[157.5^\circ, 292.5^\circ)$	1st

Note: Hazard categories: 0os (no hazard)—normal conditions with no significant impact; 1st (moderate hazard)—conditions of increased weather-related stress; 2nd (severe hazard)—extreme conditions producing substantial operational risks and higher costs.

Table 5. Classification of weather states for the Puck Bay and Baltic Sea open waters operating areas.

Weather State	Wave Height	Wind Speed	Category
c_1	[0, 2) m	[0, 17) m/s	0os
c_2	[2, 5) m	[0, 17) m/s	0os
c_3	[5, 14) m	[0, 17) m/s	1st
c_4	[0, 2) m	[17, 33) m/s	1st
c_5	[2, 5) m	[17, 33) m/s	1st
c_6	[5, 14) m	[17, 33) m/s	2nd

Note: Hazard categories: 0os (no hazard)—normal conditions with no significant impact; 1st (moderate hazard)—conditions of increased weather-related stress; 2nd (severe hazard)—extreme conditions producing substantial operational risks and higher costs.

The definition and classification of weather states, structured for each of the identified weather processes, are detailed in Tables 3–5. To illustrate the wind direction criteria, schematic wind rose diagrams for Gdynia and Karlskrona ports are provided in Figure 3.

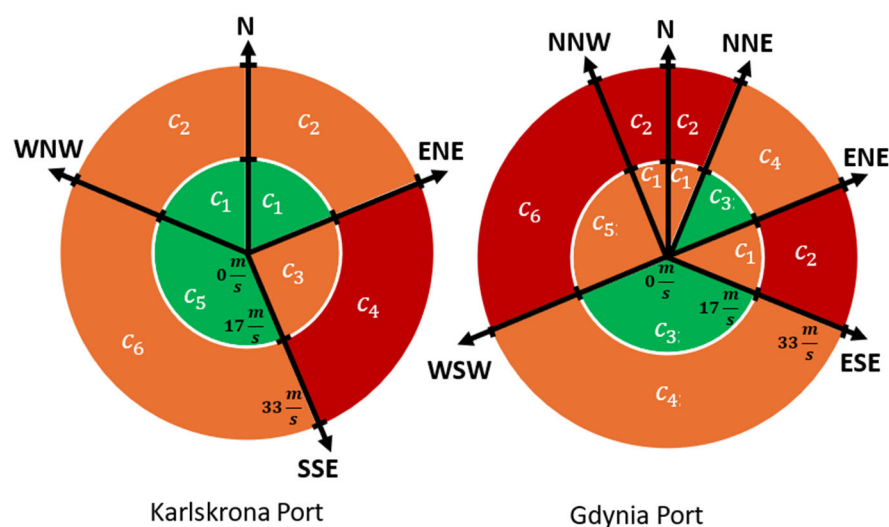


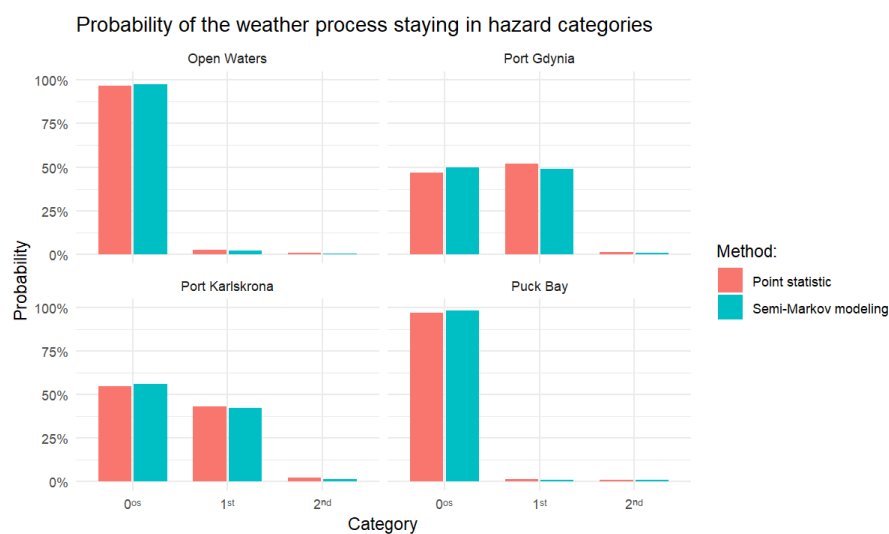
Figure 3. Graphic representation of weather states for Karlskrona (left) and Gdynia (right) ports in relation to wind direction and wind speed (weather states assigned to the inner ring correspond to wind speeds in the interval [0 m/s, 17 m/s), whereas those assigned to the outer ring correspond to wind speeds in the interval [17 m/s, 33 m/s)). Hazard levels applied for weather-state classification are: 00s—no hazard (green); 1st—moderate hazard (orange); 2nd—severe hazard (red).

Following statistical analysis, the staying probabilities of the identified weather processes in each weather state were estimated. These probabilities were computed using the methodology and formulas presented in [8] and, in parallel, via point statistics, where the probability is expressed as the proportion of the cumulative duration of a process in a specific state (recorded in the raw dataset) to the total observation period of the respective weather process. The first method is based on the assumption that the weather change process can be represented as a periodic semi-Markov process. Such a process is defined by an initial probability vector, a transition probability matrix, and a matrix of conditional sojourn-time densities, which together characterize the stochastic behavior of transitions between states. Once these components are identified, it becomes possible to determine the mean exit times from individual weather states and the stable state probabilities of the process. These, in turn, allow for the estimation of limiting values of state residence probabilities, which can then be interpreted as the unconditional probabilities of the process remaining in each of its possible weather states. Table 6 and Figure 4 present the estimated probabilities of weather process residence in individual states obtained using both the semi-Markov and point-statistic methods, together with the relative differences between them. These and all other statistical analyses and calculations presented in this study were performed using R software (Version 4.3.2, R Foundation for Statistical Computing, Vienna, Austria).

The results indicate a strong agreement between the two estimation approaches for the normal and moderate hazard categories—specifically, the 00s states across all operational areas and the 1st-degree states in port areas. In contrast, larger discrepancies are observed for the most severe weather conditions, including the 1st-degree states in the open-water and Puck Bay areas and the 2nd-degree states across all regions, where empirical data are more limited and the transition dynamics exhibit greater instability.

Table 6. Probabilities by category and method, with relative differences.

Weather Process Area	Category of Weather State	Probability by Point Statistic (p_{ps})	Probability by Semi-Markov Modeling (p_{sm})	Standard Error for Probability p_{sm}	Relative Error for Probability p_{sm}	The Confidence Intervals $CI_{95\%}$ for Probability p_{sm}	$\frac{ p_{ps}-p_{sm} }{p_{sm}} \cdot 100\%$
Port Gdynia	0os	0.468	0.499	0.008	0.82%	(0.491, 0.507)	6.63%
Port Gdynia	1st	0.519	0.491	0.008	0.84%	(0.483, 0.499)	5.39%
Port Gdynia	2nd	0.013	0.01	0.0016	8%	(0.0084, 0.0116)	23.44%
Puck Bay	0os	0.971	0.979	0.0023	0.12%	(0.9767, 0.9813)	0.82%
Puck Bay	1st	0.016	0.012	0.0017	7.5%	(0.0103, 0.0137)	24.39%
Puck Bay	2nd	0.013	0.009	0.0015	8.89%	(0.0075, 0.0105)	31.75%
Open Waters	0os	0.968	0.976	0.0024	0.12%	(0.9736, 0.9784)	0.83%
Open Waters	1st	0.025	0.019	0.0022	5.79%	(0.0168, 0.0212)	24.39%
Open Waters	2nd	0.008	0.005	0.0011	12%	(0.0039, 0.0061)	40%
Port Karlskrona	0os	0.548	0.56	0.004	0.71%	(0.5521, 0.5679)	2.19%
Port Karlskrona	1st	0.43	0.424	0.004	0.94%	(0.4161, 0.4319)	1.39%
Port Karlskrona	2nd	0.022	0.016	0.001	6.25%	(0.014, 0.018)	27.91%

**Figure 4.** Probabilities by category and method.

To quantify statistical uncertainty, the standard error (SE) and relative standard error (RSE) were calculated for each semi-Markov probability p_{sm} using the classical binomial proportion formula:

$$SE = \sqrt{\frac{p_{sm} \cdot (1 - p_{sm})}{n}}, \quad (1)$$

where $n = 15,086$ denotes the number of hourly observations per station.

The relative standard error was then computed as:

$$RSE = \frac{SE}{p_{sm}} \cdot 100\%. \quad (2)$$

Additionally, the 95% confidence intervals for each estimated probability were determined using the standard normal approximation:

$$CI_{95\%} = p_{sm} \pm 1.96 \cdot SE. \quad (3)$$

The *SE* and *RSE* values remain below 1% for dominant states, confirming their stability, but rise to 6–12% for rare, extreme states—a natural effect of lower sample frequency. Although significance symbols (*, **, ***) are not explicitly used, the narrow confidence intervals confirm the statistical robustness of the estimated probabilities. This enables a consistent comparison of estimation accuracy across weather states with different occurrence frequencies.

2.3.2. Weather Impact on Operational Costs

The integration of weather into the cost framework is achieved through the introduction of a weather adjustment coefficient $k_\beta(z_b)$, which scales the baseline cost of each operational state z_b , $b = 1, 2, \dots, \nu$, depending on the prevailing hazard category c_β , $\beta = 1, 2, \dots, w$. This mechanism reflects how open-sea navigation, maneuvering, or port operations respond differently to environmental stressors. For example, coefficients for open-sea states may reach values as high as 1.20 under severe hazard conditions, while loading and unloading operations in port are only marginally affected (1.02–1.05).

The values of the weather adjustment coefficients $k_\beta(z_b)$ for each operational state and hazard category, presented in Table 7, were established through a structured expert elicitation process conducted within the EU-CIRCLE research project. This process involved a dedicated workshop with key system operators possessing extensive experience on the Gdynia–Karlskrona route. Based on their operational expertise regarding the impact of weather hazards on subsystem workload, fuel consumption, and maintenance needs, the practitioners proposed specific coefficient values. These values were subsequently discussed and critically reviewed, with the final coefficients representing a consensus reached by all participants, thereby ensuring they are robust and reflect real-world operational challenges.

Formally, the adjusted cost of state z_b , $b = 1, 2, \dots, \nu$, under hazard category c_β , $\beta = 0, 1, \dots, w$, is defined as:

$$C_{b,\beta} = C(t)^{(b)} \cdot k_\beta(z_b), \quad t \geq 0, \quad b = 1, 2, \dots, \nu, \quad \beta = 0, 1, \dots, w, \quad (4)$$

where

- $C(t)^{(b)}$ —baseline cost of operation state z_b , $b = 1, 2, \dots, \nu$, [31];
- $k_\beta(z_b)$ —weather adjustment coefficient for state z_b , $b = 1, 2, \dots, \nu$, under category c_β , $\beta = 0, 1, 2, \dots, w$, [29];

The total expected cost under weather variability can be written as:

$$C = \sum_{b=1}^{\nu} \left[C(t)^{(b)} \cdot \sum_{\beta=0}^w (k_\beta(z_b) \cdot p_\beta) \right], \quad t \geq 0, \quad b = 1, 2, \dots, \nu, \quad \beta = 0, 1, \dots, w, \quad (5)$$

where

- ν is the total number of operational states;
- p_β is the probability of the weather change process staying in states within category c_β .

This formulation captures not only the direct increase in subsystem expenditures but also the indirect consequences of weather, such as prolonged sojourn times, elevated fuel consumption, or accelerated aging of technical components. By embedding these coefficients and probabilities into the stochastic cost model, forecasts remain sensitive

to real meteorological variability rather than relying on static long-term averages that obscure short-term volatility. From an operational perspective, the model emphasizes the asymmetric impact of weather: while port activities remain relatively stable across scenarios, open-sea navigation dominates both baseline and weather-adjusted expenditures. This insight directs attention toward adaptive routing, dynamic speed management, and condition-based maintenance as the most effective levers for mitigating weather-driven cost escalation.

Table 7. Operating costs by state and extreme weather hazard category.

Operating State z_b	Average Monthly Cost [PLN]	Cost Adjustment Coefficients by Category of Extreme Weather Hazards			Average Monthly Cost by Category of Extreme Weather Hazards [PLN]			Weather Process Area Related to Operating State z_b
		0os	1st	2nd	0os	1st	2nd	
z_1	96.69	1	1.02	1.05	96.69	98.6238	101.5245	Port Gdynia
z_2	0.42	1	1.04	1.1	0.42	0.4368	0.462	Port Gdynia
z_3	58.41	1	1.04	1.1	58.41	60.7464	64.251	Port Gdynia/Puck Bay
z_4	96.11	1	1.05	1.12	96.11	100.9155	107.6432	Puck Bay
z_5	9771.99	1	1.08	1.2	9771.99	10,553.75	11,726.388	Open Waters
z_6	59.87	1	1.06	1.15	59.87	63.4622	68.8505	Open Waters/ Port Karlskrona
z_7	2.61	1	1.04	1.1	2.61	2.7144	2.871	Port Karlskrona
z_8	15.3	1	1.02	1.05	15.3	15.606	16.065	Port Karlskrona
z_9	81.81	1	1.02	1.05	81.81	83.4462	85.9005	Port Karlskrona
z_{10}	0.42	1	1.04	1.1	0.42	0.4368	0.462	Port Karlskrona
z_{11}	0.78	1	1.02	1.05	0.78	0.7956	0.819	Port Karlskrona
z_{12}	18.98	1	1.06	1.15	18.98	20.1188	21.827	Open Waters/ Port Karlskrona
z_{13}	9136.59	1	1.08	1.2	9136.59	9867.517	10,963.908	Open Waters
z_{14}	85.73	1	1.05	1.12	85.73	90.0165	96.0176	Puck Bay
z_{15}	49.77	1	1.04	1.1	49.77	51.7608	54.747	Port Gdynia/Puck Bay
z_{16}	0.78	1	1.02	1.05	0.78	0.7956	0.819	Port Gdynia
z_{17}	2.61	1	1.04	1.1	2.61	2.7144	2.871	Port Gdynia
z_{18}	11.32	1	1.02	1.05	11.32	11.5464	11.886	Port Gdynia
Total					19,490.19	21,025.4	23,327.31	

3. Results

The simulation outcomes provide a multidimensional picture of the ferry's cost dynamics, revealing not only the absolute magnitude of expenditures but also their sensitivity to operational states and weather hazards.

To provide a comprehensive overview of cost dynamics, Table 7 presents a detailed breakdown of operating costs across all 18 states of the ferry's operational cycle. The table includes baseline monthly costs and the adjusted values under three categories of extreme weather hazards (0os—normal conditions, 1st-degree hazard, and 2nd-degree hazard), as well as the total monthly costs reflecting the influence of extreme weather conditions. Additionally, the last column indicates the relationship between the operational states and their corresponding weather change processes.

Table 8 presents the staying probabilities of the ferry's operational states within the extreme weather hazard categories, obtained using both the point-statistics and semi-Markov modeling approaches. For each operating state z_b , $b = 1, 2, \dots, 18$, the expected costs under weather variability were calculated based on the respective probability distributions derived from both methods. This comparison allows assessing the consistency

of the two approaches and quantifying the impact of weather-induced variability on operational expenditures.

Table 8. Expected operating costs under weather variability (obtained by two estimation methods).

Operating State z_b	Staying Probabilities in Extreme Weather Categories by Point Statistics			Expected Cost Under Weather Variability at Operating State z_b	Staying Probabilities in Extreme Weather Categories by Semi-Markov Modeling			Expected Cost Under Weather Variability at Operating State z_b
	0os	1st	2nd		0os	1st	2nd	
z_1	0.468	0.519	0.013	97.76	0.499	0.491	0.01	97.69
z_2	0.468	0.519	0.013	0.43	0.499	0.491	0.01	0.43
z_3	0.7195	0.2675	0.013	59.11	0.739	0.2515	0.0095	59.05
z_4	0.971	0.016	0.013	96.34	0.979	0.012	0.009	96.27
z_5	0.967	0.025	0.008	9807.17	0.976	0.019	0.005	9796.62
z_6	0.7575	0.2275	0.015	60.82	0.768	0.2215	0.0105	60.76
z_7	0.548	0.43	0.022	2.66	0.56	0.424	0.016	2.66
z_8	0.548	0.43	0.022	15.45	0.56	0.424	0.016	15.44
z_9	0.548	0.43	0.022	82.6	0.56	0.424	0.016	82.57
z_{10}	0.548	0.43	0.022	0.43	0.56	0.424	0.016	0.43
z_{11}	0.548	0.43	0.022	0.79	0.56	0.424	0.016	0.79
z_{12}	0.7575	0.2275	0.015	19.28	0.768	0.2215	0.0105	19.26
z_{13}	0.967	0.025	0.008	9169.48	0.976	0.019	0.005	9159.61
z_{14}	0.971	0.016	0.013	85.93	0.979	0.012	0.009	85.87
z_{15}	0.7195	0.2675	0.013	50.37	0.739	0.2515	0.0095	50.32
z_{16}	0.468	0.519	0.013	0.79	0.499	0.491	0.01	0.79
z_{17}	0.468	0.519	0.013	2.67	0.499	0.491	0.01	2.66
z_{18}	0.468	0.519	0.013	11.44	0.499	0.491	0.01	11.44
Total				19,563.52				19,542.66

This full tabular presentation allows for direct comparison between operational states, highlighting which phases of the voyage are most cost-intensive under normal conditions and which are most sensitive to weather-induced cost escalation. In particular, the table emphasizes the disproportionate role of open-sea navigation states (z_5 and z_{13}), while also quantifying the marginal but non-negligible contributions of port and maneuvering operations. However, since open-sea navigation states dominate the ferry's operational profile and the probability of 1st- and 2nd-degree weather hazard states in these areas is low, the overall impact of weather variability on operating costs remains minimal for the entire operation (the total operating costs obtained by the two methods (19,563.52 PLN and 19,542.66 PLN) are almost identical to the baseline value of 19,490.19 PLN, representing the operation costs without weather impact).

3.1. Baseline Operating Costs Across States

The ferry's operational cycle is composed of 18 distinct states (z_1 – z_{18}), each characterized by specific durations and subsystem utilization. Under normal operating conditions (0os), the total average monthly operating cost was estimated at 19,490.19 PLN. A highly uneven distribution of costs is observed (Table 9). Two open-water navigation states, z_5 and z_{13} , dominate the cost structure, accounting together for nearly 97% of the baseline monthly cost.

Table 9. Baseline monthly operating costs across ferry operational states.

Operating State	Avg. Monthly Time [h]	Monthly Cost [PLN]	Share of Total [%]
z ₅	261.36	9771.99	50.1
z ₁₃	252.72	9136.59	46.9
z ₁	27.36	96.69	0.5
z ₄	25.92	96.11	0.5
z ₉	26.64	81.81	0.4
Others	126	307	1.6
Total	720	19,490.19	100

Specifically:

- z₅ contributes 9771.99 PLN (50.1%);
- z₁₃ contributes 9136.59 PLN (46.88%).

All remaining 16 states together contribute only 3.02% of the baseline cost. The dominance of open-water navigation reflects both the long duration of these phases (261.36 h for z₅ and 252.72 h for z₁₃ per month) and the relatively high hourly rates. While such phases as berthing, maneuvering, or loading/unloading are operationally critical, they impose only marginal financial burdens. This imbalance underscores the need for targeted interventions in long-duration navigation phases rather than across the entire cycle.

3.2. Weather-Adjusted Costs

To model high-risk scenarios and substantiate the impact of potential, increased, and severe weather events on the vessel, extreme weather hazard coefficients were applied to assess cost amplification under first-degree (1st) and second-degree (2nd) scenarios. The results (Table 10) indicate a clear escalation:

- Normal (0os): 19,490.19 PLN (baseline);
- 1st-degree: 21,025.40 PLN (+8.1%);
- 2nd-degree hazard: 23,327.31 PLN (+19.4%).

Table 10. Total monthly costs under weather hazard categories.

Scenario	Total Cost [PLN]	Increase vs. Baseline [%]
Normal (0os)	19,490.19	-
1st-degree	21,025.40	+7.88
2nd-degree	23,327.31	+19.69

This effect is non-linear. Port activities such as loading/unloading or mooring increase only marginally ($\leq 5\%$), while open-sea navigation states experience cost surges of up to 20%. The results therefore validate the asymmetric role of weather: short-duration port phases remain financially stable, while long open-sea phases exhibit extreme sensitivity to environmental volatility. It should be noted that the above results represent conditional operating costs, assuming that extreme weather states persist throughout the entire period of operation.

In contrast, the unconditional costs (Table 11), derived from the total probability of occurrence of all weather states, are much lower (amounting to 19,563.52 PLN or 19,542.66 PLN, depending on the estimation method). These values are only about 0.3–0.4% higher than the baseline operating cost, which indicates that, in probabilistic terms, the

overall financial impact of weather variability on the ferry's operation remains negligible. This can be attributed to the low probability of extreme weather conditions within the open-sea weather process. Since this process governs the operational states that contribute most significantly to the total operating costs, the overall financial impact of weather variability remains minimal.

Table 11. Unconditional total monthly costs under weather hazard categories.

Operating State	Baseline Monthly Cost [PLN]	Unconditional Monthly Cost [PLN] (by Point Statistics)	Increase vs. Baseline [%]	Unconditional Monthly Cost [PLN] (by Semi-Markov Modeling)	Increase vs. Baseline [%]	Share of Total [%]
z_5	9771.99	9807.17	+0.36	9796.62	+0.25	50.13
z_{13}	9136.59	9169.48	+0.36	9159.61	+0.25	46.87
Others	581.61	586.87	+0.90	586.43	+0.83	3.00
Total	19,490.19	19,563.52	+0.38	19,542.66	+0.27	100

3.3. Discussion of Results

The analysis highlights several key observations regarding the operational and economic dynamics of the examined ferry system. Above all, the distribution of costs across operational states reveals a striking disproportionality. This extreme concentration of financial exposure in the open-sea navigation phases (z_5 and z_{13}) resonates with the core principle of resilience in maritime systems, which emphasizes the identification and fortification of critical components [38]. In our case, the ‘critical component’ is not a physical asset but a specific operational phase. This finding provides a quantitative backbone to systematic reviews of maritime resilience [39], which often call for pinpointing key vulnerabilities. By demonstrating that over 97% of costs are driven by just two states, our model offers a precise and actionable target for building cost resilience, moving the concept from a theoretical goal to a tractable engineering and management problem. Despite the complexity of the vessel's 18-state operational cycle, it is the two open-sea navigation phases (z_5 and z_{13}) that almost exclusively determine the overall cost profile. This finding aligns with and quantitatively refines the empirical research of Yang et al. (2022), who identified open-water transit as the primary domain for cost-saving measures through speed and routing optimization [40]. Our study confirms this focus but provides a sharper, more extreme quantification, revealing that over 97% of costs are concentrated in these phases, thereby offering a more precise target for operational interventions. Together, they account for nearly the entire monthly operating expenditure, leaving all other states with only marginal contributions. Such concentration is not surprising, as these phases are inherently the most exposed to hydro-meteorological variability and therefore most susceptible to cost amplification [37]. The extent to which this dominance was confirmed by the model, however, is noteworthy. From a theoretical perspective, these findings challenge the adequacy of cost models that assume a balanced contribution of operational states to overall financial performance. Instead, the results demonstrate that maritime cost structures are highly state-dependent. From a practical perspective, the implication is clear: strategies to enhance the cost resilience of ferry operations should focus primarily on navigation phases that are both prolonged and environmentally exposed. Investments in advanced weather routing, predictive maintenance, or adaptive speed management appear to offer the highest potential return [40]. This operational perspective aligns with broader frameworks of critical infrastructure protection developed for the Baltic Sea region, which emphasize the integration of safety, legal, and environmental dimensions in maritime system management [41].

The role of weather hazards further reinforces this conclusion. The model quantifies the direct financial impact of weather hazards, with cost increases of approximately 8% and 20% under moderate (1st-degree) and severe (2nd-degree) scenarios, respectively. These quantified increments provide a subsystem-level explanation for the macro-level estimates reported in industry benchmarks. For instance, UNCTAD (2024) notes that weather disruptions account for a significant portion of operational costs in Baltic shipping [19]. Our results substantiate this claim by demonstrating the specific mechanical pathway through escalated subsystem workload and accelerated degradation by which these macro-level costs materialize, thereby bridging a gap between high-level industry reports and detailed technical modeling. Projected over longer time horizons, these increments compound to levels that may substantially undermine the economic sustainability of ferry services, especially under fixed-ticket pricing schemes. Moreover, the probabilistic representation of weather events emphasizes the clustered nature of risks. Consecutive storm episodes exert a magnified effect, as subsystem fatigue accelerates and maintenance intervals shorten. This clustering property distinguishes the present model from traditional deterministic cost assessments and aligns with empirical observations from the Baltic Sea.

Equally noteworthy is the limited role of port and maneuvering operations. While operationally critical, these states do not translate into significant financial exposure when viewed through the lens of weather sensitivity. This underscores the importance of adopting a differentiated approach: not all operational states require the same level of adaptive investment, and resources should be concentrated where both exposure and financial impact are greatest.

Finally, the methodological dimension deserves emphasis. By integrating weather hazard categories directly into the cost model, the analysis moves beyond treating weather as an external disturbance and instead incorporates it as an endogenous variable. This not only provides a more accurate representation of the real operating environment but also strengthens the decision-making capacity of operators and policymakers. In this way, the study contributes to the ongoing shift toward climate-resilient maritime asset management and demonstrates how probabilistic cost modeling can serve as a bridge between academic research and operational practice.

3.4. Sensitivity of Total Operational Costs to Weather and Technical Parameters

To further evaluate the responsiveness of the cost model to environmental and technical variations, a two-dimensional sensitivity analysis was performed. Two independent factors were considered: the weather deterioration coefficient, which modifies the probabilities of adverse weather states, and the subsystem cost-increase coefficient, which scales the cost coefficients of all technical subsystems.

The first parameter alters the structure of the weather-state probabilities according to the following relationships:

$$\begin{cases} \bar{p}_{2nd} = 2 \cdot \alpha \cdot p_{2nd} \\ \bar{p}_{1st} = \alpha \cdot p_{1st} \\ \bar{p}_{0os} = 1 - \bar{p}_{1st} - \bar{p}_{2nd} \end{cases} \quad (6)$$

where α denotes the weather deterioration coefficient.

Here, p_{1st} and p_{2nd} represent the baseline residence probabilities of the 1st and 2nd category weather states, respectively, while $\bar{p}_{0os}$, $\bar{p}_{1st}$, $\bar{p}_{2nd}$ denote their modified values under the deteriorated-weather scenario. The second parameter increases subsystem cost coefficients multiplicatively within the range of 1.0–1.5.

Table 12 presents the resulting total operational costs C_{ps} and C_{sm} , together with their percentage increases relative to the baseline scenario. The results reveal a cumulative, nonlinear growth pattern. Under moderate deterioration ($\alpha = 1.25$) and a 25% increase in

subsystem cost coefficients, total monthly expenditures rise by approximately 1.5% (C_{ps}) and 1.1% (C_{sm}). The most severe simulated scenario ($\alpha = 1.75$; cost factor = 1.5) results in increases of 4.12% and 3.14%, respectively.

Table 12. Sensitivity analysis of unconditional total monthly costs under weather hazard scenarios.

Weather Deterioration Coefficient (α)	Subsystem Cost-Increase Factor	Total Cost C_{ps} After Change [PLN]	Total Cost C_{sm} After Change [PLN]	Cost Increase C_{ps} [%]	Cost Increase C_{sm} [%]
1	1	19,563.52	19,542.66	0	0
1	1.1	19,649.21	19,608.36	0.44	0.34
1	1.25	19,777.8	19,706.91	1.1	0.84
1	1.5	19,992.11	19,871.19	2.19	1.68
1.1	1	19,570.85	19,547.93	0.04	0.03
1.1	1.1	19,665.14	19,620.18	0.52	0.4
1.1	1.25	19,806.56	19,728.59	1.24	0.95
1.1	1.5	20,042.31	19,909.29	2.45	1.88
1.25	1	19,582.81	19,555.8	0.1	0.07
1.25	1.1	19,689.94	19,637.93	0.65	0.49
1.25	1.25	19,850.67	19,761.13	1.47	1.12
1.25	1.5	20,118.54	19,966.45	2.84	2.17
1.5	1	19,600.18	19,568.88	0.19	0.13
1.5	1.1	19,728.78	19,667.44	0.84	0.64
1.5	1.25	19,921.62	19,815.29	1.83	1.4
1.5	1.5	20,243.06	20,061.69	3.47	2.66
1.75	1	19,619.47	19,582.02	0.29	0.2
1.75	1.1	19,769.47	19,697	1.05	0.79
1.75	1.25	19,994.46	19,869.49	2.2	1.67
1.75	1.5	20,369.49	20,156.94	4.12	3.14

These outcomes demonstrate that the semi-Markov cost model responds coherently to probabilistic variations in weather-state structure, while slightly attenuating the impact of extreme parameter combinations due to its inherent smoothing of short-term fluctuations. This property highlights the model's robustness and practical relevance for forecasting operational expenditures under increasing weather volatility.

Overall, the analysis confirms that even moderate weather deterioration can lead to a measurable increase in operating costs, emphasizing the importance of adaptive cost management and weather-responsive operational planning in maritime transport systems.

3.5. Practical Implications for Operators

The findings of this study translate into three critical, actionable insights for ferry operators aiming to enhance cost resilience and operational efficiency in the face of increasing weather variability. Firstly, the analysis reveals an extreme concentration of financial exposure, with the two open-sea navigation states (z_5 and z_{13}) constituting over 97% of the baseline monthly costs. This stark disproportion necessitates a paradigm shift in resource allocation and strategic planning. Operators should prioritize investments in advanced weather routing systems and dynamic speed optimization technologies that specifically target these high-impact phases. For instance, leveraging real-time data analytics and machine learning algorithms can identify optimal paths and speeds that minimize fuel consumption and vessel stress while avoiding adverse weather conditions. By focusing efforts on these critical states, operators can achieve significant cost savings more effectively

than through a scattershot approach spread uniformly across all operational phases. This targeted strategy directly addresses the core finding of our model: that over 97% of costs are driven by just two states (z_5 and z_{13}), making them the primary leverage points for financial resilience.

Secondly, the model quantifies the direct financial impact of weather hazards, with cost increases of approximately 8% and 20% under moderate (1st-degree) and severe (2nd-degree) scenarios, respectively. This quantification provides a robust, evidence-based foundation for justifying investments in meteorological intelligence and decision-support tools. For example, the implementation of high-resolution weather forecasting services and integrated bridge systems can enable proactive storm avoidance and adaptive voyage planning, thereby directly mitigating the ~8% and ~20% cost escalations quantified in our model for moderate and severe weather scenarios. The strategic benefit of speed reduction in adverse weather conditions, which we recommend for mitigating the identified ~8% and ~20% cost escalations, is strongly supported by recent empirical research. *Taskar & Andersen (2020)* explicitly quantified the economic and environmental benefits of adaptive speed management, demonstrating its effectiveness as a primary lever for optimizing ship operations in a volatile environment, thereby validating our model's key practical implication [42].

Thirdly, the study highlights that elevated costs under severe weather conditions are not merely transient but reflect accelerated degradation of key vessel systems—most critically the propulsion and steering subsystems (S_2) that dominate operational costs during the open-sea navigation states (z_5 and z_{13}). This insight underscores the critical need to transition from traditional time-based maintenance to predictive, condition-based maintenance regimes. By integrating environmental data such as wave height, wind speed, and vessel motion metrics into maintenance scheduling, operators can trigger interventions based on actual accumulated stress rather than arbitrary intervals. For instance, installing vibration sensors on main engines and monitoring structural fatigue in real-time can alert crews to impending failures before they occur, thus avoiding unplanned downtime and costly emergency repairs. Furthermore, aligning maintenance activities with forecasted weather windows can enhance crew safety and operational efficiency. This proactive approach not only mitigates the risk of catastrophic failures but also optimizes lifecycle costs by extending the service life of critical components, thereby fostering long-term sustainability and reliability in ferry operations.

4. Conclusions, Limitations, and Future Research Directions

4.1. Conclusions

This study makes three distinct contributions to the field of maritime operational cost modeling. First, methodologically, it introduces a novel framework that moves beyond convention by integrating a high-resolution semi-Markov weather process as an endogenous and probabilistic driver directly within a state-dependent cost model. This represents a significant departure from conventional Lifecycle Costing (LCC) models, which rely on historical averages [11,12], and an advancement over standard stochastic reliability models that typically treat environmental factors as exogenous inputs [20–23]. Our approach uniquely captures the path-dependent and clustered nature of weather impacts, where a short sequence of storms can inflict greater financial damage than prolonged periods of moderate conditions.

Second, empirically, the application of this framework to the Gdynia-Karlskrona ferry route yields a critical and quantifiable finding: operational costs are not uniformly distributed but are hyper-concentrated, with over 97% of monthly expenditures arising from just two open-sea navigation states (z_5 and z_{13}). This finding sharpens the focus of prior re-

search, such as that by Yang et al. (2022) which highlighted open-water transit as a key cost domain [40], by providing a precise, state-specific quantification of that dominance. Furthermore, the model quantifies the asymmetric sensitivity of these critical states to weather hazards, demonstrating cost escalations of ~8% and ~20% under moderate (1st-degree) and severe (2nd-degree) scenarios, respectively. This offers a mechanistic, subsystem-level explanation for the macro-level observations of weather-driven cost disruptions reported in industry analyses like UNCTAD (2024) [19].

Consequently, from a practical perspective, these findings provide a clear and actionable mandate for ferry operators and policymakers. Cost resilience cannot be achieved through blanket measures but requires a targeted strategy focused on the disproportionately exposed open-sea navigation phases. Investments in adaptive weather routing [22,23], dynamic speed optimization [42], and condition-based maintenance for propulsion and steering subsystems offer the highest potential return. By transforming weather variability from an unmanageable externality into a quantifiable input within a rigorous methodological framework [38,39,43,44], our study provides a transparent basis for climate-resilient investment and operational decision-making in semi-enclosed seas, directly addressing the need for enhanced resiliency in maritime transport networks [30,45–47].

4.2. Limitations

The present study is subject to several limitations that should be considered when interpreting the results. First, the hourly cost values assigned to the ferry's technical subsystems (S_1 – S_5) were derived from a structured expert elicitation process and serve as illustrative parameters rather than empirically measured accounting data. As such, the resulting figures are model-based estimates designed to demonstrate the framework's functionality. Second, the analysis focused exclusively on these technical subsystems and did not include other significant expenditure categories such as crew wages, port fees, or insurance. While this simplification was deliberate to isolate the weather and system cost relationship, it necessarily omits other drivers of financial performance. Finally, the modeling framework was applied to a single ferry route in the Southern Baltic, and thus the generalizability of the specific quantitative findings to other vessel types or maritime regions requires further validation.

A key limitation of estimating weather state residence probabilities using semi-Markov process characteristics lies in the implicit assumption of periodicity in the weather cycle. Under the influence of global warming and broader climate change, this periodicity is likely to be disturbed, resulting in a non-stationary process where extreme weather states may occur with increasing frequency compared to model-based predictions.

4.3. Future Research Directions

Future research should build directly upon the foundation established here. The immediate priority is to calibrate the subsystem cost parameters with real operational and financial datasets obtained from ferry operators to improve empirical robustness. Subsequently, the scope of the framework should be expanded to multiple vessel types (e.g., container ships, tankers) and diverse maritime regions to test its generalizability and identify region-specific risk profiles. Further work could also integrate the omitted cost categories (crew, port fees, insurance) to create a more comprehensive total-cost model. From a methodological perspective, a promising avenue is the coupling of this probabilistic cost model with real-time decision-support systems, potentially leveraging machine learning to dynamically adapt routing and maintenance strategies based on live weather forecasts and vessel performance data. Such advancements would further

transform climate risk from a reactive burden into a strategically managed parameter for operational innovation.

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