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Research paper

Evaluating the influence of marine weather parameters uncertainties on the ship fuel consumption with Monte Carlo analysis

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ABSTRACT

This study analyzes the impact of weather parameter uncertainties on ship fuel consumption using Monte Carlo simulations. A feed-forward neural network (FFNN) is trained on ship and weather data to predict fuel use. The voyage route is discretized, and ensemble weather data from ECMWF ERA5 (1940–2024) are collected for each point. Probability distributions are fitted to these variables, and randomized scenarios are generated. The generated FFNN model is then used to simulate fuel consumption under varying conditions, and the resulting uncertainties are assessed using statistical metrics such as standard deviation, confidence intervals, and density plots. The generated FFNN models achieved high predictive accuracy, with MAE ranging between 0.6065 and 0.7240 $kg{\cdot}min^{-1}$ and MAPE from 0.9743 % to 1.1690 %, with $R^2 = 0.99$. The goodness-of-fit analysis of the weather variables reveals that the Lognormal distribution provides the best fit for most variables based on log-likelihood, AIC, and BIC criteria. In addition, the analysis highlights that fuel consumption variability is closely tied to changing weather conditions along the route, with higher standard deviations indicating unstable fuel usage due to environmental fluctuations, while lower values reflect more consistent and stable operating conditions.

1. Introduction

Optimizing fuel consumption in the maritime industry is a critical challenge connected with environmental sustainability and economic efficiency (Moradi et al., 2022; Wang et al., 2023). Marine weather parameters' variability and their complex nature significantly influence fuel usage during voyages. Precise predictions and strategic planning are vital for reducing operational costs and minimizing greenhouse gas emissions (He et al., 2024). Addressing these challenges requires robust analytical methods capable of accounting for the inherent uncertainties in weather data.

The source of marine weather parameters uncertainties is multifaceted, arising from the inherent complexity and variability of atmospheric and oceanographic conditions (Palmer, 2000; Olafsson and Bao, 2020). These uncertainties stem from several factors. The atmosphere is a chaotic system, where small changes in initial conditions can lead to significant variations in weather patterns (Vettor et al., 2021). This intrinsic unpredictability limits the precision of long-term weather forecasts. Weather prediction models use mathematical approximations to simulate atmospheric processes. These simplifications can introduce errors, particularly in capturing complex interactions between atmospheric, oceanic, and surface processes (Slingo and Palmer, 2011).

A critical distinction in marine environmental modeling is between the natural variability inherent in atmospheric and oceanographic conditions, and the uncertainties introduced by observational limitations and numerical modeling errors. Natural variability refers to the true fluctuations in environmental parameters driven by geophysical processes such as storms, wave growth and decay, seasonal cycles, and ocean currents. In contrast, uncertainty-induced variability arises from limitations in the accuracy and resolution of measurement instruments, model structures, and initial condition sensitivity in numerical forecasts. Recognizing and accounting for both components is essential for a robust assessment of ship fuel consumption. While this study primarily focuses on characterizing variability based on historical reanalysis data, a clear understanding of this dual nature is critical when interpreting the probabilistic results.

The quality and resolution of observational data used in initializing weather models can be the source of uncertainties (Dickson et al., 2019). Gaps in data coverage, especially over oceans, and limitations in sensor accuracy can affect model outputs. Marine weather parameters such as

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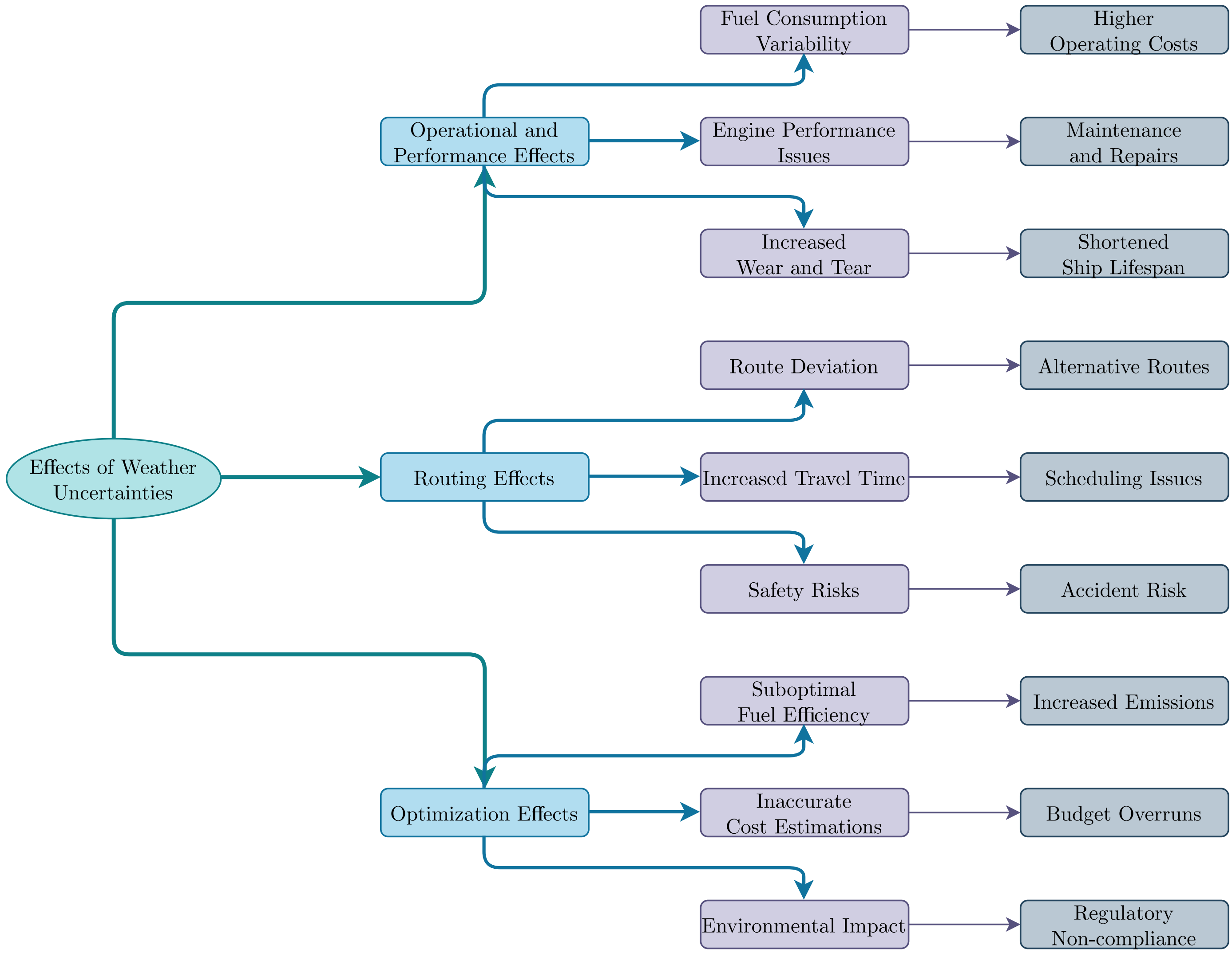


Fig. 1. The effects of marine weather parameters uncertainties on ship operations and performance.

wind speed, wave height, and sea surface temperature exhibit significant temporal and spatial variability (Mahmoodi and Nowruzi, 2022). This variability can be challenging to model and predict accurately over different scales. Variability in external factors such as solar radiation, volcanic activity, and anthropogenic influences can affect weather patterns, adding another layer of uncertainty to predictions (Prpić-Oršić et al., 2020).

The above factors contribute to the uncertainties in marine weather parameters, impacting various aspects of ship operations, performance, routing, and optimization. Fig. 1 shows the effects of marine weather parameters uncertainties on ship operations and performance. Uncertainty of weather conditions can lead to higher fuel consumption as ships may need to navigate through adverse conditions (Vettor and Soares, 2022). Variations in fuel consumption directly translate to fluctuating operating costs, affecting the profitability of voyages. Uncertainties can lead to unplanned delays as ships might need to wait for safer conditions. Weather uncertainties can cause delays in arrival and departure times, impacting overall logistics and supply chain operations (Ksciuk et al., 2023). Moreover, it can create navigational hazards, increasing the risk of collisions, groundings, and other maritime accidents. Ensuring the safety of the crew becomes more challenging under uncertain weather conditions. Inaccurate weather predictions can lead to suboptimal speed and routing decisions (Esmailian et al., 2022). Increased fuel consumption due to inefficient routing contributes to higher greenhouse gas emissions and impacts environmental sustainability (Zhou et al., 2023). In general, it can be said that the uncertainty in weather conditions makes it difficult to estimate fuel costs and voyage expenses accurately.

Some studies have been done to evaluate the influence of marine weather uncertainties on the maritime industry. Tillig et al. (2018) investigated the accuracy of fuel consumption predictions for ships using a generic energy systems model for a RoRo ship and a tanker. It categorized and handled uncertainties across four phases of a ship's life, from design to operation. Monte Carlo simulations showed that prediction uncertainty decreases from about 12 % in early design to less than 4 % in late phases. Plessas et al. (2018) focused on the quantification of the effect of weather uncertainty on fuel consumption. It used a probabilistic approach from reliability theory to analyze the impact of seaway conditions (spectral wave height, period, and heading) on added resistance and ultimately fuel consumption. Prpić-Oršić et al. (2020) examined the impact of real environmental conditions on ship speed and fuel consumption. It addressed the increased fuel consumption and emissions of greenhouse gases due to speed loss under varying weather conditions.

A probabilistic approach discussed in Vettor et al. (2021) to account for weather uncertainties in ship route optimization. It highlighted the use of ensemble weather forecasts and classical reliability methods to evaluate the probability of failure and variability in fuel consumption and time of arrival1. Vettor and Soares (2022) examined methods to investigate uncertainties in ship fuel consumption using ensemble weather forecasts. It compared different approaches, including brute-force and probabilistic models, for a containership's North Atlantic passage. Mason et al. (2023) developed strategies to quantify and reduce stochastic uncertainty in weather routing for wind-propelled ships. It identified routes sensitive to forecast uncertainty and proposed adaptive strategies to enhance carbon savings from wind propulsion.

While various studies have explored the influence of uncertain weather conditions on ship fuel consumption, many have primarily employed deterministic or scenario-based simulation approaches, which offer limited representation of the full range of variability in marine environmental parameters. Several previous works have successfully utilized Monte Carlo simulation to investigate uncertainty in ship energy efficiency and fuel consumption (Coraddu et al., 2014; Tran, 2020; Fan et al., 2020; Tran, 2021). However, these studies often focus on individual parameters or generalized assumptions, and typically do not incorporate high-resolution ensemble weather data across a full route. In contrast, recent advances in ensemble reanalysis products such as ERA5 now allow for more detailed spatio-temporal modeling of environmental variability. This study builds upon previous research by integrating Monte Carlo analysis with machine learning-based fuel prediction and ensemble-derived weather uncertainty to characterize fuel consumption probabilistically across an entire voyage.

The considered approach allows for a thorough assessment of how fluctuations in weather parameters can alter fuel consumption estimates by simulating a wide range of potential weather conditions. A cruise ship is selected as a case study to illustrate the practical application of this methodology. The research employs a wide FFNN to map the complex relationships between weather conditions and fuel consumption, using comprehensive onboard ship performance data as the foundation. The spatio-temporal ensemble marine weather parameters are collected from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 dataset (Copernicus Climate Change Service, 2023). The research proceeds by fitting probability distributions to each weather and ship variable at discrete points along the considered route. A series of potential input scenarios can be generated using fitted distributions for feeding the FFNN model. The subsequent Monte Carlo simulations produce a distribution of fuel consumption outcomes. Various statistical tools are employed to characterize the results. It provides a comprehensive understanding of the potential deviations in fuel usage.

The novelty of this study lies in its comprehensive and data-driven approach to quantifying the impact of marine weather uncertainties on ship fuel consumption. Unlike previous studies that often rely on limited short-term datasets or simplified stochastic methods, this work utilizes high-resolution onboard operational data in conjunction with ensemble-based historical weather data spanning over seven decades. Furthermore, a wide FFNN is applied to develop a predictive model that maps complex nonlinear relationships between ship and environmental parameters and fuel consumption. The integration of Monte Carlo simulations with best-fitted probability distributions for each weather variable at discrete route points enables a robust uncertainty quantification framework. This detailed spatio-temporal analysis allows for a more realistic and granular understanding of fuel consumption variability.

While the present study primarily aims to assess the influence of long-term metocean variability on ship fuel consumption, it does not account for the temporal evolution of weather along the ship route. The simulation treats each route point as statistically independent, allowing for an evaluation of spatially distributed uncertainties. However, real-world weather systems evolve continuously over space and time, and their effects are typically correlated along a voyage.

This research not only emphasizes the importance of considering weather uncertainties in ship fuel consumption, but also contributes to broader efforts to increase fuel efficiency and reduce the environmental footprint of the maritime industry. By comprehensively understanding and addressing the effects of uncertainty in marine weather parameters, the marine industry can increase operational efficiency, ensure safety, and promote environmental sustainability. Furthermore, this research contributes to academic knowledge and practical applications in maritime transportation and provides a strong framework for future studies and practical implementation aimed at improving fuel efficiency and operational reliability.

The subsequent sections of this research discuss the methodology and findings of this research. Section 2 outlines the specific ship, route, and data sources employed in the study. This is followed by a detailed description of the FFNN architecture and the Monte Carlo simulation framework. Section 3 presents the results obtained from the application of these models, providing insights into the potential impact of weather conditions on ship performance. Finally, Section 4 summarizes the key findings and suggests avenues for future research.

2. Methods and materials

Fig. 2 shows a detailed flowchart of the methodology used in this research to estimate the ship fuel consumption uncertainties. The methodology is structured into several detailed steps. First, onboard ship performance data and related weather condition parameters are collected from the case study ship on a specific voyage, forming the basis for developing a predictive model. A wide FFNN is then constructed using performance data to map the relationships between weather parameters and ship fuel consumption. Next, the considered maritime route is discretized into specific points to facilitate detailed analysis. Spatio-temporal ensemble marine weather data is gathered from the ECMWF ERA5 dataset for each route point, covering a wide temporal range from 1940 to 2024. This rich dataset ensures the fine-grained analysis accounts for a broad spectrum of weather conditions along the voyage.

The collected weather data is subjected to probability distribution fitting for each variable at each route point. Various distributions are tested, and the best fit is selected based on goodness-of-fit measures including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and log-likelihood. This step is important for accurately capturing the uncertainties in weather parameters. Subsequently, a large number of random input values are generated based on the best-fitted probability distributions. These random inputs are used to run the wide FFNN model, employing Monte Carlo simulations to build a distribution of possible fuel consumption outcomes. This approach allows for a robust assessment of the impact of weather uncertainties. The resulting fuel consumption outcomes are characterized using several statistical measures, including standard deviation, histograms, box plots, KDE, and confidence interval. These visual and numerical tools help in understanding the extent and nature of the uncertainties. Finally, the results are thoroughly analyzed to draw conclusions and make recommendations.

2.1. Considered ship

A medium-sized cruise ship is considered in this study. This ship is a modern vessel built in 2017, equipped with substantial power and designed for efficiency and comfort. It has a gross tonnage of 99,000 and a maximum speed of 21.7 knots, supported by a total installed power of 48,000 kW. The ship measures 295.3 m in length overall, with a beam of 42.3 m and a draught of 8.2 m. It is equipped with four marine diesel engines connected to two electric propulsion motors via a diesel-electric propulsion system. These engines are paired with electric generators that feed the ship's power systems, including propulsion and hotel loads. These specifications illustrate the ship's capability to undertake long voyages with substantial cargo and passenger capacities.

2.2. Considered route

The case study route spans from April 6, 2018, to April 13, 2018, across the Atlantic Ocean, as depicted in Fig. 3. A total of 8961 points along this route are chosen for generating the predictive model, sampled at one-minute intervals. Moreover, 150 points along this route are

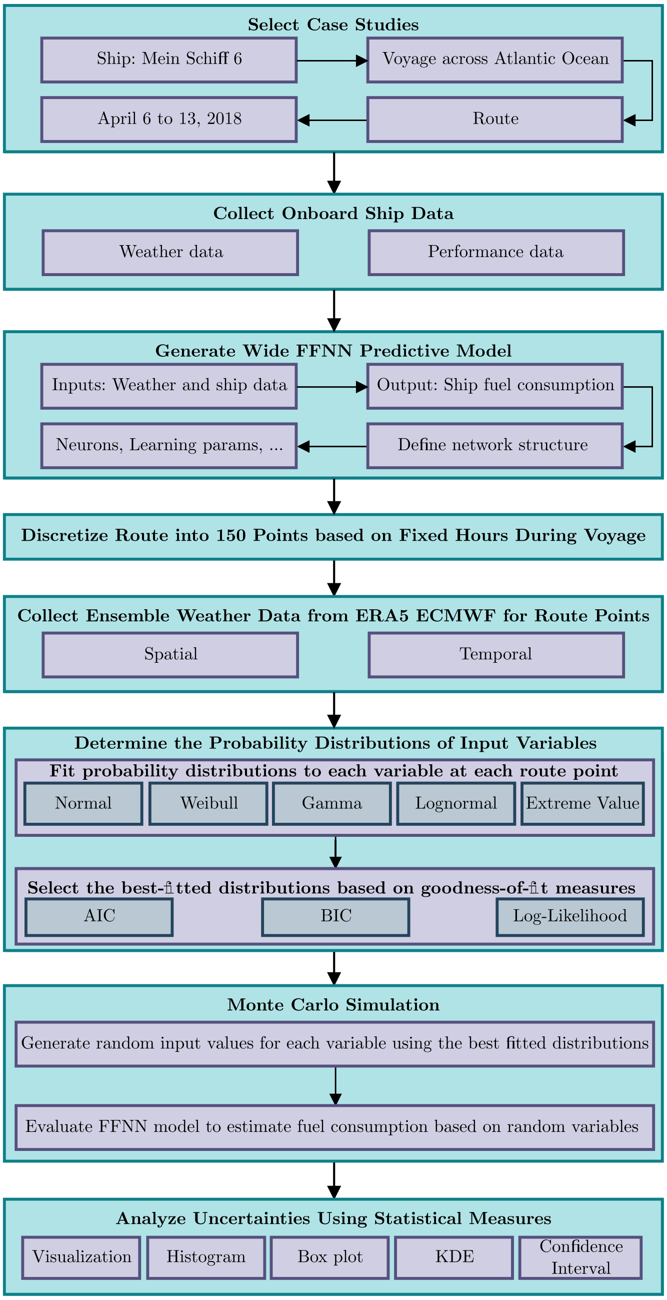


Fig. 2. Flowchart of the considered methodology to estimate the ship fuel consumption uncertainties.

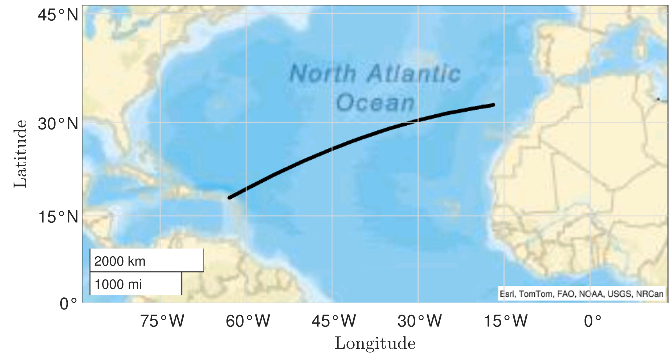


Fig. 3. Considered case study route [Black line].

chosen for uncertainty analysis. These points are chosen in such a way as to ensure that their ERA5 ensemble weather data are available and the ship is in motion, not docked at a port.

2.3. Marine weather data

The research leverages ECMWF ERA5 hourly data on single levels from 1940 to 2024 (Copernicus Climate Change Service, 2023; Hersbach et al., 2023). ERA5 represents the fifth generation of reanalysis produced by ECMWF, providing comprehensive data on global climate and weather patterns spanning the last 80 years. ERA5 reanalysis provides horizontal resolutions of $0.25° \times 0.25°$ for the atmosphere and $0.5° \times 0.5°$ for ocean waves, with mean, spread, and members at $0.5° \times 0.5°$ for the atmosphere and $1° \times 1°$ for ocean waves. Moreover, an uncertainty estimate is obtained from an underlying 10-member ensemble sampled at three-hourly intervals.

As mentioned, the considered ship route is discretized into some points. The ensemble weather parameters should be collected for each point of the route according to the time and location (latitude and longitude). The collected data will be used to generate probability distribution fittings, which can then be utilized in Monte Carlo simulations. The distributions derived from these datasets thus reflect both the natural variability of environmental conditions and the residual uncertainty inherent in the data. Random samples of the weather parameters are generated using their respective statistical distributions. The weather parameter ensemble members of considered points are collected from 1940 to 2024. Therefore, 850 data points on average are available for each variable of a route point, except for sea surface temperature which is 85 points. The collected ERA5 marine weather parameters are Sea surface temperature, 10m neutral wind speed, 10m neutral wind direction, Significant height of combined wind waves and swell, Mean wave period, and Mean wave direction. The hourly spatio-temporal mean of the considered variables across the studied area from January to July 2024 is shown in Fig. 4. The open-source Matlab code (Pereira, 2024) is used to plot the wind and wave roses.

Sea surface temperature refers to the temperature of seawater near its surface. The 10m neutral wind speed is the horizontal speed of wind at a height of ten meters above the Earth's surface. This wind speed is crucial for driving the wave model. The 10m neutral wind direction indicates the compass direction from which this neutral wind originates, measured in degrees clockwise from true north, at the same height. The significant height of combined wind waves and swell denotes the average height of the highest one-third of surface waves generated by both wind and swell (Mahmoodi, 2024; Mahmoodi et al., 2025). Mean wave direction refers to the average direction from which surface ocean waves come, calculated across all frequencies and directions in the two-dimensional wave spectrum (Copernicus Climate Change Service, 2023; Mahmoodi et al., 2020). This direction is given in degrees true, relative to the geographic north pole. The mean wave period is the average wave period calculated over all frequencies and directions in the two-dimensional wave spectrum.

2.4. Onboard ship data

The onboard data includes different collected variables of the considered voyage, ship, and weather. The route parameters are voyage segments time stamps and position (latitude and longitude). Other collected parameters are Ambient Temperature (AT), Ambient Humidity (AH), Sea surface temperature (SST), Relative wind speed (RWS), Relative wind direction (RWD), Significant wave height (SWH), Relative wave direction (RWaD), Wave Period (WP), Ship speed (speed through water) (STW), Motors load (ML), and Motors fuel consumption (MFC). The descriptive statistics for all considered onboard ship variables are presented in Table 1. The number of passengers is considered to be fixed

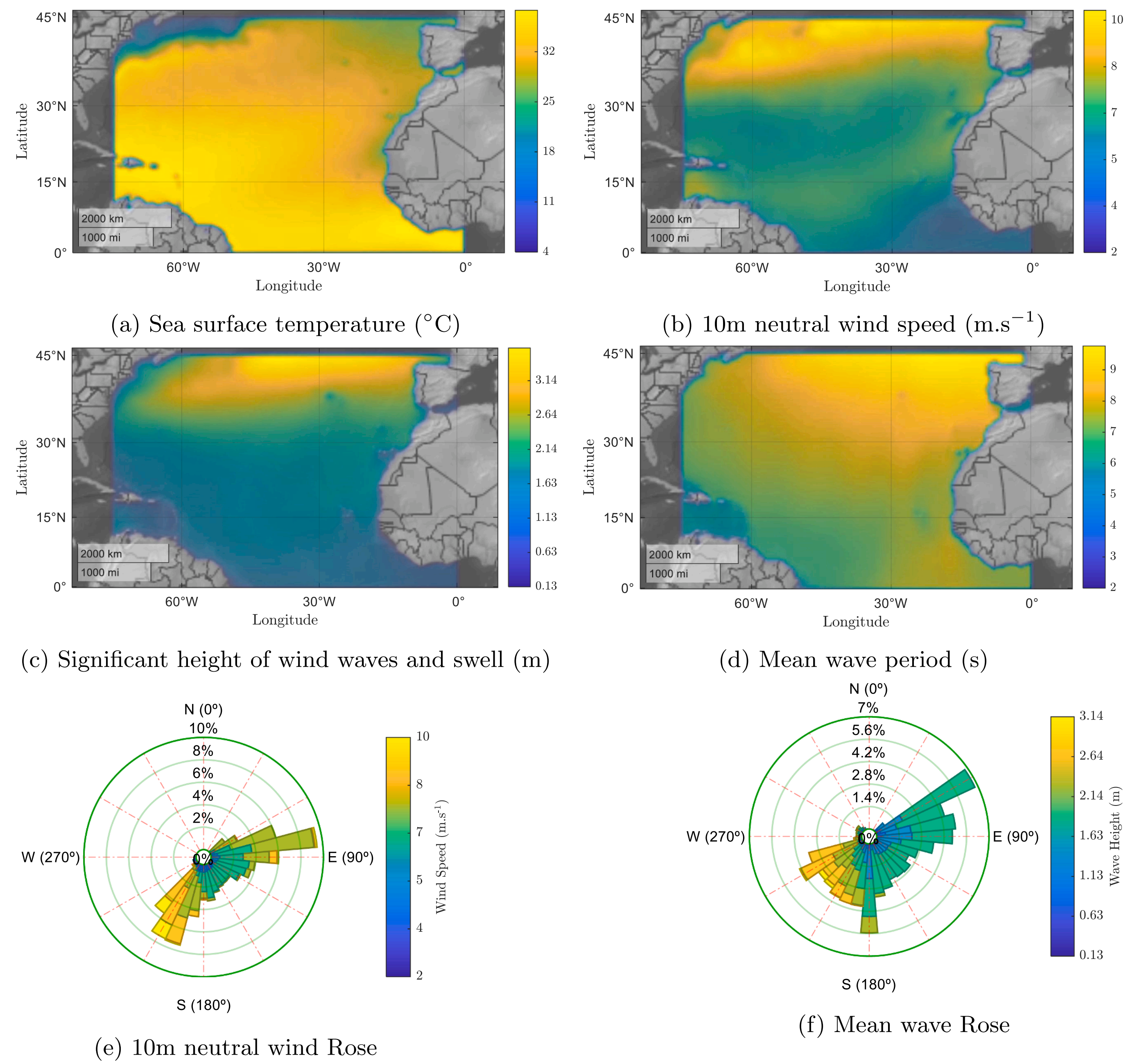


Fig. 4. The hourly spatio-temporal mean of the considered ECMWF ERA5 variables across the studied area from January to July 2024.

Table 1
Descriptive statistics for all considered onboard ship variables collected during the studied voyage.

Variable (unit)	Mean	Median	Std Dev	Variance	IQR	Skewness	Kurtosis
Ambient temperature (Â°C)	21.32	21.31	2.89	8.33	5.09	-0.03	1.92
Ambient humidity (%)	70.91	69.34	10.08	101.65	12.01	0.90	3.71
Sea temperature (Â°C)	22.38	22.15	2.55	6.49	4.49	0.13	1.78
Relative wind speed (knots)	21.45	21.20	5.79	33.52	6.43	0.45	3.79
Relative wind direction (Â°)	101.32	93.53	67.81	4598.80	48.67	2.00	6.88
Significant wave height (m)	2.11	2.06	0.51	0.26	0.78	0.47	2.44
Relative wave direction (Â°)	141.70	20.53	143.94	20717.77	268.21	0.28	1.20
Wave period (s)	7.89	8.09	0.89	0.79	1.39	-0.46	2.30
Ship speed (knots)	17.68	18.06	1.86	3.45	2.45	-1.75	11.51
Total fuel consumption (kg·min^{-1})	70.20	82.18	13.90	193.10	23.80	-0.48	2.21

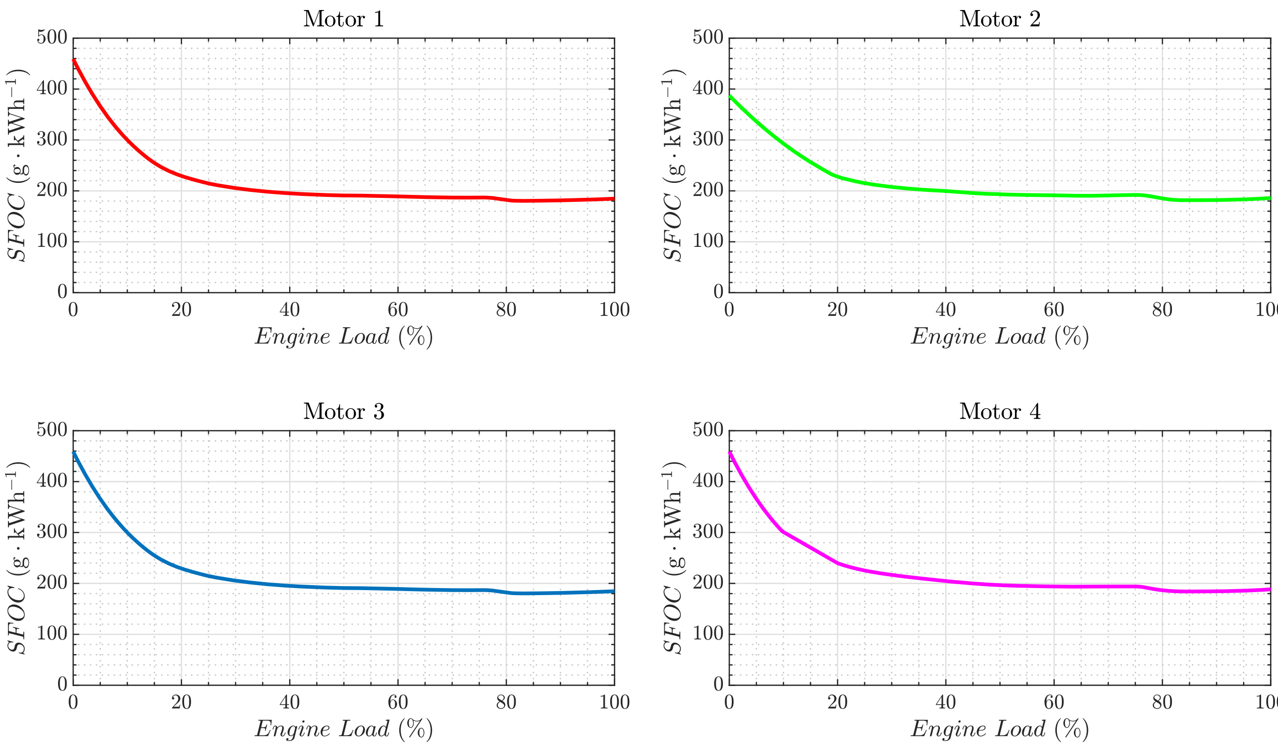


Fig. 5. The motors SFOC curves of the considered ship.

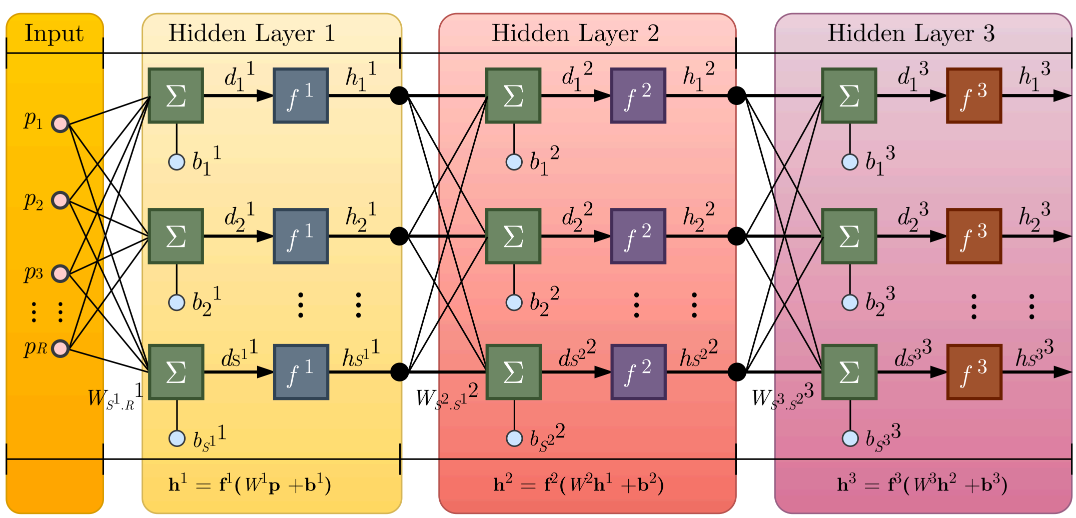


Fig. 6. A schematic diagram of a FFNN neural network with three layers.

during the voyage. The considered ship is equipped with four Wartsila engines. The Specific Fuel Oil Consumption (SFOC) curves of motors are illustrated in Fig. 5. The SFOC curves are graphical representations that show the relationship between the fuel consumption of the ship's engine and its load.

2.5. Feed-forward artificial neural network

A FFNN can be applied to both regression and classification problems. FFNN can approximate a wide variety of functions given sufficient hidden neurons and layers. FFNN is an artificial neural network where information flows in a single direction from the input nodes, through any hidden nodes, and finally to the output nodes. A general schematic diagram of a FFNN neural network architecture is presented in Fig. 6. A typical FFNN consists of three types of layers Input Layer, Hidden Layer(s), and Output Layer (Mahmoodi et al., 2022, 2019). The input Layer is responsible for receiving the input data. Each neuron in this layer corresponds to a single feature in the input data. Hidden layers are responsible for learning the complex patterns in the data that are placed between the input and output layers. They consist of neurons that process inputs from the previous layer, apply weights, add biases, and use activation functions to produce outputs (Vaghefi et al., 2020). The output layer provides the final output of the network. Each neuron in this layer represents one output feature.

Neurons (nodes) are the fundamental units within the network layers. Each input is multiplied by a weight, and the results are summed. A bias term is added to the weighted sum (Kim et al., 2025). Weights and biases are typically initialized with small random values. The result is passed through an activation function to introduce non-linearity. Common activation functions include Sigmoid, Tanh, and ReLU (Rectified

Linear Unit). During forward propagation, input data passes through the network layer by layer (Hwang et al., 2024). Each neuron processes the inputs, applies the weights and biases, and uses the activation function to produce an output (Minuzzi and Farina, 2024). This process continues until the output layer generates the final predictions. The loss function quantifies the difference between the network's outputs and the actual target values. Backward propagation is used to update the network's weights and biases. Gradients are used to adjust the weights and biases in the direction that minimizes the loss function. This adjustment is typically performed using an optimization algorithm such as Gradient Descent.

A wide FFNN structure is used in this study to map the relations between the ship and weather parameters with the fuel consumption. A wide FFNN is a type of neural network architecture that features a relatively large number of neurons in one or more of its hidden layers. This design contrasts with deep neural networks, which have many layers with fewer neurons in each layer. Each hidden layer has a large number of neurons, making the network wide.

2.6. Monte Carlo analysis

Monte Carlo simulation is a widely adopted method used for assessing the impact of uncertainty in complex systems. The scientific basis for employing the Monte Carlo method in this study is grounded in its robustness for uncertainty propagation, its compatibility with data-driven models, and its proven applicability in marine engineering contexts. The method allows for a statistically sound and operationally meaningful interpretation of the variability in ship fuel consumption due to weather uncertainties, thus supporting more informed decision-making for energy-efficient maritime operations. In essence, it involves running a model repeatedly with randomly sampled inputs to evaluate the probabilistic distribution of the output. This technique is particularly effective when analytical solutions are intractable due to nonlinearity, high dimensionality, or uncertainty in input parameters (Görmüş et al., 2022). Traditional deterministic simulations use fixed input values and therefore fail to capture the natural variability of environmental conditions. By contrast, Monte Carlo simulation enables a probabilistic exploration of possible outcomes (Liu et al., 2024). This probabilistic framework enables a comprehensive and realistic characterization of fuel usage variability due to environmental uncertainties. Unlike deterministic approaches, the Monte Carlo simulation reveals not only the expected (mean) fuel consumption but also the spread and likelihood of deviations from the mean, which is essential for robust decision-making in energy-efficient ship operation and route planning.

This study applies Monte Carlo analysis to assess the impact of marine weather parameter uncertainties on ship fuel consumption. The process involves generating a large number of random samples for the uncertain weather parameters, running simulations for each set of parameters, and then analyzing the results to understand the range and probability distribution of possible outcomes. Algorithm 1 shows the process of simulations for assessing fuel consumption under weather uncertainty using the Monte Carlo methodology. The process begins with the collection of historical marine weather data. For each discretized route point, the hourly weather data over a long historical period (1940–2024) is extracted. Various probability distributions are then fitted to each weather parameter using goodness-of-fit measures. The best-fitting distribution is selected for each variable. Each parameter is characterized by its statistical distribution, which is derived from historical weather data. Random samples of the weather parameters are generated using their respective statistical distributions. This involves creating a large number of different scenarios, each representing a possible state of the marine environment. For each set of randomly generated weather parameters, the ship fuel consumption model is run to predict the fuel consumption. This step results in a distribution of fuel consumption outcomes corresponding to the different weather scenarios. The results from the simulations are analyzed to assess the impact of weather uncertainties on fuel consumption.

It is important to note that in this work, the weather parameters at each route point are treated as statistically independent for sampling purposes. While this simplification facilitates the assessment of local uncertainty at each location, it inherently neglects the spatio-temporal correlations of weather patterns that typically evolve continuously along the route. The generated samples reflect the historical distribution of environmental variables at each point rather than a dynamically evolving weather system experienced by a vessel during an actual voyage. As such, the results provide a spatially resolved, probabilistically rich understanding of variability but do not represent a specific meteorological realization over time.

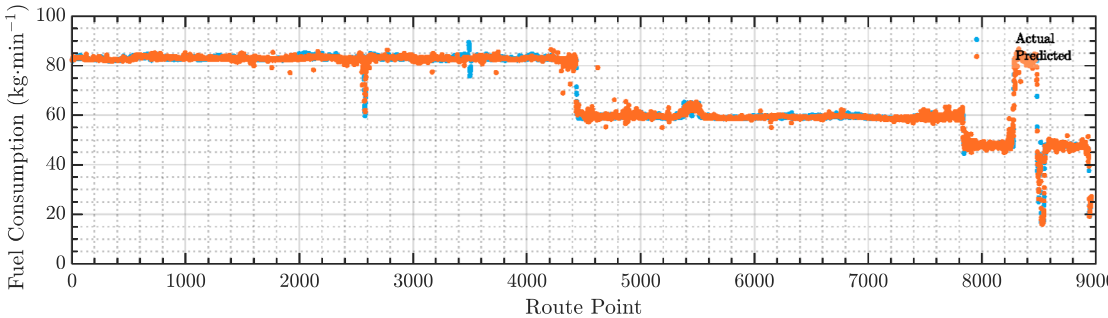
Algorithm 1: Monte Carlo simulation for assessing fuel consumption under weather uncertainty.

Input: Trained fuel consumption model $\mathcal{M}$ (e.g., FFNN);
Historical weather data along the ship route;
Number of Monte Carlo samples N;
Output: Distribution of predicted fuel consumption and associated statistics;

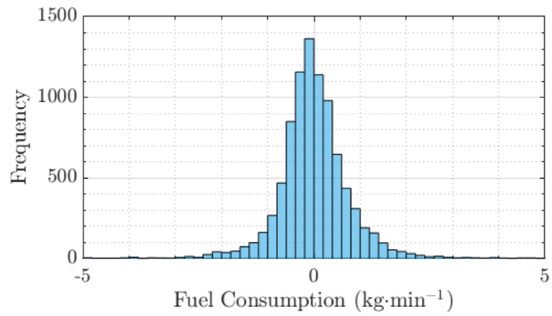
Step 1: Fit Statistical Distributions to Weather Parameters;
foreach *weather parameter* w_j **do**
    Fit a suitable probability distribution $\mathcal{D}_j$ using historical data;
    Store the distribution parameters;
end
Step 2: Generate Random Weather Scenarios;
for $i \leftarrow 1$ **to** N **do**
    foreach *weather parameter* w_j **do**
        Sample $w_j^{(i)} \sim \mathcal{D}_j$;   `// Draw from fitted distribution`
    end
    Form input vector $\mathbf{x}^{(i)} = [w_1^{(i)}, w_2^{(i)}, \dots, w_m^{(i)}]$;
end
Step 3: Simulate Fuel Consumption for Each Scenario;
for $i \leftarrow 1$ **to** N **do**
    Predict fuel consumption $y^{(i)} = \mathcal{M}(\mathbf{x}^{(i)})$;
end
Step 4: Analyze Results;
Compute statistical summaries of the output set $\{y^{(i)}\}_{i=1}^{N}$:;
    Mean, standard deviation, confidence intervals;
    Visualizations: histograms, KDE plots, box plots;
Step 5: Report Findings;
Interpret the variability in fuel consumption and quantify the uncertainty impact;

3. Results

As mentioned, a Monte Carlo simulation framework in conjunction with a trained wide FFNN is employed to assess the impact of weather condition uncertainties on fuel consumption. Various probability distributions (such as Weibull, Gamma, and Lognormal) are statistically fitted to each weather parameter at every route point using long-term historical data from ERA5. The best-fitting distribution for each variable is selected based on criteria such as the AIC, BIC, and log-likelihood. In the simulation phase, a large number of random samples are generated from these fitted distributions, which reflect the potential variability in future weather conditions. These randomly generated input scenarios are then fed into the trained FFNN model, which outputs the corresponding ship fuel consumption values. By repeating this process across thousands of



(a) The training actual vs. predicted values.



(b) Error Histogram

Fig. 7. The generated wide FFNN predictive model of the Total Fuel Consumption for Model 2.

simulations, a probabilistic distribution of fuel consumption outcomes is constructed which allows for a robust quantification of uncertainties stemming from environmental variability.

3.1. Generating the ship fuel consumption prediction model

A wide FFNN is used to map the relationships between input weather data, ship properties, and the resulting fuel consumption. The network was trained multiple times to improve accuracy, and the results from the best-performing model are presented. In Table 1, the Total Fuel Consumption is considered as the network output variable (Response), and other variables are considered as network inputs (Predictors). The generated FFNN predictive models are characterized as regression neural networks and utilize standardized predictor data. The network comprises two layers with 100 neurons in the hidden layer, employing the ReLU activation function, while the output layer has no activation function. The data is split into 70 % for training, 15 % for validation, and 15 % for testing. Initial weights are set using the Glorot method (Glorot and Bengio, 2010), and biases are initialized to zero. The training process involves the limited memory Broyden-Fletcher-Goldfarb-Shanno quasi-Newton algorithm (LBFGS) (Nocedal and Wright, 2006) with no regularization (Lambda = 0), a relative gradient tolerance of 1e-6, and a loss tolerance of 1e-8. The model performance is evaluated using the Mean Square Error (MSE) metric, with a maximum of 1000 epochs, and employs 5-fold cross-validation to ensure robustness and generalization of the model.

The neural network is trained several times to get the best results. The summary results of the best ten generated FFNN models are presented in Table 2. The performance criteria are Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Scatter Index (SI), and the square of the correlation coefficient R^2. As shown in Table 2, the generated models exhibit similar levels of accuracy, with only slight differences between them. Here, the best predictive model is selected for further calculations. Model 2 provides the most accurate predictions with the least error, making it the best-performing model in this comparison. Fig. 7 shows a comparison between the training Total Fuel Consumption actual values and the values predicted by the neural network for Model 2. Moreover, the prediction error histogram is shown in this figure. Table 3 presents a comparison of the contributions of various predictors across ten different models using minimum redundancy maximum relevance (MRMR) algorithm (Darbellay and Vajda, 1999; Ding and Peng, 2005). The values in the table indicate the influence or importance of each predictor within a given model. This table helps identify which environmental and operational factors are most critical in influencing the outcome of the models, providing valuable insights for further analysis and decision-making.

Table 2
The performance of the generated wide FFNN models for ship fuel consumption.

Models	MAE (kg·min^{-1})	MAPE (%)	RMSE (kg·min^{-1})	SI (%)	R^2
Model 1	0.6391	1.0211	1.2510	1.7821	0.9959
Model 2	0.6203	0.9743	1.1845	1.6873	0.9964
Model 3	0.6690	1.0695	1.2645	1.8014	0.9959
Model 4	0.7240	1.1690	1.4377	2.0481	0.9946
Model 5	0.6497	1.0238	1.2345	1.7585	0.9960
Model 6	0.6624	1.0644	1.3324	1.8980	0.9954
Model 7	0.6964	1.1237	1.3580	1.9345	0.9952
Model 8	0.6631	1.0679	1.2783	1.8209	0.9958
Model 9	0.6065	0.9884	1.2337	1.7574	0.9961
Model 10	0.6348	1.0169	1.2908	1.8387	0.9957

According to Table 3, some predictors, such as Ambient Temperature and Ship Speed, show consistent contributions across all models, indicating their stable importance. Others, like Sea Temperature and Wave Period, exhibit significant variability, suggesting that their impact is more context-dependent and may change based on the specific configuration of each model. Significant Wave Height and Ship Speed stand out as consistently influential across all models, indicating their critical role in predicting ship-related metrics. Ambient Humidity tends to have lower contributions, suggesting a lesser impact on the models compared to other predictors. Overall, while some predictors maintain a stable impact across models, others vary significantly, reflecting the complexity and varying dynamics in the models' predictions.

Table 3
MRMR-based feature ranking of the generated wide FFNN models for ship fuel consumption.

Model	AT	AH	SST	RWS	RWD	SWH	RWaD	WP	STW
Model 1	0.2348	0.1131	1.1166	0.1909	0.1720	0.9115	0.2111	0.1546	0.3019
Model 2	0.1621	0.1083	0.1551	0.1577	0.1410	0.8967	0.1610	1.0902	0.1995
Model 3	0.2361	0.0982	1.1468	0.2000	0.1640	0.9300	0.2100	0.1623	0.3026
Model 4	0.2116	0.1145	1.0759	0.1664	0.1480	0.8770	0.1863	0.1344	0.2744
Model 5	0.2386	0.0873	1.1311	0.1855	0.1719	0.9183	0.2224	0.1599	0.3100
Model 6	0.2489	0.0930	1.1633	0.2035	0.1798	0.9396	0.2373	0.1736	0.3088
Model 7	0.2223	0.1075	1.0935	0.1773	0.1595	0.8928	0.2049	0.1505	0.2942
Model 8	0.2403	0.1272	1.1216	0.1991	0.1859	0.9125	0.2330	0.1619	0.3060
Model 9	0.2356	0.1019	1.1453	0.1858	0.1891	0.9300	0.2126	0.1580	0.3178
Model 10	0.2358	0.1287	1.1155	0.1901	0.1634	0.9105	0.2035	0.1460	0.2962

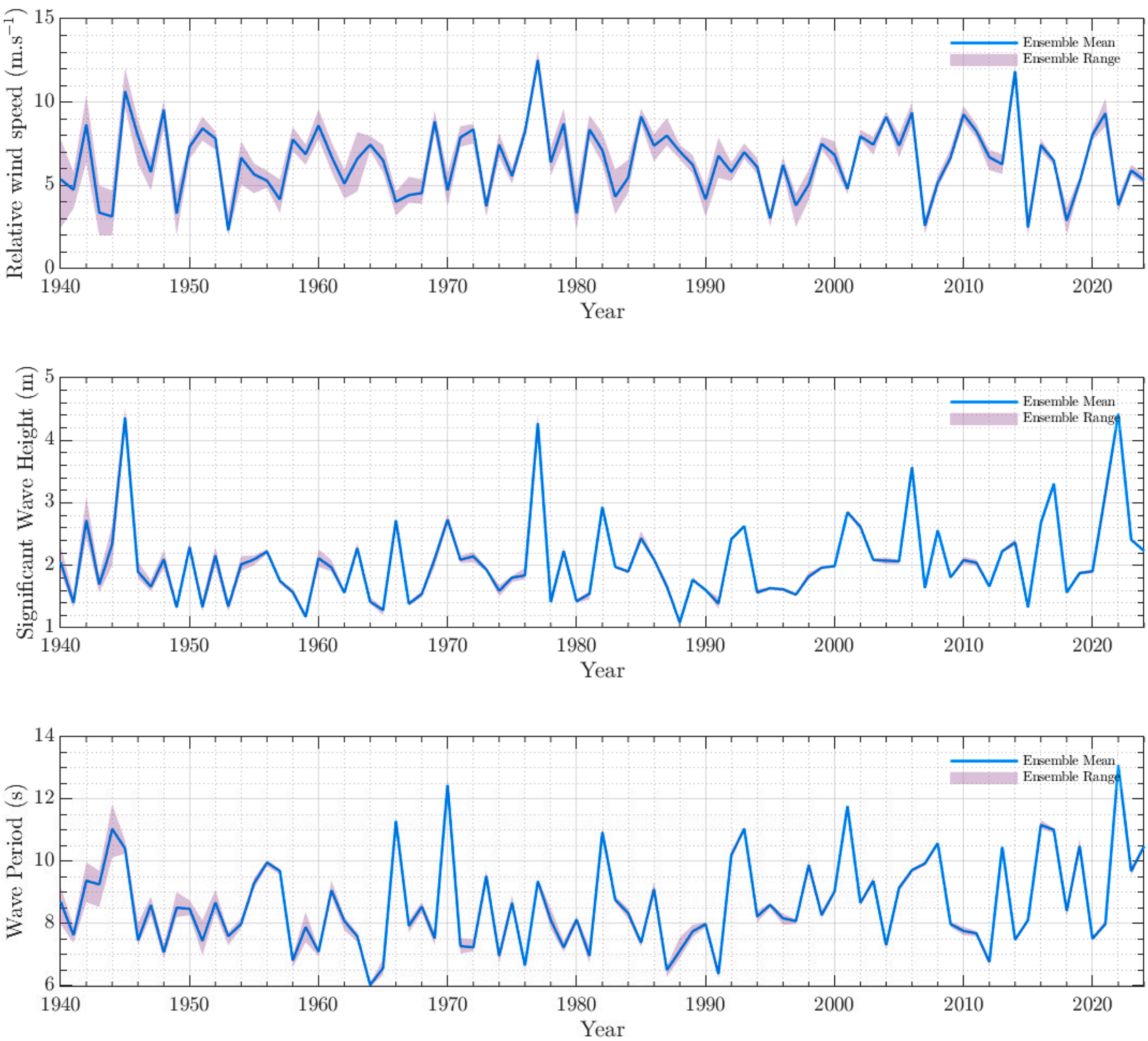


Fig. 8. The considered ECMWF ERA5 ensemble variables for a route point. The solid line represents the mean of ensemble members, while the shaded area around it indicates the ensemble range.

3.2. Determine the probability distributions of input variables

This step involves fitting different distributions to historical weather data parameters along the route points. It includes the type of probability distribution selection that best represents the uncertainty of each variable based on goodness-of-fit measures, including AIC, BIC, and log-likelihood. The considered distributions in this study are Normal, Weibull, Gamma, Lognormal, and Extreme Value. This process should be done for all considered weather variables at every point of the ship route. After the probability distributions of each variable at any point of the ship's route are established, these obtained distributions will be used to produce a large number of random inputs based on the specified distributions. This involves creating a large number of different scenarios, each representing a possible state of the marine environment.

It is essential to mention that the ensemble weather parameter statistics used in this study reflect long-term climatological distributions, derived from decades of ECMWF ERA5 reanalysis data. These distributions primarily capture the natural variability of marine environmental

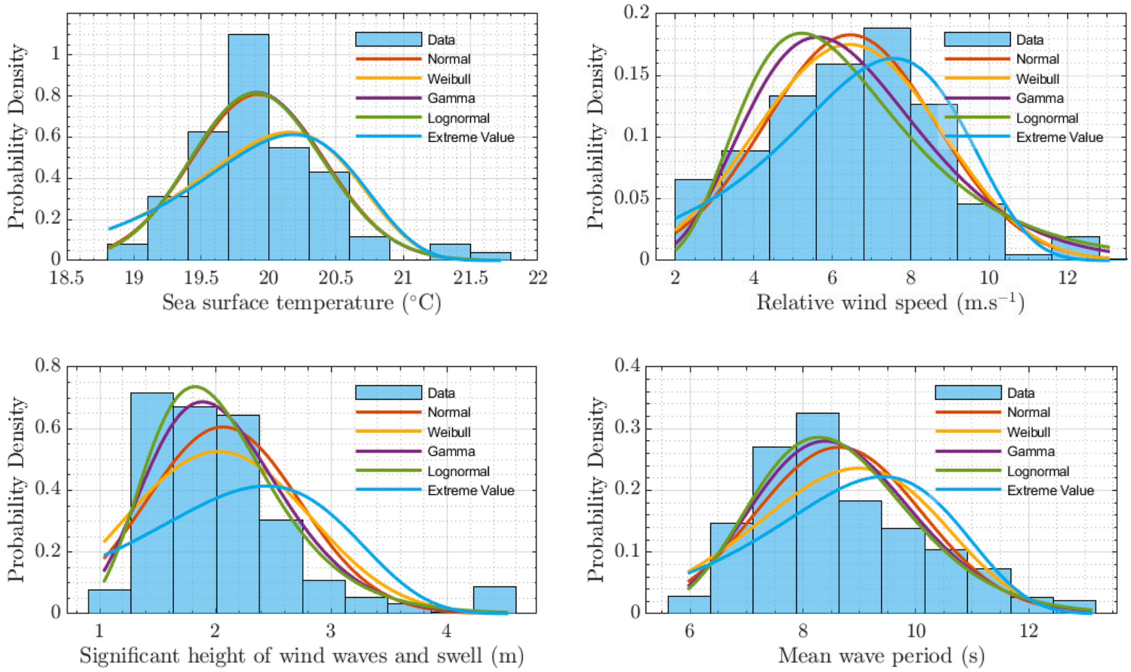


Fig. 9. Fitted distributions to the considered ECMWF ERA5 variables of a route point.

conditions over space and time, rather than the short-term ensemble spread commonly used in operational probabilistic forecasting. Nevertheless, this approach remains valid for estimating historically informed variability bounds.

For the uncertainty analysis, 150 points along the route are selected. These points are chosen based on two key criteria: firstly, ensuring the availability of ERA5 ensemble weather data, and secondly, confirming that the ship was in motion rather than docked at a port. For each point on the route, identified by specific time and geographical coordinates (latitude and longitude), the 10-member ensemble data for the selected weather variable are gathered from the years 1940 to 2024. Therefore, on average, 850 data points are available for each variable at each route point, except for sea surface temperature which consists of 85 points. For instance, Fig. 8 depicts the gathered ensemble data on Relative Wind Speed, Significant Wave Height, and Wave Period for a specified route point.

It is necessary to explain that in the uncertainty analysis, the effect of uncertainties in the variables of Ambient Temperature, Ambient Humidity, and Ship Speed are not taken into account. Therefore, the values of each of these variables at every route point are considered to be deterministic. Fig. 9 shows the different fitted distributions to the considered ECMWF ERA5 variables of a route point. Moreover, the results of goodness-of-fit measures of this considered point are presented in Table 4. To interpret the results, higher values of Log-Likelihood indicate a better fit. Lower values of AIC and BIC indicate a better fit, taking into account model complexity (number of parameters). The log-likelihood for each distribution is calculated by summing the log of the probability density function (PDF) evaluated at each data point. AIC is computed

Table 4
The goodness-of-fit measures of the fitted distributions to the considered ECMWF ERA5 variables of a route point.

Variable	Distribution	Log-likelihood	AIC	BIC
Sea surface temperature (°C)	Normal	-60.06	124.12	129.01
	Weibull	-76.55	157.10	161.98
	Gamma	-59.57	123.13	128.02
	Lognormal	-59.34	122.68	127.57
	Extreme value	-78.67	161.34	166.22
Relative wind speed (m.s^{-1})	Normal	-1867.90	3739.80	3749.30
	Weibull	-1862.80	3729.70	3739.20
	Gamma	-1887.60	3779.30	3788.80
	Lognormal	-1924.90	3853.90	3863.40
	Extreme value	-1953.30	3910.70	3920.10
Significant height of wind waves and swell (m)	Normal	-850.33	1704.70	1714.10
	Weibull	-863.90	1731.80	1741.30
	Gamma	-750.22	1504.40	1513.90
	Lognormal	-719.20	1442.40	1451.90
	Extreme value	-1105.80	2215.60	2225.10
Mean wave period (s)	Normal	-1537.40	3078.90	3088.40
	Weibull	-1593.20	3190.50	3200.00
	Gamma	-1508.90	3021.70	3031.20
	Lognormal	-1499.40	3002.80	3012.30
	Extreme value	-1680.50	3365.00	3374.50

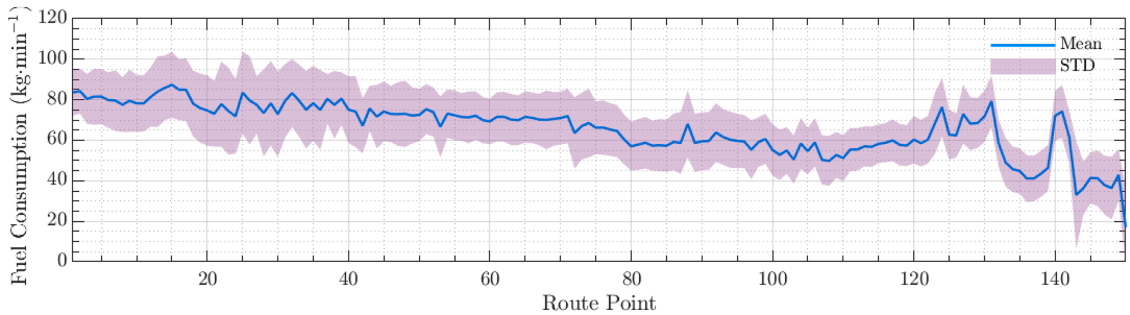


Fig. 10. The ship fuel consumption uncertainties of the considered route points based on weather data collected from 1940 to 2024. The solid line is the consumption mean at each point, while the shaded area is the points' standard deviation.

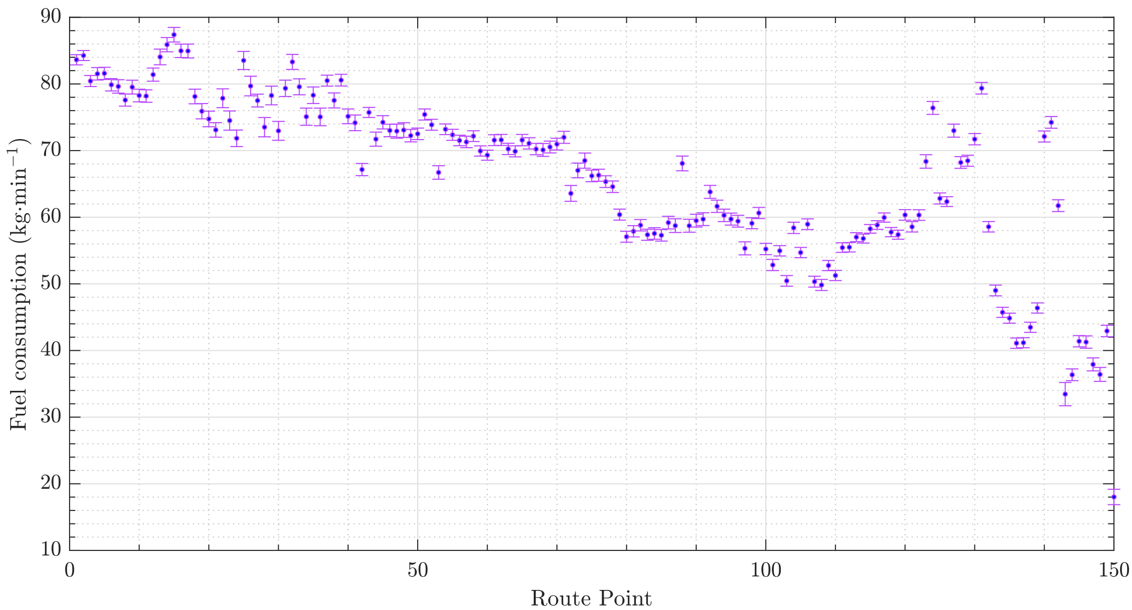


Fig. 11. 95 % Confidence interval around the overall mean of each point fuel consumption for all route points based on weather data collected from 1940 to 2024.

using the formula $2k - 2\ln(L)$, where k is the number of parameters and L is the likelihood. BIC is computed using the formula $k\ln(n) - 2\ln(L)$, where n is the number of data points.

The goodness-of-fit analysis demonstrates that different marine weather variables require distinct probability distributions for accurate uncertainty modeling. The Lognormal distribution proves to be the best fit for sea surface temperature, significant wave height, and mean wave period. Meanwhile, relative wind speed is best represented by the Weibull distribution, which is commonly used in meteorological studies. These findings highlight the importance of selecting appropriate distributions to enhance the reliability of Monte Carlo simulations for ship fuel consumption predictions.

3.3. Uncertainty analysis

In this subsection, the predictive wide FFNN model 2 (See Section 3.1) is fed with different possible weather scenarios of the considered route points generated using Monte Carlo simulations based on the determined probability distributions of input weather variables in the previous subsection. For this purpose, 100,000 different weather scenarios are simulated. The amount of fuel consumed is estimated for each scenario using the generated artificial neural network model. This approach allows for a comprehensive analysis of the potential variability in fuel consumption, providing a robust framework for understanding how changes in weather conditions can impact fuel usage. By utilizing a wide range of simulated scenarios, the model accounts for the inherent uncertainty in weather forecasting and offers a more reliable prediction by capturing the possible extremes and variabilities in weather patterns.

Fig. 10 shows the ship fuel consumption uncertainties of the considered route points based on weather parameters collected from 1940 to 2024. The higher mean values indicate areas of higher average fuel consumption. Points with a mean over 80 (e.g., points 1 to 16) suggest more fuel-intensive sections of the route. Conversely, points with means under 50 (e.g., points 134 to 146) represent sections of the route with lower average fuel consumption. A higher standard deviation indicates more variability in fuel consumption at certain points. For example, the std is above 20 for some points (like 22, 23, and 25), indicating high variability, possibly due to varying weather conditions. Lower standard deviations (e.g., points 132 to 137, with std around 9-10 kg·min^{-1}) suggest more consistent fuel consumption, indicating stable conditions across these route points. The beginning route points (1 to 16) generally have higher means and moderately high std, indicating a consistently fuel-intensive part of the route with some variability. As the route progresses, the means and stds gradually decrease which suggests the middle parts of the route are less fuel-intensive and more stable. The last few points (140-150) show significant variability (high std at point 134) followed by low mean values towards the end (points 148 and 150). This could indicate irregular weather conditions.

Fig. 11 shows the 95 % confidence interval around the overall mean of each point fuel consumption for all route points. The margin of error provided for each of the 150 ship route points represents the range within which the true mean fuel consumption is expected to fall, with

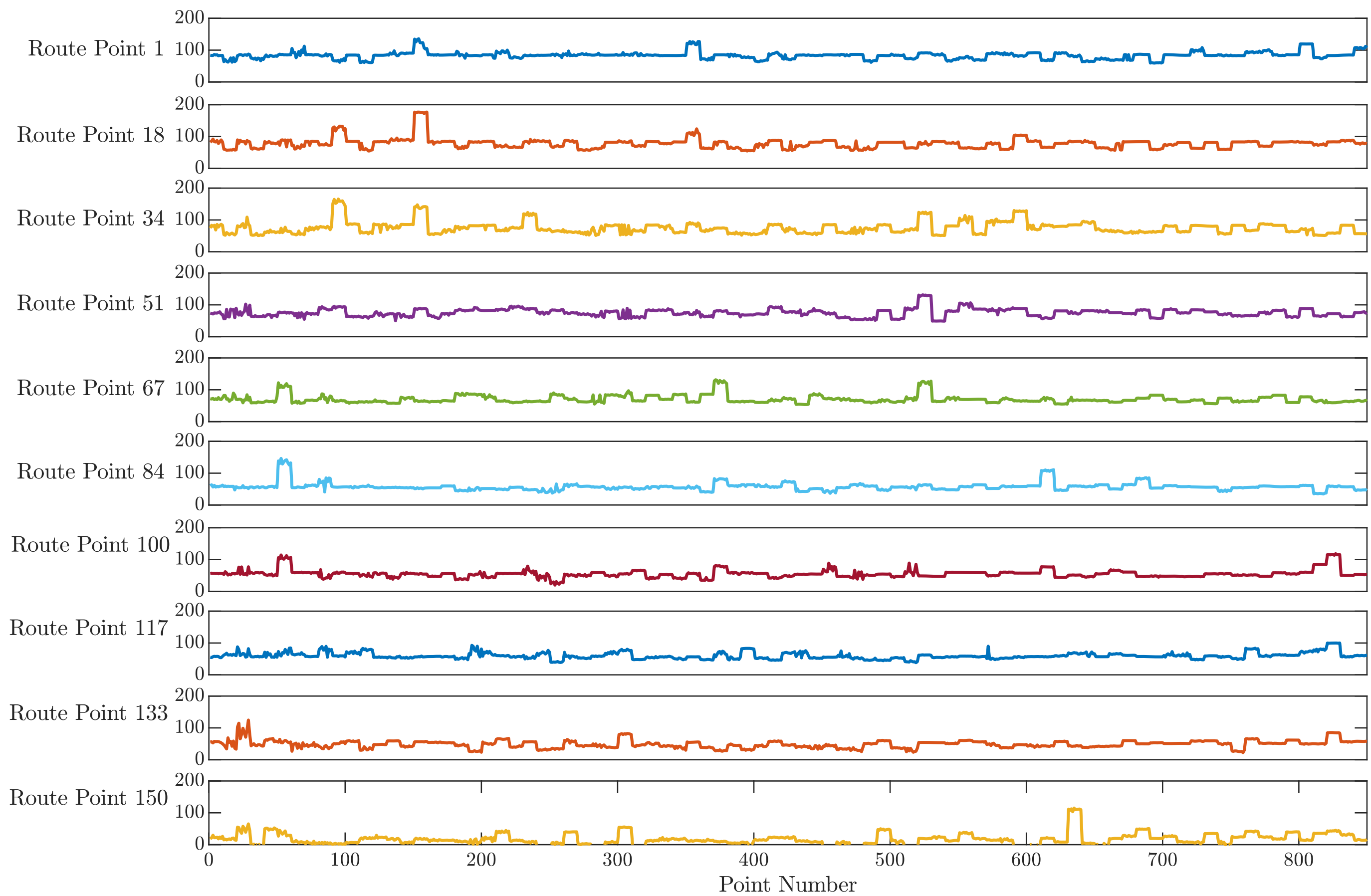


Fig. 12. The ship fuel consumption variations (kg·min^{-1}) of the considered ten route points based on weather data collected from 1940 to 2024.

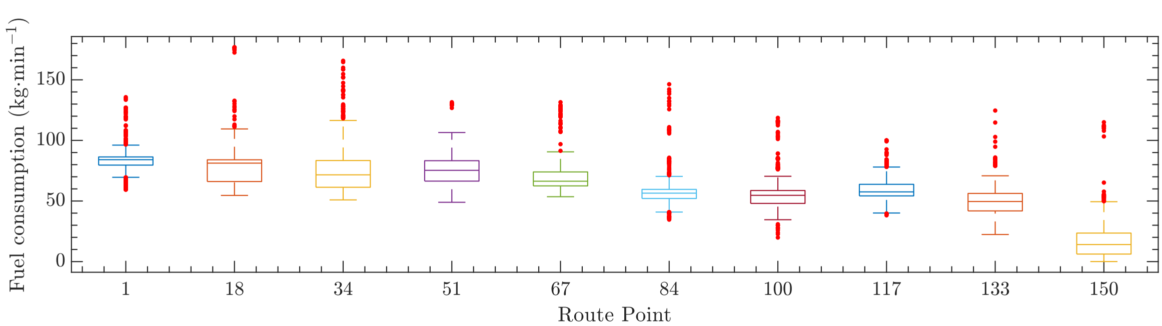


Fig. 13. The ship fuel consumption box plots of the considered ten route points based on weather data collected from 1940 to 2024.

95 % confidence. Smaller margins of error indicate higher precision in estimating the true mean fuel consumption, while larger margins suggest greater uncertainty. The margin of error varies across the 150 route points, ranging from as low as 0.64 kg·min^{-1} to as high as 1.74 kg·min^{-1}. Points with higher margins of error, such as the point with a margin of 1.74 kg·min^{-1}, indicate greater uncertainty in the mean fuel consumption estimate at that point. Points 12-25, for example, generally have higher margins of error (e.g., 1.18, 1.45, 1.42 kg·min^{-1}), indicating that these sections of the route may experience more variability in conditions affecting fuel consumption (like weather, currents, etc.). The latter part of the route, particularly from points 130-150, has lower margins of error (e.g., around 0.67 to 0.83 kg·min^{-1}), suggesting that the ship's fuel consumption is more predictable in these areas.

The fluctuations in fuel consumption and variability could be attributed to different weather conditions experienced over the years. Moreover, changes in navigation strategies or alterations in route choices might have contributed to the observed patterns. Understanding these trends can help optimize fuel consumption by adjusting routes or speeds in sections with higher means and variability. Identifying points with high std can help in planning for contingencies in case of adverse weather conditions or other unforeseen factors affecting fuel consumption.

In the following, only 10 points of the route are investigated for better visualization of ship fuel consumption variations. The selected points are: 1, 18, 34, 51, 67, 84, 100, 117, 133, 150. The ship fuel consumption variations of the considered ten route points are illustrated in Fig. 12. Moreover, The box plot of these points is depicted in Fig. 13. According to this figure, points like 18, 34, and 84 show high variability in fuel consumption, suggesting these are areas where environmental factors or other conditions significantly impact fuel usage. Points like 67 and 117 exhibit relatively low variability, indicating more stable conditions. The median values provide insights into the typical fuel consumption at

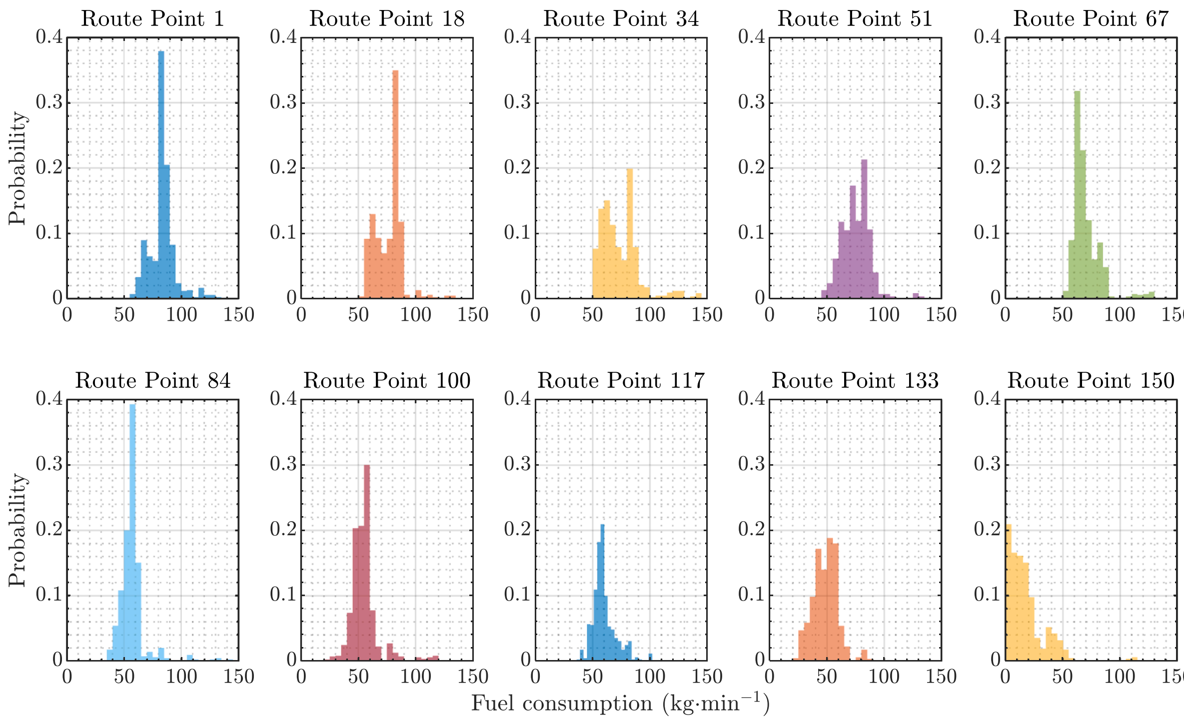


Fig. 14. The probability histogram plot of the considered ten route points based on weather data collected from 1940 to 2024.

each point. The spread between the quartiles (interquartile range, IQR) indicates the degree of variability in the central 50 % of the data. Points like 67 and 117 show more symmetric distributions with narrower IQRs that suggest stable and predictable fuel consumption patterns. These points might represent areas with consistent environmental conditions, where fuel consumption is more uniform. For stable points, the focus can be on fine-tuning operational efficiency, as the predictability allows for better planning and fuel optimization. These points might also serve as benchmarks for assessing the impact of environmental variations at other points. Points with wider IQRs, such as 18 and 34, indicate greater uncertainty in fuel consumption. This suggests that even under normal conditions, fuel consumption can vary significantly. For points with wider IQRs, adaptive strategies, such as dynamic route adjustments based on real-time data, could be necessary for maintaining efficiency.

The probability histogram plot of the considered ten route points is shown in Fig. 14. According to this figure and Fig. 12, data shows a mixture of right-skewed and left-skewed distributions across different points, indicating the presence of outliers that pull the distribution toward the higher or lower end of fuel consumption. Points like 18, 84, and 100 have a median closer to the lower quartile and a long tail towards higher values. This suggests that while typical fuel consumption might be moderate, there are instances of very high consumption, likely due to adverse weather or other challenging conditions. For right-skewed points, strategies should focus on identifying and mitigating the causes of these high-consumption values, such as optimizing speed, route adjustments, or scheduling around known weather patterns. Point 150 is particularly notable for having low values, indicating potential anomalies or special cases. These points represent rare but beneficial conditions that could be studied and replicated. The variability and skewness of fuel consumption at different points suggest that route optimization cannot be a one-size-fits-all approach. Instead, it must be dynamic and tailored to the specific conditions likely to be encountered at each point.

The KDE of the considered route points is provided in Fig. 15. KDE plot gives a smoothed, continuous approximation of the data's PDF. By comparing KDE plots of different points along the route, it is possible to identify which segments of the route have more consistent (narrower, sharper peak) or variable (wider, flatter) fuel consumption distributions. Differences in the shape of the KDE plots across points can highlight the influence of changing environmental conditions, such as wind and waves, or operational factors like speed adjustments. The KDE plots can show a single peak (unimodal) or multiple peaks (multimodal). Route Point 51 shows a single peak around 80–90 kg·min^{-1} with a moderate spread. The ship's fuel consumption is more consistent at this route point, with most values clustering around the mean, but with some variability that may reflect occasional changes in external factors like weather.

Multiple peaks could indicate that there are distinct weather regimes or conditions under which fuel consumption varies significantly. For example, there are two distinct peaks in Route Point 18, indicating two probable ranges of fuel consumption around 60 and 90 kg·min^{-1}. Route Points with bimodal distributions (e.g., Points 18 and 67) indicate higher uncertainty, with two dominant operational conditions. It suggests that different external factors (like severe weather vs. calm conditions) could significantly impact fuel consumption. Route points with unimodal distributions (e.g., Points 51 and 84) are associated with more predictable fuel consumption which indicates lower uncertainty and more stable operational conditions.

The highest peak in the KDE plot corresponds to the most likely fuel consumption level at that point. A narrow, tall peak suggests a high level of certainty about the fuel consumption around that value. If there are secondary peaks, these may represent alternative operating conditions or environmental scenarios that occur less frequently but still significantly affect fuel consumption. Route Point 67 shows a dominant sharp peak around 50–60 kg·min^{-1} and a smaller secondary peak near 90 kg·min^{-1}. This suggests a primary operating condition where fuel consumption is lower, but occasionally it spikes, possibly due to extreme weather conditions or different ship operations at this point. A wider distribution in the KDE plot indicates greater uncertainty, as the fuel consumption values are spread over a larger range. Narrower distributions suggest more predictability and less uncertainty. The distribution can be symmetric or skewness around the mean. Skewed distributions suggest that extreme values on one side are more likely, indicating potential high variations in fuel consumption. Heavy tails indicate a higher probability of extreme values (either low or high fuel consumption).

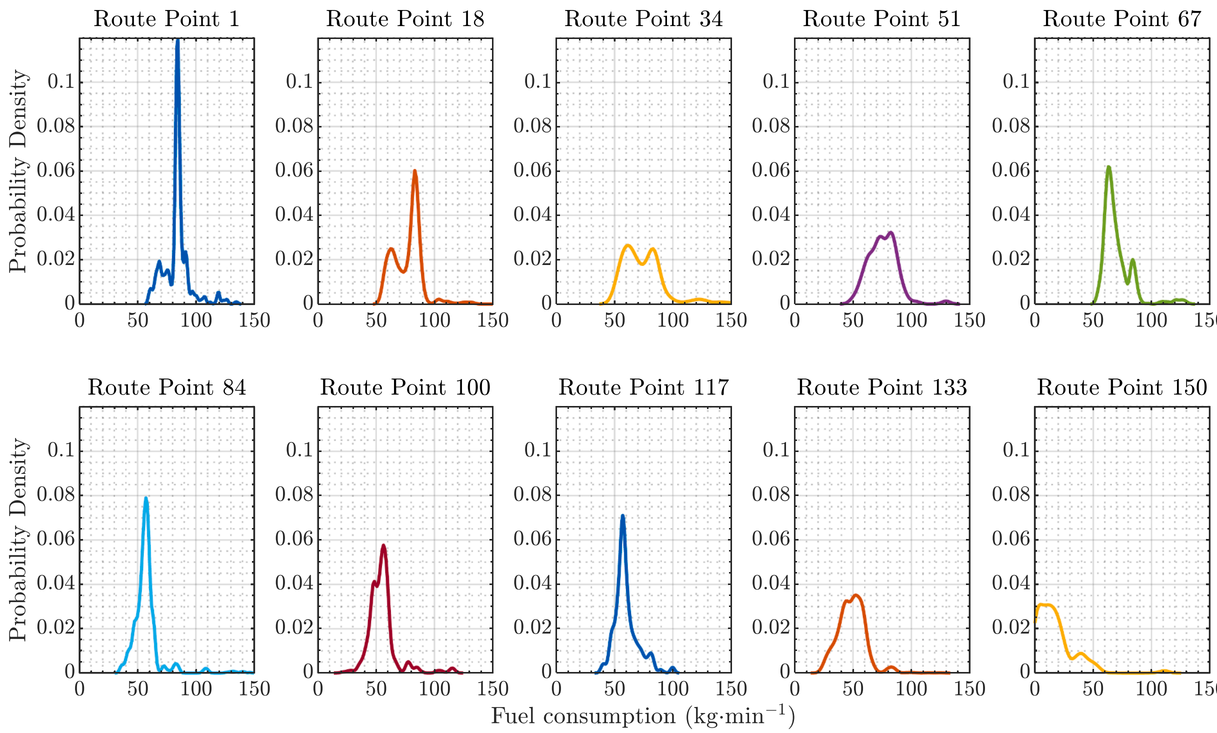


Fig. 15. The kernel density plot of the considered ten route points based on weather data collected from 1940 to 2024.

3.4. Discussion

In the context of maritime fuel consumption, environmental conditions such as wind speed, wave height, and sea surface currents are inherently uncertain and vary across time and space. Traditional deterministic models often fail to capture the full spectrum of possible environmental scenarios, leading to overly confident or biased predictions. To address this limitation, this study applied the Monte Carlo method to rigorously evaluate how uncertainties in weather conditions influence ship fuel consumption. To contextualize the findings within the broader literature, the discussion is expanded to compare the results with previous studies that have examined weather-induced variability in ship fuel consumption. Several deterministic routing studies (e.g., Dickson et al. (2019), Li et al. (2022), Mason et al. (2023) and Ksciuk et al. (2023)) report that ignoring meteorological uncertainty can lead to systematic underestimation of fuel use, whereas probabilistic approaches such (Vettor et al., 2021; Vettor and Soares, 2022) show wider prediction envelopes but more reliable upper bounds. The proposed framework confirms that propagating ensemble-derived weather variability through a data-driven model expands the 95 % confidence band of fuel consumption by up to 14 % on the most exposed segments. This magnitude is comparable to the spreads reported by Vettor and Soares (2022).

The findings of this study align closely with prior research that has emphasized the dominant role of environmental variability-particularly wind and wave conditions-in driving uncertainty in ship fuel consumption predictions. When using Monte Carlo simulations, weather-induced variability substantially outweighs other sources of uncertainty in ship performance models (Aldous et al., 2015; Tillig et al., 2018). Consistent with these conclusions, the results of this study reveal that variations in marine weather parameters-quantified through ensemble datasets-significantly influence the predicted fuel consumption profiles. Moreover, this study builds upon the established practice of using ensemble methods to represent uncertainty in route-based performance metrics, where the output is better captured by a distribution (e.g., mean Â± standard deviation or percentile bands) rather than a deterministic value. Importantly, while earlier data-driven approaches such as support vector regression (SVR) and feed-forward neural networks have demonstrated promise in fuel consumption prediction, they often neglect the uncertainty inherent in weather inputs. By integrating an FFNN model with ensemble-based meteorological inputs from ERA5, the proposed approach advances this line of research by offering a probabilistic framework that realistically captures the spread of possible outcomes. This not only validates prior observations but also extends the literature by providing a practical and scalable method for uncertainty quantification in operational ship routing and fuel management.

A key challenge in interpreting the uncertainty in fuel consumption lies in separating the contributions from natural environmental variability and forecast or model uncertainties. The probability distributions generated in this study using long-term reanalysis data primarily represent the natural variability of environmental conditions encountered across decades of marine operations. These reflect true fluctuations due to storm events, seasonal dynamics, and ocean circulation patterns. However, they may also embed residual uncertainties due to the data assimilation processes or observational errors inherent in the ERA5 reanalysis. While the used Monte Carlo simulations quantify how variations in weather parameters impact predicted fuel consumption, they do not explicitly differentiate the fraction of variability attributable to forecast errors. Future extensions of this work could incorporate ensemble forecast spreads or sensitivity analysis frameworks to more rigorously distinguish these components.

The observed spatial variability in uncertainty across route points reflects localized historical environmental patterns. However, it must be noted that due to the independent sampling assumption, no temporal coherence exists across these points. In reality, a ship traveling through multiple points would experience weather conditions that are temporally and spatially correlated. Therefore, these results represent a conservative estimate of potential variability rather than a time-consistent forecast. Future work may integrate trajectory-based spatiotemporal modeling to improve the realism of the uncertainty propagation.

4. Conclusion

This study presented a comprehensive methodology for assessing ship fuel consumption uncertainties by integrating advanced data-driven modeling techniques with probabilistic analysis. By identifying how weather parameter uncertainties affect fuel consumption, this research provided valuable insights that can help maritime operators better predict and manage fuel usage, leading to cost savings and more efficient operations. A predictive model using a wide FFNN was developed to capture the relationship between various weather parameters and fuel consumption. The route was discretized into specific points, allowing for detailed analysis at each stage of the voyage. Historical marine weather data spanning from 1940 to 2024 was gathered from the ECMWF ERA5 dataset. By applying multiple probability distributions to each weather variable at every route point and selecting the most suitable distributions, it was possible to generate a comprehensive ensemble of potential input scenarios. These scenarios were used in Monte Carlo simulations to produce a distribution of possible fuel consumption outcomes. The integration of FFNN and Monte Carlo simulations provided useful predictive tools that can be adopted by the maritime industry for better decision-making and strategic planning, particularly in the context of uncertain and variable weather conditions. The research used a set of statistical tools, such as histograms, box plot, KDE, and confidence intervals, to characterize and visualize uncertainties, offering clear insights into the weather parameters' impacts on ship fuel consumption.

The findings reveal significant variations in fuel consumption estimates due to weather prediction uncertainties, highlighting the crucial need for advancements in weather forecasting and operational strategies in maritime transportation. The analysis of fuel consumption across different points along the ship's route reveals several key insights into the variability and predictability of fuel usage. Higher mean values indicate segments where the ship consistently consumed more fuel which points to areas of higher average fuel demand. Meanwhile, the standard deviation provided a measure of variability, with higher values indicating points where fuel consumption fluctuated significantly, likely due to changing environmental conditions or operational factors. Conversely, lower standard deviations suggest points of more consistent fuel consumption, reflecting stable conditions that enable more predictable fuel use. Smaller margins of errors indicate higher confidence in the mean fuel consumption values, while larger margins suggest greater uncertainty and potential variability. Furthermore, the shape and spread of the data distributions offer additional insights. Points with symmetric distributions and narrower IQRs suggest stable and predictable fuel consumption patterns, typically occurring in areas with consistent environmental conditions. These points are indicative of uniform fuel usage, making them less risky in terms of fuel planning. On the other hand, points with wider IQRs reflect greater uncertainty and variability, highlighting segments of the route where fuel consumption is less predictable. The comparison of KDE plots across different route points enhances this analysis by visually identifying segments with either more consistent (narrower, sharper peaks) or more variable (wider, flatter distributions) fuel consumption patterns. This comparative approach allows for a better understanding of the route which aids in the identification of specific segments where operational adjustments may be necessary to ensure efficient and reliable fuel usage throughout the voyage.

This methodological framework not only offers a more detailed understanding of the factors affecting fuel consumption but also serves as a practical tool for optimizing voyage planning and fuel management in maritime operations. The insights gained from this study can inform policymakers and regulatory bodies about the importance of accurate weather forecasting and its impact on fuel consumption. Future research could expand upon this work by applying the methodology to different types of vessels and routes, as well as integrating real-time data for dynamic fuel consumption forecasting. Implementing dynamic routing, where the ship's path is adjusted in real-time based on predictive models and current data, could significantly improve fuel efficiency. This is particularly relevant for points with high variability or where extreme conditions have historically occurred. Additionally, future studies are recommended to incorporate multiple weather datasets, such as NOAA GFS or satellite observations, to further validate and enrich the uncertainty analysis of ship fuel consumption. Moreover, while the current approach emphasizes spatially distributed uncertainty based on long-term variability, future studies should incorporate temporal dynamics, enabling a more accurate modeling of evolving weather conditions and their cumulative effect on voyage-scale fuel consumption.

Ethical approval

This paper is the author's original work and has not been previously published elsewhere.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT and Microsoft Copilot to refine the language and improve clarity. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Kumars Mahmoodi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization; **Jari Böling:** Writing – original draft, Methodology, Funding acquisition, Conceptualization; **Roberto Vettor:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Data availability

The study's supporting data can be accessed by contacting the corresponding author upon request.

Declaration of competing interest

The authors declared no potential conflicts of interest concerning the research, authorship, and/or publication of this paper.

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