Data-Driven Modelling for Battery Retrofit Feasibility Assessment of Auxiliary Loads on Short-Route Ferries

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***Abstract*— Ship electrification is becoming increasingly feasible for short-route ferries due to advances in battery technology and shore-side charging infrastructure. However, full electrification of existing diesel ferries remains financially and technically challenging. As a practical alternative, replacing the diesel-powered auxiliary engine with a battery-based system for supplying auxiliary load offers a lower-cost, incremental decarbonization pathway. Despite this potential, few studies have quantitatively assessed the feasibility of such retrofits using operational data, leaving uncertainties around auxiliary load predictability, battery sizing, and shore-side charging requirements. This study addresses this gap by developing a data-driven framework to evaluate the battery retrofit requirements for auxiliary loads on short-route ferries. Operational data from a roll-on/roll-off vessel is used to model auxiliary power demand. An XGBoost regression model is trained on environmental and operational parameters, achieving good performance, with R^2 score of 0.97. Based on the model predictions, the required battery capacity is estimated at 12.26 MWh, with a mass of 61,290 kg and volume of 20.43 m3. A shore-side charging power of 2.56 MW is needed to fully recharge the battery without operational disruption. The proposed framework can support decision making for ship operators and naval architects by enabling reliable auxiliary load forecasting and early-stage planning for battery retrofits. It provides a basis for evaluating the feasibility of battery integration and contributes to the transition toward low-emission maritime operations.**

Keywords—Ship electrification, auxiliary load modeling, battery energy storage system, battery sizing, XGBoost regression, short-route ferry.

I. Introduction

The maritime sector is under growing pressure to reduce greenhouse gas emissions and transition to cleaner energy sources. Global shipping accounts for nearly 3% of anthropogenic CO_2 emissions [1], and regulatory bodies such as the International Maritime Organization (IMO) and regional actors like the European Maritime Safety Agency (EMSA) are intensifying efforts to accelerate maritime decarbonization. For short sea shipping segments such as roll-on/roll-off passenger (RoPax) ferries, which operate on predictable routes with frequent port calls, battery electrification has emerged as a technically and operationally feasible alternative, enabled by advances in battery energy density and shoreside charging infrastructure. However, fully electrifying conventionally powered vessels, particularly those originally designed for diesel operation, presents significant technical, financial, and regulatory challenges. These include limited space and weight margins for accommodating large battery systems, high upfront capital costs, and the need for extensive upgrades to shore-side infrastructure. As a result, many operators are exploring incremental retrofit strategies rather than full conversions. One of these approaches involves fully replacing the auxiliary engine, dedicated to powering non propulsion or hotel systems (such as HVAC, lighting, galley, refrigeration etc.) with a battery energy storage system (BESS).

Auxiliary, or hotel, loads are frequently overlooked in maritime decarbonization strategies, despite constituting a substantial share of total energy consumption, particularly on passenger vessels. For instance, Brækken et al. [2] reported that hotel loads account for approximately 20% of the annual energy usage on a cruise ship operating in Nordic climates. Other studies have similarly shown that hotel load contributions can vary significantly depending on vessel type, operational profile, and environmental conditions, yet consistently highlight their importance in overall energy demand [3]. Nonetheless, the majority of ship electrification research continues to focus on propulsion systems, powertrain architectures, hybrid configurations, and shore power integration [4].

Although several studies have explored battery retrofitting in the shipping sector [5, 6], retrofits targeting only auxiliary loads on RoPax ferries remain notably underexplored. Most existing frameworks assume either full-ship electrification or hybrid configurations that address both propulsion and auxiliary demands simultaneously. In such hybrid configurations, batteries are typically used for load leveling, peak shaving, or as power reserve, which makes it difficult to evaluate the feasibility

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of auxiliary-only battery systems. Broader reviews of shipboard energy storage technologies point to a wide range of system topologies, including mechanical-electrical hybrids, partial electrification, and full battery-electric systems, but also emphasize the lack of detailed data on auxiliary loads [7, 8]. Consequently, many retrofit studies rely on fixed load factors or standardized assumptions that may not reflect the operational variability of hotel loads across different conditions and seasons [9].

Without a data-driven understanding of auxiliary load profiles, it remains challenging to appropriately size battery systems and evaluate the technical feasibility of such retrofits. This creates a knowledge gap that constrains informed decision making around battery retrofits for auxiliary loads. Similarly, studies estimating shipboard power and energy demands typically treat auxiliary loads in aggregate or focus on anchorage/berth conditions, without coupling temporal load pattern modelling with battery sizing for auxiliary systems per se [10].

This study addresses that gap by developing a data driven framework to estimate battery requirements for auxiliary (hotel) loads on diesel RoPax ferries. Operational data from real vessels is used to model auxiliary loads as a function of environmental and operational variables. The model output is then applied to battery system design, accounting for depth of discharge, efficiency losses, and reserve margins. Charging requirements are assessed with respect to port turnaround times and shore-power constraints.

This research contributes in three distinct ways: it provides empirical quantification of auxiliary load behaviour using real ship data, rather than relying on standardized assumptions; it develops a predictive model using XGBoost to forecast auxiliary power demand under varying conditions; and it bridges the gap between modelling and practical implementation by analysing the battery sizing and charging requirements. Taken together, the approach seeks to enable more targeted, feasible retrofits that shipowners can realistically adopt in the near term, accelerating the maritime transition to low emission operations.

The rest of the paper is organized as follows. Section II describes the proposed methodology. Section III presents the case study vessel considered in this study, and Section IV presents and discusses the results. Finally, the paper summarizes the key points in Section V.

II. Methodology

This study develops a data-driven framework to estimate the battery energy storage system requirements for auxiliary loads onboard RoPax ferry. The methodology, as illustrated in Fig. 1, consists of four sequential steps: (1) data collection and preprocessing, (2) predictive modelling using XGBoost, (3) battery system sizing based on model predictions and system constraints, (4) charging feasibility assessment during port turnaround times. Each step is described in detail in the following subsections.

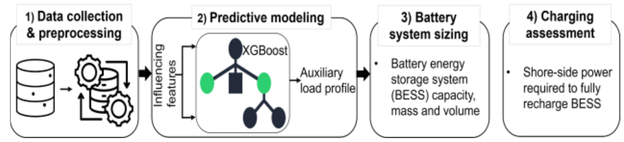

Fig. 1. Methodology workflow for estimating battery retrofit requirements

A. Data Collection and Preprocessing

To effectively model auxiliary loads, it is important to identify and integrate the parameters that meaningfully influence their behaviour. These typically include passenger occupancy, environmental conditions, and operational parameters, alongside actual auxiliary power consumption data. A dataset that includes all these aspects enables the development of predictive models capable of capturing the variation in auxiliary loads under changing conditions. However, preprocessing is a critical step before model development, as raw data often contains missing values, anomalies, and noise. To ensure the dataset is reliable and suitable for predictive modelling, several preprocessing techniques were applied, as detailed in our prior work [11]. These include missing data imputation, outlier treatment, data smoothing, and feature engineering techniques to enhance the data's relevancy for model development.

B. Predictive Modelling

Following data preprocessing, the auxiliary load was modelled using XGBoost, a gradient boosting algorithm that builds ensembles of decision trees. XGBoost is particularly well-suited for structured datasets and is known for its ability to capture complex nonlinear relationships between input features and target variables with high computational efficiency [12].

The algorithm builds decision trees sequentially. Each new tree aims to minimize the residuals from previous trees. During training, key hyperparameters, such as the number of estimators, maximum tree depth, and learning rate, were tuned using grid search combined with cross-validation to ensure model generalization. As training progresses, the model refines its predictions by aggregating the outputs of all preceding trees, as illustrated in Fig. 2, progressively improving accuracy. The prediction for a given input at iteration t is computed using equation (1):

$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i) \qquad (1)$$

where $\hat{y}_i^{(t)}$ is the prediction for the ith sample, $\hat{y}_i^{(t-1)}$ is the previous iteration's prediction, and $f_t(x_i)$ is the output of the new decision tree.

The model's predictive performance was evaluated using four metrics: root mean squared error (RMSE), mean absolute error (MAE), and R^2 score. These metrics are defined by equations (2) to (4):

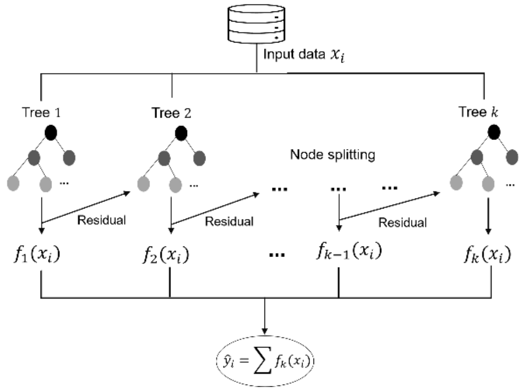

Fig. 2. Schematic representation of the XGBoost learning process (Okonkwo et al., 2025)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (2)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \overline{y_i})^2} \quad (4)$$

where y_i represents the actual value for the ith datapoint, $\hat{y}_i$ denotes the predicted value and N is the total number of datapoints.

C. Battery Sizing

Once the prediction of auxiliary power demand using the XGBoost model is obtained, the next step involves determining the battery capacity, mass and volume. In this study, lithium nickel manganese cobalt oxide (NMC) battery chemistry is assumed as the basis for electrification analyses, given its high energy density and proven maritime application.

To determine the appropriate battery capacity required to supply auxiliary loads, the total energy demand per round trip ($E_{auxilary}$) was first estimated based on predicted load profiles and then adjusted to account for system inefficiencies. Specifically, DC/AC conversion efficiency ($\eta_{converter}$) and discharging efficiency ($\eta_{discharge}$) were each assumed to be 90%, consistent with values reported in similar ferry electrification study [13]. The effective energy required from the battery ($E_{battery}$), is therefore calculated using equation (5):

$$E_{battery}(kWh) = \frac{E_{auxilary}}{\eta_{converter} \times \eta_{discharge}} \quad (5)$$

Furthermore, the battery sizing process accounts for the depth of discharge (DOD), which represents the proportion of the battery's total capacity that can be safely utilized during operation. Consistent with marine battery manufacturer recommendations, a maximum DOD of 80% is adopted in this study. This means that only 80% of the battery's capacity is usable, helping to preserve battery health and extend its service life. To further enhance reliability, a 10% reserve margin (R_m), is included to accommodate operational uncertainties, such as unexpected load spikes or environmental fluctuations. The total battery capacity required is therefore calculated using equation (6):

$$C_{battery}(kWh) = \frac{E_{battery}}{DOD_{max} \times (1-R_m)} \quad (6)$$

In addition to ensuring that the battery can technically meet the energy requirements, its mass and volume were also estimated using equation (7) and (8), respectively.

$$Mass_{battery}\ (kg) = \frac{C_{battery}}{Gravimetric\ energy\ density} \quad (7)$$

$$Volume_{battery}\ (L) = \frac{C_{battery}}{Volumetric\ energy\ density} \quad (8)$$

Based on standard energy density values for lithium-ion NMC batteries, typically ranging from 150 - 250 Wh/kg for gravimetric energy density and 500 - 700 Wh/L for volumetric energy density (Niu et al., 2024), this study adopts representative values of 200 Wh/kg and 600 Wh/L, respectively.

D. Charginging Assessment

The final step involves assessing whether the proposed battery system can be feasibly recharged during regular port turnaround periods. This is a critical consideration for ensuring that the retrofit does not disrupt the vessel's operational schedule or exceed the shore-side power delivery capabilities.

To begin this assessment, the effective charging window is defined by subtracting operational overheads from the vessel's total port stay duration. These overheads typically include safety checks, cable connection procedures, and power handshake delays. For short-route ferry operations, a buffer of approximately three minutes is commonly deducted from the port stay time to reflect a realistic timeframe available for actual charging operations [13]. The required charging power (P_{charge}) is then computed using equation (9):

$$P_{charge}(kW) = \frac{E_{battery}}{T_{charge} \times \eta_{charge}} \quad (9)$$

where $E_{battery}$ is the energy to be replenished, T_{charge} is the effective charging time and η_{charge} is the charging efficiency assumed as 90%. Equation (11) yields the minimum continuous shore power required to fully recharge the battery system within the given time window. The resulting charging power is then compared against typical shore-side power capabilities to determine its feasibility.

III. Case Study

The case study focuses on a RoPax vessel operating between Tallinn, Estonia, and Helsinki, Finland, a route selected for its high passenger turnover and year-round operation in varying weather conditions. The ferry operates seven days a week, making four trips on weekdays and up to six on weekends to accommodate higher demand. Each single trip includes approximately 2.5 to 3 hours of sailing, followed by around 1 hour berthed at the Helsinki port. After a complete round trip, the vessel remains at the Tallinn port for a minimum of 3.5 hours during the day and rests overnight before the next cycle.

The ferry's existing power system consists of four main diesel engines, and three auxiliary generator sets that supply auxiliary loads during sailing and when berthed at the Helsinki port. While at the Tallinn port, the vessel connects to shore power, allowing the auxiliary generator sets to remain off for part of the turnaround time. Fig. 3 illustrates the measured daily load profile of the ferry, showing both auxiliary power consumption and vessel speed across different operational phases. The profile clearly reflects the generator set status, ON during sailing and Helsinki port stays, and OFF when connected to shore power at the Tallinn port.

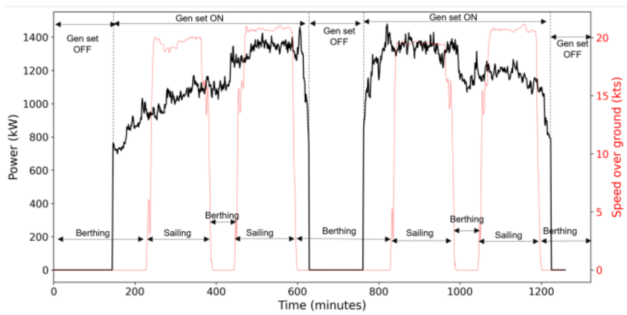

Fig. 3. Measured load profile of case study vessel across different operational phases

IV. Results and Discussion

To validate the proposed data-driven approach, a large dataset encompassing diverse sets of influencing factors and auxiliary power consumption was acquired through a monitoring system installed on the case study ship. The acquired dataset spans a total of 921 trips over a seven-month period, covering May to August 2023, and then from October to December 2023, continuing through January 2024. Data was recorded at a frequency of 1 second. The data was further pre-processed for predictive modeling. The resulting data instances used for modelling are presented in Fig. 4.

A. Model Prediction Performance

As described in section 2.2, the model hyperparameters were tuned using grid search combined with cross-validation and the optimal hyperparameter configuration was selected based on the lowest mean cross-validation RSME on the training dataset. The final model performance was evaluated on the reserved test set to assess the model's generalization capability to unseen data; results are presented in Table I. These results indicate consistent performance across both the training and test datasets. The RMSE and MAE values of the test set align closely with those of the training set, suggesting that the model does not overfit and generalizes well. Relative to the average power consumption, the test RMSE and MAE correspond to 3.7% and 2.4% errors respectively, indicating reasonable prediction performance. Additionally, the R^2 score of 0.97 indicates that the model explains most of the variability in auxiliary load. The results across all metrics suggest that the model effectively captures the underlying patterns in the data and can reliably inform battery sizing.

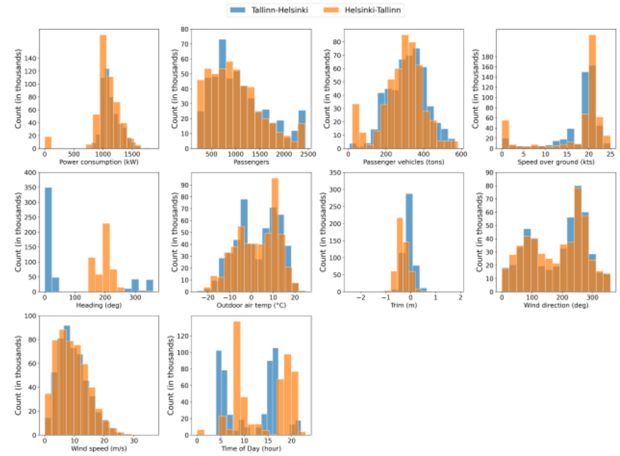

Fig. 4. Representation of data instances used for modelling

TABLE I. MODEL PERFORMANCE

Performance metrics	***Training set***	***Test set***
RMSE (kW)	38.8	39.6
MAE (kW)	25.9	26.4
R^2 Score	0.97	0.97

B. Battery Requirements for Auxiliary Load

The required battery capacity to supply auxiliary loads for each round trip was estimated, as detailed in section 2.3. Table II presents the distribution of required battery capacities (minimum, mean, 95th percentile, and maximum values), calculated based on the measured and model-predicted auxiliary load profiles. The close alignment between the capacities derived from measured load profile and those from model predictions confirms that the model effectively captures the temporal and operational variability of auxiliary loads. This demonstrates its reliability for realistic battery sizing in retrofit applications. Importantly, while measured profiles are only available after ship operation, predictive modeling enables proactive estimation of auxiliary load demand, supports scenario testing, and facilitates early-stage feasibility assessments for retrofitting [14]. Compared to conventional auxiliary load estimation approaches that rely on fixed load factors or generalized assumptions, the use of a predictive model offers a more accurate and dynamic basis for early design decisions, reducing the risk of oversizing or under sizing the battery system.

TABLE II. MODEL PERFORMANCE

Required battery capacity	**Estimates based on**	
	Measured load profile (kWh)	***Predicted load profile (kWh)***
Minimum capacity	7007.8	7007.6
Mean capacity	9857.9	9858.3
Maximum capacity	14773.2	14756.2
95th percentile	12270.0	12258.0

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Fig. 5 visualizes the required battery capacity for each round trip based on model predictions, with the 95th percentile value indicated as the recommended capacity. This corresponds to an estimated usable battery energy of approximately 8.83MWh, accounting for an 80% depth of discharge and a 10% reserve margin. This value captures typical peak demand while avoiding oversizing for rare extremes. Furthermore, based on the estimated battery capacity, the corresponding battery mass is around 61,290 kg, with a volume of approximately 20,430 L. These values offer a preliminary indication of the space and weight requirements that would need to be considered in a retrofit context. For comparison, the Danish electric ferry Ellen operates with a usable battery capacity of 4.3 MWh and a reported battery mass of approximately 50,800 kg [15], placing our estimate in a feasible range for retrofits. While full integration is not covered in this study, the estimated weight and volume appear broadly feasible within the physical and operational scale of large RoPax ferries.

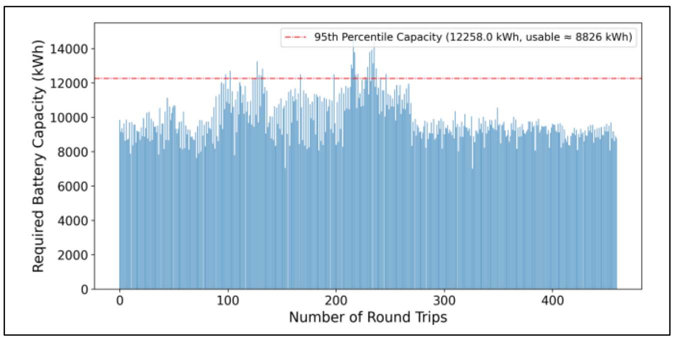

Fig. 5. Estimated Battery Capacity per Round Trip Based on Predicted Auxiliary Load.

C. *Charging power requirements*

Given the operational profile of the case study vessel, which returns to its departure port (Tallinn) after each round trip, it is essential to assess whether the available port layover durations allow for full battery recharge without disrupting operations. The vessel typically remains berthed at the Tallinn port for a minimum of approximately 3.5 hours between round trips during the day and up to 8.5 hours overnight. To fully recharge the required battery energy of 8.8 MWh within these timeframes, a charging power of approximately 2.56 MW is needed during the day and 1.05 MW overnight.

The charging power demand was evaluated against the existing shore power infrastructure at the Port of Tallinn. According to the Port of Tallinn [16], shore power is available at five berths in the Old City Harbour, with an installed capacity of up to 8 MW per connection, compliant with IEC/IEEE 80005-1 high-voltage shore connection (HVSC) standards. This capacity significantly exceeds the maximum required charging power for the battery system, indicating technical feasibility from an infrastructure standpoint. Therefore, the available shore-side capacity at Tallinn is sufficient to support full battery recharging after each round trip, both during daytime and overnight stays. However, practical implementation would require coordination with berth scheduling, grid load management, and potential shared use of the shore power infrastructure.

V. Conclusion and Future Work

This study presents a data-driven framework for estimating battery requirements for auxiliary (hotel) loads on diesel RoPax ferries, addressing a key gap in the literature where such loads are often treated in aggregate or based on standard assumptions. Auxiliary power demand was modelled using XGBoost based on real operational and environmental conditions, achieving good prediction performance ($R^2 = 0.97$). The model reliably captures temporal variability, enabling robust battery sizing under diverse voyage conditions.

A battery capacity of 12.26 MWh is required to meet the auxiliary energy demand for the case study vessel, with an estimated battery mass and volume of approximately 61,290 kg and 20.43 m^3, respectively. A shore-side charging assessment confirms that the existing port infrastructure is technically capable of supporting the required charging power of 2.56 MW during the day and 1.05 MW overnight without operational disruption.

The proposed framework offers a scalable and flexible solution for estimating battery requirements across diverse vessel profiles and operating conditions. It supports early-stage planning, scenario testing, and retrofit feasibility assessments. Future work should assess the economic feasibility of battery retrofitting for ship auxiliary load, followed by a full life cycle analysis to evaluate long-term environmental impacts.

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