Electrifying Island Ferries: Insights from Interviews and Explainable AI

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***Abstract*— Electrification is seen as a key pathway toward more sustainable transport systems. This paper examines a Swedish island ferry conversion from diesel to battery electric propulsion by integrating quantitative and qualitative insights: (i) a route-level efficiency assessment to map energy savings across comparable service legs; (ii) an explainable gradient boosting model (SHAP) to quantify the operational and environmental drivers of trip-level energy use; and (iii) interviews with 55 passengers and three captains to capture perceived benefits, operational constraints, and adaptation strategies. The model achieves high predictive accuracy ($R^2 = 0.97$), showing that vessel speed and propulsion type dominate variation in energy intensity, while route geometry and wind contribute smaller but systematic effects. Electrification reduces energy intensity across routes by 10-87%, driven primarily by higher conversion efficiency. Interview results reveal improved onboard comfort, tighter operational margins around charging and schedule adherence, and heating loads as critical constraints in colder seasons. The combined use of EMS data, interpretable ML, and stakeholder interviews provides a rare, system-level perspective on the technical and human factors shaping electric ferry performance. Viewed through a multi level perspective, the findings indicate that electric ferries scale most effectively on short, predictable routes when infrastructure, timetables, and procurement incentives align with the operational characteristics of electric propulsion.**

***Index Terms*: Island ferry electrification, Gradient boosting, Explainable AI (XAI), Semi-structured interviews, Multi-level perspective (MLP).**

I. Introduction

Electrification is seen as one of the solutions to achieve sustainable transports [1]. Although the maritime sector lags behind the road sector, electrification has begun to have an impact, not least in segments that are publicly procured, such as waterborne public transport and road ferries. This is partly because public authorities have strict sustainability goals and requirements in their procurements and, partly because the technology is currently suitable for these segments [2]. From a sociotechnical transitions perspective [3], ferry electrification can be interpreted as a niche innovation interacting with incumbent diesel based regime under landscape pressures. According to the multi level perspective (MLP), transitions unfold as alignment processes among landscape dynamics, regime structures, and niche developments [4]. Scaling of a niche depends not only on techno economic performance, but also on organizational routines, professional norms, procurement and governance logics, and users' expectations [5], factors that often remain underexamined in maritime applications.

Despite the growing number of electric ferries in Northern Europe [6], [7], there is still limited empirical understanding of how energy use, operational flexibility, and onboard experience change when a diesel vessel is converted to full electric propulsion. Many studies are performed as techno economic [8], [9], [10], [11] feasibility studies before electrification (eg. [12], [13]). Few studies draw simultaneously on high-resolution energy-management-system (EMS) data, explainable machine learning (ML) models, and qualitative insights from operators and passengers. Research in transitions and energy social science shows that the spread of clean technologies depends on multiple forms of social acceptance—political support, market willingness, and user trust [14].

This paper makes three contributions. First, it provides a comparison of diesel and electric ferry operations that is grounded in empirical evidence. This comparison uses high-resolution EMS data to enable consistent, route-level analysis of energy intensity across matched service legs. Second, it develops an explainable ML model that uses SHapley Additive exPlanations (SHAP) [15] analysis to quantify the impact of speed, propulsion type, route characteristics, and environmental conditions on trip-level energy use. Third, it offers qualitative insights from captain and passenger interviews, revealing the effects of electrification on work routines, energy management strategies, comfort, and the overall service experience. Together, these contributions offer a systems-level understanding of how ferry electrification reshapes technical performance and human-centered operational practices. They clarify the conditions under which battery-electric ferries can provide reliable, efficient, and socially acceptable service.

II. Background

A. Study Context

The Stockholm archipelago relies on ferry services for daily mobility, tourism, and access to islands where road connectivity is limited. Ferry traffic within the Stockholm municipality contributes to 11% of the CO2 emissions [16], and the Stockholm region is actively working on reducing CO2 emissions from shipping. Many routes are operated under public procurement, which tends to prioritize reliability, accessibility, and environmental performance. This governance context makes archipelago ferries a relevant setting for studying electrification as a sociotechnical transition, because technical decisions (vessel design, charging infrastructure) are closely tied to timetables, service obligations, and public accountability.

The case vessel in this study, built in the 1970's and converted to electric propulsion with 780 kWh batteries during the spring 2025, operates short, repeatable legs between defined stops, with scheduled layovers that can be used for shore-based charging. These characteristics match the typical "niche suitability" conditions for battery-electric propulsion.

B. Literature Review

Ferry electrification is increasingly seen as a promising pathway for reducing emissions from domestic maritime transport. Ferries are well suited to electrification because they typically operate on fixed routes, with predictable schedules and repeated port calls. However, electrification is not merely a vessel-technology shift; it also depends on charging infrastructure, grid capacity, route characteristics, financing and governance [10], [17].

Island ferries are especially relevant because they provide essential mobility for island communities while operating in environmentally sensitive coastal areas. Previous research [18] show that zero-emission ferry lines can be integrated into smart island energy systems, but feasibility depends on route length, island size, renewable energy availability and storage needs. Battery-electric solutions are generally most suitable for shorter routes, while hydrogen may be more relevant for longer or high-speed services [19].

Environmental and economic studies show that electric ferries can substantially reduce emissions when powered by low-carbon electricity. Kanchiralla et al. [20] find that battery-electric ferries can reduce climate-change impacts by more than 90% compared with marine gas oil, although some impacts shift upstream to battery production and resource use. Kortsari et al. [21] further show that electric ferries may have higher investment costs but lower operating costs, allowing cost parity with diesel alternatives under favourable conditions.

III. METHOD

A. Vessel Operational Data (GPS-Based)

We perform a data analysis based on data retrieved from the Blueflow energy management system, which is installed on the ferry. The system records GPS-based coordinates, vessel speed and direction, and fuel/electricity consumption, all measured at 1-second resolution. In addition, historical wind data from the Swedish Meteorological and Hydrological Institute (SMHI) [22] are utilized.

Raw GPS data recorded at one-second intervals, enriched with speed and fuel/electricity consumption, and combined with stop location data and weather observations (e.g., wind speed and direction), are segmented into trip legs following the methodology proposed in in [23]. Here, a trip leg denotes a single observed vessel movement between two consecutive stops, while routes are defined by origin-destination stop pairs over which multiple trip-leg observations are aggregated.

The analysis compares the summer period 2023, when the ship was operating on diesel, and summer 2025, the first season after conversion to electric propulsion, enabling a direct comparison of operational performance between diesel and electric propulsion.

B. Passenger Interviews

In addition, we interviewed 55 passengers using random sampling on board during summer 2025. The interviews followed a questionnaire that was formed to be able to answer in the specific environment on board and for note-taking. The gender distribution was fairly even. The average age was 58 years and 60% of the respondents were frequent or very frequent users of the ferry. 67% had traveled with the ship before. Most of the respondents originated from the Stockholm area but international tourists were also in the sample.

C. Captain Interviews

Further, at the end of 2025 interviews with three captains, with experience on the studied vessel under diesel and/or electric configurations were conducted. These interviews were semi-structured, conducted digitally and transcribed via MS TEAMS. The researchers used the same interview questionnaire where background, transition to electric, operations (eco-driving, instruments, charging, maintenance), and future outlook were the main themes. The research used thematic coding across several domains reported in the results. Limitations are the small number of interviews, the single vessel and operator, and self-reported data.

D. Route-Level Efficiency Assessment

Each trip leg observation includes traveled distance d (m), total fuel consumption V_{fuel} (L) for diesel operation or total electrical energy consumption E (kWh) for electric operation, average vessel speed v (knots), wind speed w (m/s), an origin-destination stop pair $(from, to)$, and an associated trajectory geometry. Energy intensity is defined as energy consumption per unit distance, I (kWh/km).

To enable a physically consistent comparison between diesel and electric ferry operations, all energy measurements were expressed in a common unit of electrical energy (kWh). Diesel fuel consumption, originally measured in liters, was converted to energy using an equivalent chemical energy conversion factor based on the lower heating value of marine diesel.

Specifically, the diesel energy conversion factor k_{diesel} was derived from a lower calorific value of 42,700 kJ/kg reported in IMO Resolution MEPC.281(70) [24], together with a representative fuel density of 0.83 kg/L:

$$k_{\text{diesel}} = \frac{42{,}700 \text{ kJ/kg} \times 0.83 \text{ kg/L}}{3.6 \text{ MJ/kWh}} \approx 9.85 \text{ kWh/L}. \quad (1)$$

Algorithm 1 Route-Level Diesel-to-Electric Energy Efficiency Comparison

Input: Diesel trip-leg dataset D_{23}, electric trip-leg dataset D_{25}, diesel energy conversion factor k_{diesel}, optional distance tolerance δ_d
Output: Route-level comparison table R with energy intensity and efficiency gain G

0. Energy Normalization
for each trip leg $i \in D_{23}$ **do**
  $I_i \leftarrow (V_{\text{fuel},i} \cdot k_{\text{diesel}})/(d_i/1000)$ ▷ Diesel energy intensity [kWh/km]
end for
for each trip leg $j \in D_{25}$ **do**
  $I_j \leftarrow E_j/(d_j/1000)$ ▷ Electric energy intensity [kWh/km]
end for

1. Aggregate Trip Legs to Routes
for each unique route $(from, to)$ in D_{23} and D_{25} **do**
  Compute route-level statistics:
  median, mean, 25th/75th percentiles of I
  mean distance d, mean speed v, mean wind w
  representative geometry g
end for

2. Match Routes Between Years
$M \leftarrow$ inner join of 2023 and 2025 aggregated datasets on $(from, to)$
if distance difference filter applied **then**
  Retain only routes with $|d_{23} - d_{25}|/d_{23} \leq \delta_d$
end if

3. Compute Route-Level Efficiency Gain
for each route $k \in M$ **do**
  $G_k \leftarrow (I_{k,23} - I_{k,25})/I_{k,23} \cdot 100$ ▷ Percent improvement diesel → electric
end for

4. Output
$R \leftarrow \{from, to, I_{23}, I_{25}, G, v, w, g\}$
return R

For simplicity and consistency across the analysis, this value was rounded to

$$k_{\text{diesel}} = 9.9 \text{ kWh/L}, \tag{2}$$

which is used throughout the study to convert diesel fuel consumption into equivalent electrical energy units. This conversion represents chemical input energy and does not account for drivetrain efficiency, which is considered separately where propulsion-level comparisons are performed.

As outlined in Algorithm 1, energy consumption was subsequently normalized by traveled distance to obtain an energy intensity metric (kWh/km), enabling direct comparison across propulsion systems and operating conditions. Trip leg observations were then aggregated to the route level based on origin-destination stop pairs, producing representative statistics for each route, including central tendencies and dispersion of input-energy intensity, as well as average operational and environmental conditions.

Only routes present in both the 2023 (diesel) and 2025 (electric) datasets were retained. To account for minor variations in route geometry and measurement noise, a maximum relative distance deviation threshold δ_d of 50% was applied when matching routes across years, although in practice most deviations were below 10%. This filtering step reduces the risk of mismatched route comparisons while preserving sufficient data coverage.

Finally, route-level efficiency gains G_k are computed to quantify the reduction in energy intensity achieved by electrification for each matched route.

Algorithm 2 Explainable Route-Aware Machine Learning for Energy Intensity Prediction

Input: Diesel trip leg dataset D_{23}, electric trip leg dataset D_{25}, diesel energy conversion factor k_{diesel}, feature set $F = \{d, v, w, from, to, p\}$
Output: Trained model $\mathcal{M}$, cross-validated performance (MAE, R^2), SHAP attributions Φ

0. Unified Energy Representation
for each trip leg $i \in D_{23}$ **do**
  $I_i \leftarrow (V_{\text{fuel},i} \cdot k_{\text{diesel}})/(d_i/1000)$ ▷ Diesel energy intensity [kWh/km]
  $p_i \leftarrow$ "diesel" ▷ Propulsion type indicator
  $r_i \leftarrow (from_i, to_i)$ ▷ Route identifier for grouping
end for
for each trip leg $j \in D_{25}$ **do**
  $I_j \leftarrow E_j/(d_j/1000)$ ▷ Electric energy intensity [kWh/km]
  $p_j \leftarrow$ "electric"
  $r_j \leftarrow (from_j, to_j)$
end for
Combine datasets: $D \leftarrow D_{23} \cup D_{25}$ ▷ Unified modeling dataset

1. Feature and Target Construction
for each observation $k \in D$ **do**
  $X_k \leftarrow \{d_k, v_k, w_k, from_k, to_k, p_k\}$ ▷ Operational, environmental, and route features
  $y_k \leftarrow I_k$ ▷ Target: energy intensity [kWh/km]
  $g_k \leftarrow r_k$ ▷ Grouping variable to prevent route leakage
end for

2. Preprocessing
Partition features:
  Numeric: $\{d, v, w\}$ ▷ Distance, speed, wind
  Categorical: $\{from, to, p\}$ ▷ Route and propulsion
Define preprocessing operator $\mathcal{P}$:
  Median imputation for numeric features
  One-hot encoding for categorical features

3. Model Definition
Initialize gradient-boosted regressor $\mathcal{M}_0$ ▷ Histogram-based tree ensemble
Define full pipeline: $\mathcal{M} \leftarrow \mathcal{P} \rightarrow \mathcal{M}_0$ ▷ End-to-end mapping $X \rightarrow y$

4. Route-Aware Cross-Validation
Define grouped splitter: GroupKFold($K = 5$) ▷ Ensures routes are not split across folds
for each fold $f = 1 \ldots K$ **do**
  Split (X, y) into train/test using grouping g
  Fit $\mathcal{M}_f$ on training data
  Predict $\hat{y}$ on test data
  Compute metrics:
  $\text{MAE}_f \leftarrow \text{mean}(|y - \hat{y}|)$ ▷ Absolute error
  $R^2_f \leftarrow 1 - \frac{\sum(y-\hat{y})^2}{\sum(y-\bar{y})^2}$ ▷ Explained variance
end for
Aggregate performance across folds:
  $\text{MAE} \leftarrow \frac{1}{K}\sum_f \text{MAE}_f$
  $R^2 \leftarrow \frac{1}{K}\sum_f R^2_f$

5. Final Model Training
Fit $\mathcal{M}$ on full dataset (X, y) ▷ Used for inference and explanation

6. Explainability via SHAP
Transform features: $X' \leftarrow \mathcal{P}(X)$ ▷ Model-compatible representation
Compute SHAP values: $\Phi \leftarrow \text{SHAP}(\mathcal{M}_0, X')$ ▷ Feature attributions
Derive explanations:
  Global importance: $\sum |\Phi_j|$ per feature j
  Local explanations: $\Phi(x_k)$ for individual predictions

7. Outputs
return $\mathcal{M}$, (MAE, R^2), Φ

E. Explainable Trip-Level Energy Modeling

We employ a route-aware supervised learning framework to predict vessel energy consumption from operational and environmental covariates. To enhance interpretability, post-hoc explainable AI (XAI) techniques based on SHAP values [25] are applied to quantify feature contributions and to compare diesel and electric operating regimes.

The learning task predicts route-normalized energy intensity at the input-energy level, using chemical fuel energy for diesel operation and grid electricity consumption for electric operation. The model is implemented using the HistGradientBoostingRegressor from scikit-learn, a histogram-based gradient boosting algorithm conceptually similar to LightGBM [26], but with level-wise tree growth and seamless integration into the scikit-learn ecosystem.

Algorithm 2 summarizes the training pipeline. Diesel and electric observations are first normalized to a common energy-per-distance metric, followed by the construction of operational, environmental, and route-level features. A gradient-boosted regression model is trained using route-aware cross-validation to prevent data leakage between similar routes. Model performance is evaluated using MAE and R^2, and SHAP values are computed to provide both global and local explanations of predicted energy consumption.

IV. RESULTS

A. Passenger perception

Overall passengers are satisfied with the comfort of the ferry. The reduced noise level is often highlighted as one of the major benefits of electric propulsion. When asking about noise level, 50% considered it to be lower or positive, 32% stated a neutral attitude or that they didn't think about it, whereas the remaing 8% considered it to be louder. Male people tended to be more positive. We also explored the willingness of the respondents to pay higher fees for electrified ferry transport service, and their acceptance for longer travel time and lower frequency of travels due to the electrification of the ferry transport service. The large majority, 73%, stated they would accept to pay more as well as to accept longer travel times, but concerning frequency the relationship was reversed and 58% stated they would not accept lowered frequency.

B. Operational Experiences Reported by Captains

1) Work Environment and Vessel Handling: Captains consistently report substantial improvements in the onboard environment compared to diesel vessels. Lower levels of noise and vibration, the absence of exhaust fumes, and simplified start-up and monitoring routines contribute to a noticeably better workplace. Maintenance demands are also reduced, with the removal of tasks such as oil changes, and the redundancy offered by dual propellers provides an additional layer of operational security.

2) Operational Performance: Energy Use, Scheduling, and Systems: Energy consumption is described as highly sensitive to speed, and the final few knots above an eco-speed incur disproportionately high power draw. Efficient practice therefore focuses on pacing to meet scheduled arrival times precisely while avoiding unnecessary maneuvering. However, electrification introduces tighter operational margins: the need for predictable charging windows and finite onboard energy reduces flexibility for unplanned tasks and can amplify the effects of small disturbances, particularly on routes involving transfers.

Charging routines are generally reliable and supported by remote technical oversight. Standard operations rely on moderate charging during longer layovers, with higher power used when schedules are constrained or state of charge is low. Although initial training was considered adequate, captains noted limited guidance on eco-driving for electric vessels. They also reported that current monitoring systems provide incomplete visibility of electric specific parameters and would benefit from more intuitive, actionable interfaces rather than extensive raw data.

3) Seasonal and Strategic Considerations: Environmental conditions strongly influence energy use. Headwinds and crosswinds increase both hydrodynamic resistance and maneuvering demand, while operations in colder seasons impose substantial thermal loads. In contrast to diesel vessels, where engine waste heat provides high-temperature heating, electric vessels rely on heat pumps, adding roughly 20 kW to loads during space heating. These requirements can significantly constrain effective range on cold days.

Captains are generally positive about the future of electrification on appropriate routes, but they emphasize ongoing constraints related to battery energy density, mass, and shorepower availability. Hybrid configurations are viewed as a pragmatic option for longer or more exposed routes and to maintain reliability in colder seasons. Several captains also noted that future service patterns may benefit from the deployment of a larger number of smaller electric vessels on short, predictable commuter services.

C. Route-Level Energy Efficiency Results

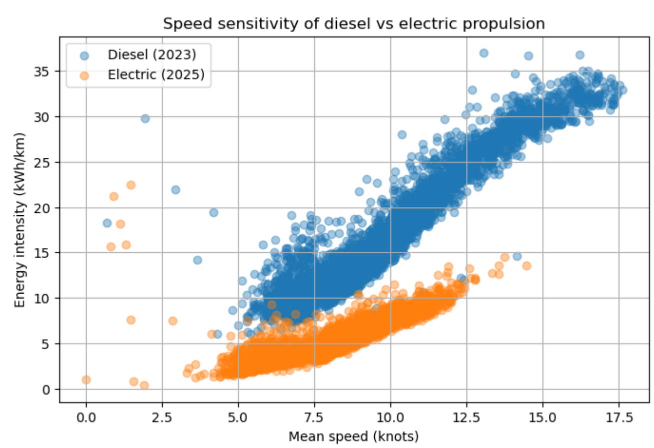

Fig. 1. Comparison of diesel and electric propulsion energy intensity as a function of vessel speed.

Figure 1 compares the energy intensity of electric and diesel ferry operations based on the route-level aggregation described in Algorithm 1. The results show that, when expressed in terms of equivalent energy units, electric propulsion exhibits substantially lower energy intensity than diesel operation at comparable conditions.

In addition, the figure indicates that the electrified ferry operates at lower average speeds than its diesel predecessor. This operational difference suggests that part of the observed energy reduction may be influenced by speed-dependent effects, with potential implications for scheduling and service design.

To facilitate interpretation, we distinguish between two energy comparison perspectives. System-level energy refers to the total input energy required to operate the vessel, comparing diesel chemical fuel energy (lower heating value) with grid electricity consumption. In contrast, propulsion-level energy refers to useful shaft energy delivered to the propeller, obtained by applying representative drivetrain efficiency factors for diesel and electric propulsion systems.

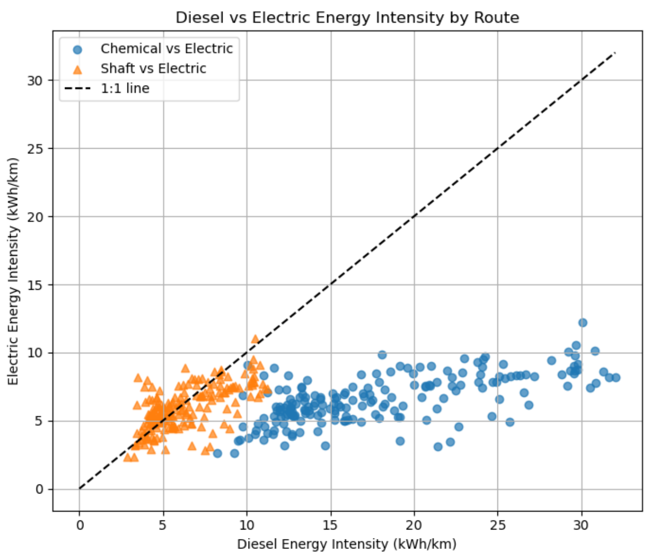

Fig. 2. Comparison of diesel and electric ferry energy intensity by route.

Figure 2 provides a more detailed comparison by distinguishing between system-level and propulsion-level energy use. At the system level (circles), electric operation requires significantly less energy than diesel when accounting for the full chemical energy input. In contrast, propulsion-level comparisons (triangles), based on shaft energy, show values closer to the 1:1 parity line, indicating more modest differences in propulsive energy demand.

This distinction highlights that the majority of the observed energy savings from electrification arise from higher upstream and conversion efficiencies, rather than from substantial reductions in the hydrodynamic or operational energy demand of the vessel itself. The analysis assumes a diesel engine efficiency of 35% and an electric propulsion-system efficiency of 90%.

Figure 3 presents the distribution of route-level efficiency gains resulting from electrification. The results indicate substantial variability across the network, with efficiency improvements ranging from approximately 10% to 87%.

Higher efficiency gains are generally observed on longer routes with fewer intermediate stops and greater exposure to open-water conditions. In contrast, routes constrained by complex geography, such as archipelagic areas with frequent maneuvering and shorter segments, tend to exhibit lower relative improvements.

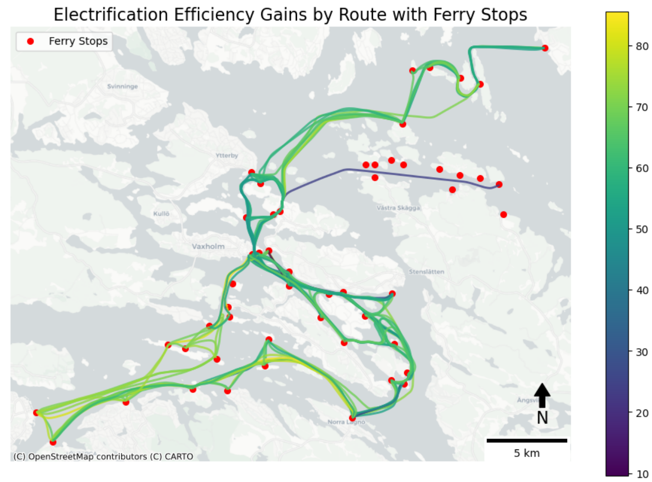

Fig. 3. Distribution of electrification efficiency gains across routes.

These patterns suggest that operational profiles, particularly speed regimes, stop frequency, and maneuvering requirements, play a key role in determining the realized benefits of electrification. Routes that previously operated at higher speeds under diesel propulsion, for example, may offer greater potential for efficiency gains when transitioned to electric systems.

D. Trip-Level Model Performance and Explainability

The results of the explainable trip-level energy modeling demonstrate high predictive accuracy, achieving a MAE of 0.96 and a R^2 value of 0.97. These results indicate that energy intensity can be reliably predicted from key operational and contextual variables, including vessel speed, propulsion type, and route geometry (trip leg distance and origin-destination stops).

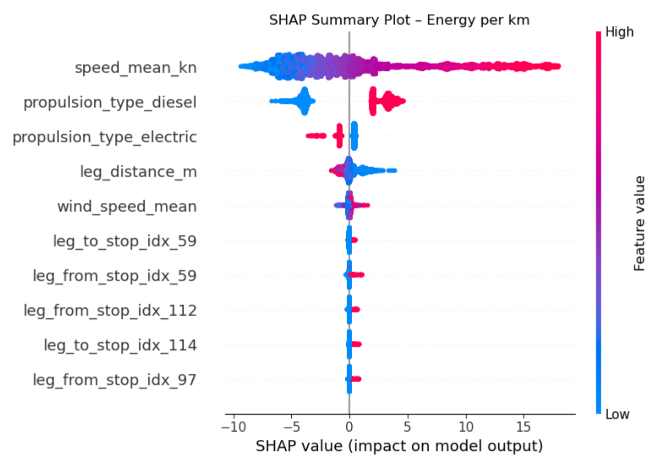

Fig. 4. SHAP global importance (beeswarm) plot.

Figure 4 presents a SHAP beeswarm plot [27] illustrating the global importance of input features, including both the magnitude and direction of their contributions to predicted energy intensity (kWh/km). The results show that operational

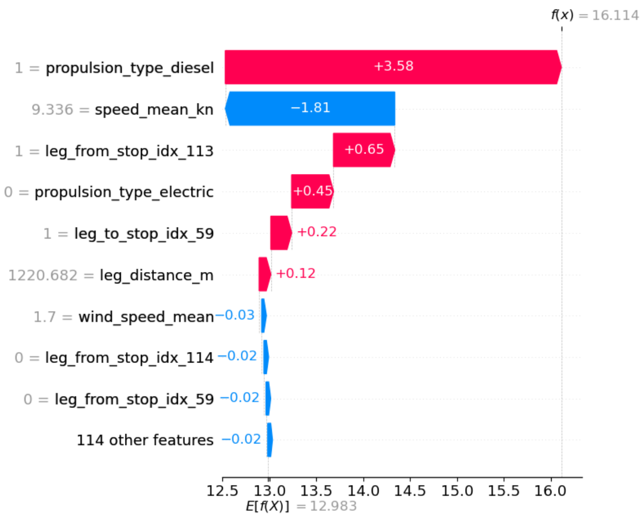

Fig. 5. SHAP waterfall plot for a single trip leg.

speed is the most influential predictor, with higher speeds consistently associated with increased energy consumption per kilometer. In addition, propulsion type has a strong and systematic effect: diesel propulsion is associated with higher predicted energy intensity, whereas electric propulsion contributes to lower energy demand.

Figure 5 shows a SHAP waterfall plot [27] for an individual trip leg, decomposing the prediction into feature-level contributions relative to the global baseline (approximately 13 kWh/km). The plot illustrates how each feature shifts the prediction upward or downward. In this example, propulsion type and vessel speed dominate the prediction: diesel propulsion increases the estimated energy intensity, while a relatively low operational speed (9.3 kn) reduces it. Smaller contributions from route-specific features further refine the final prediction.

V. Discussion

The results indicate that benefits experienced directly by crews and passengers, such as reduced noise, vibration, and improved air quality, are immediate and clearly noticeable. In contrast, constraints related to energy use and schedule adherence require broader, system-level optimization. A route-specific eco-speed envelope emerges as a key operational tool: because hydrodynamic resistance for displacement hulls increases nonlinearly with speed, even modest reductions can substantially extend operating range while supporting timetable flexibility.

Effective decision support is a key theme within the overall efforts of transport digitization [28]. It should prioritize transparent state-of-charge-to-range conversions (expressed in remaining nautical miles or minutes) and provide distinct visibility of loads (e.g., heating and cooling) relative to propulsion demand. This separation enables captains to make explicit trade-offs among vessel speed, onboard comfort, and punctuality. Thermal management stands out as a critical limiting factor during operations in colder temperatures; improvements in insulation, more efficient HVAC systems, or supplemental hybrid power can help maintain service reliability in low-temperature conditions.

From a strategic perspective, hybrid propulsion offers enhanced resilience on longer routes or those exposed to adverse weather, whereas fully electric solutions are well suited to short, regularly timed commuter services with dependable shore power and consistent layover durations, something that was also noted by [29].

The energy intensity analysis shows that transitioning from diesel to electric propulsion substantially reduces energy use at the route level. This system-level reduction is primarily driven by the higher conversion efficiency of electric propulsion systems and is further supported by operational differences, such as lower average speeds. However, when examined at the propulsion level, the gap narrows, indicating that hydrodynamic demand remains similar across systems. These results suggest that most system-level gains arise from improved energy conversion efficiency rather than from fundamental changes in how the vessel moves or is maneuvered.

The SHAP-based explainability analysis reinforces this interpretation. Vessel speed is the dominant predictor of trip-level energy intensity; even modest increases lead to disproportionately higher energy consumption. Propulsion type consistently influences energy use downward under electric operation, while secondary factors, such as wind conditions and route geometry, introduce smaller, yet still measurable, variations.

Taken together, the empirical energy-intensity results and the explainability analysis provide a coherent picture: Electrification significantly lowers the energetic cost of ferry operations. However, operational discipline, particularly with respect to speed management and environmental exposure, remains critical for achieving stable and efficient energy performance.

VI. Conclusion

This paper brings together detailed operational data, explainable machine learning, and interviews with captains and passengers to understand what changes when a Swedish island ferry moves from diesel to battery-electric propulsion. We find clear and immediate benefits: quieter, smoother onboard experience, which both crews and passengers notice, and less day-to-day maintenance. At the same time, electric operation makes energy management more “tight”. Speed, timetable, available charging time, and auxiliary loads like heating become closely linked, leaving less buffer than in diesel operation.

The explainable model supports this picture. Propulsion type and speed explain most of the variation in energy use per kilometre, while route differences and wind add a smaller layer of variation. Captains describe the same dynamic in practical terms: pushing above an eco-speed quickly becomes expensive in energy terms, so good outcomes depend on a steady speed, reliable charging windows, and decision-support tools that turn state of charge into something practical like remaining range or time. Passengers mainly point to comfort, especially lower noise, and they are generally less willing to accept reduced frequency than slightly longer trips or higher fares. That suggests operators should protect service frequency and instead manage energy through speed discipline, charging strategy, and infrastructure. Cold temperatures also stands out as a challenge because heating draws directly from the battery rather than using waste heat from an engine, so insulation improvements, more efficient HVAC, or hybrid support may be needed on tougher routes.

Seen through the multi-level perspective, battery-electric ferries look like a strong niche option that can scale when the surrounding system supports them. That means charging infrastructure that fits the layover pattern, timetables that reflect route-specific eco-speed operation, procurement requirements that reward local environmental gains without undermining reliability, and onboard tools that help crews balance speed, comfort loads, and punctuality. Hybrid setups can also be a practical stepping-stone for longer, more exposed routes, or for winter-critical services where margins are tight.

Next steps are to test the approach across more vessels and operators, include other season operations, and evaluate whether changes such as timetable adjustments, clearer energy and range displays, and thermal upgrades actually improve both measured energy use and the perceived quality of service.

Acknowledgement

This work has been supported by Interreg Central Baltic Programme and co-funded by the European Union under Grant CB0300186.

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