

MACHINE LEARNING-BASED STATE OF CHARGE ESTIMATION FOR THE ENERGY MANAGEMENT SYSTEM OF A 3 GT HYBRID BATTERY-SOLAR ELECTRIC BOAT

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Abstract

Small-scale electric boats face highly restricted energy margins due to limited battery capacities, whereas a single fishing cycle typically lasts up to eight hours. In operational contexts, the state of charge (SoC) acts as the primary decision variable in the Energy Management System (EMS), making the overall system accuracy heavily dependent on the precision of SoC estimation. For LiFePO₄ batteries, the highly flat open-circuit voltage (OCV) curve in the middle SoC range causes conventional estimation methods to lose their sensitivity. This study proposes an integrated simulation model for a 3 GT electric fishing boat, combining a 48 V 200 Ah LiFePO₄ battery pack using an OCV-resistance-RC approach, an 860 Wp photovoltaic array, and a 10 kW Brushless DC (BLDC) motor. This modeling generates an eight-hour mission dataset at a one-minute resolution, comprising 60 voyage variations equivalent to 28,800 samples. Random Forest and Long Short-Term Memory (LSTM) algorithms are evaluated using data leakage-free feature engineering that relies solely on measured quantities from the battery management system, excluding cumulative current integration. Based on 5,052 test samples, the LSTM method achieves superior accuracy with an RMSE of 0.587 and an R² of 0.9970, outperforming Random Forest, which yields an RMSE of 0.696 and an R² of 0.9958. However, the LSTM computation demands approximately 33 times longer training time. Energy audit results demonstrate that the photovoltaic array supplies 29.4% of the total mission energy requirement, with 8 out of 60 voyages reaching the battery protection threshold. This confirms that accurate SoC estimation is an absolute operational requirement to ensure the electrical reliability of fishing boats.

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INTRODUCTION

Small-scale capture fisheries serve as a primary pillar of the coastal economy, with their fleets almost entirely driven by petroleum-based internal combustion engines. A study by Lukuyu et al. (2020) indicates that fishing boats on Lake Victoria consume an average of 20 liters of diesel per trip. Within the Indonesian context, Farisyi and Ma'arif (2024) report that converting fishing boats to

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electric propulsion in Belitung Island is technically feasible but requires policy interventions for economic viability. On a macro scale, maritime transportation is a major contributor to global greenhouse gas emissions, with shipping CO₂ emissions reaching 1.076 billion tons in 2018 (Xie et al., 2021). Given that the tank-to-wake efficiency of full-electric ships can reach 70% compared to 30% for diesel-mechanical propulsion (Lucà Trombetta et al., 2024), the transition to maritime electrification becomes increasingly urgent amidst strict energy efficiency regulations (Czermański et al., 2022).

The feasibility of electrification in the small-boat class has been demonstrated in various studies. Lukuyu et al. (2020) converted a wooden fishing boat using a 16 kW electric outboard motor and an 18.2 kWh battery pack, estimating an investment payback period of around three years. The hybridization of fishing vessels has also been shown to reduce emissions significantly. Kim et al. (2022) found that adding an energy management control algorithm provides a greater efficiency contribution than mere physical hardware replacement. Regarding propulsion, the use of interior permanent magnet BLDC motors for maritime applications can achieve an average efficiency of up to 89% (Mandasari et al., 2024). To extend the cruising range, the integration of photovoltaic modules is a highly prospective hybrid solution (Minak, 2023). Deploying solar arrays on the deck has been proven to increase overall ship energy efficiency (Karatuğ & Durmuşoğlu, 2020; Yuan et al., 2018), supported by growing research on the capacity optimization of photovoltaic-battery systems for electric boats (Bukar et al., 2020; Indradjaja et al., 2020). However, the fluctuating nature of solar power output due to varying irradiation requires real-time control strategies for the battery bank (Obaid et al., 2019).

Boat electrification introduces new technical challenges related to limited energy storage capacity. A 3 GT boat configuration with a 48 V 200 Ah LiFePO₄ battery only provides about 9.6 kWh of usable energy, while a single fishing cycle generally requires eight hours or more. Shipboard energy storage systems must perform peak shaving, load leveling, and spinning reserve functions (Kolodziejewski & Michalska-Pozoga, 2023). With such narrow energy margins, power distribution decisions can no longer rely on operator intuition. Therefore, an Energy Management System (EMS) plays a vital role in planning energy resources (Xie et al., 2021). EMS approaches vary from rule-based fuzzy logic (Obaid et al., 2019; Capillo et al., 2022) to machine learning-based optimization strategies designed to predictively reduce consumption and operating costs (Antonopoulos et al., 2021; Singh et al., 2024).

All of these EMS strategies depend on one critical variable: the SoC, which acts as a major inequality constraint in energy optimization formulations (Xie et al., 2021; Obaid et al., 2019; Lukuyu et al., 2020). A primary limitation is that SoC cannot be measured directly using hardware sensors (How et al., 2019). Basic estimation methods like coulomb counting are prone to cumulative error over time, while OCV measurement requires battery relaxation periods that are impractical for highly dynamic boat operations (Abbas et al., 2019). Model-based approaches, such as adaptive Kalman filters, also face convergence issues and sensor noise uncertainties (Tran et al., 2021; Fu et al., 2022). This estimation challenge is further complicated by the use of LiFePO₄ chemistry, which exhibits an extremely flat OCV curve in the middle SoC range (Tian et al., 2021).

As an alternative for improving accuracy, data-driven methods have shown promising performance. Neural network algorithms like LSTM and its derivatives have been proven to yield estimation errors below 2% even when the initial SoC is unknown (Chemali et al., 2018; Yang et al., 2019; Bian et al., 2020). In the realm of non-parametric tree algorithms, Random Forest has also proven reliable in computational estimation with very low Mean Absolute Percentage Errors (Lipu et al., 2023; Chandran et al., 2021; Sutanto et al., 2023). However, most previous studies have focused on testing standardized land-based electric vehicle (EV) current profiles. The current profile of a fishing boat features specific characteristics, including intermittent high-propulsion loads combined with opportunistic charging from solar panels, causing the electric current to change directions multiple times. If models are trained solely on reference profiles for land vehicles, there is a risk of performance degradation in real maritime operations due to the covariate shift problem (Tian et al., 2021; Lukuyu et al., 2020).

Addressing these research gaps, this study focuses on three main contributions: first, developing an integrated physical simulation model to synthesize an eight-hour mission dataset at a one-minute resolution; second, implementing data leakage-free feature engineering that operates

comprehensively without cumulative current integration features; and third, evaluating the performance of Random Forest vis-à-vis LSTM using cross-voyage validation to ensure model generalization for embedded system applications in ship electrical systems.

METHOD

This research employs numerical simulation and predictive modeling in five stages: physical modeling of the boat's electrical system, dataset synthesis, feature engineering, training of two machine learning models, and evaluation on unseen test voyages. The implementation is written in Python using NumPy, pandas, scikit-learn, TensorFlow/Keras, and Matplotlib, utilizing a fixed random seed to ensure reproducibility.

System Configuration and Mission Profile

The modeling object is a 3 GT fishing boat with the configuration detailed in Table 1. The 10 kW motor rating is treated as peak power rather than cruising power, as operating at full throttle for one hour would demand 10 kWh, exceeding the total installed capacity. The eight-hour mission is divided into a one-hour outbound transit, a five-hour fishing period with low throttle and intermittent maneuvering, and a two-hour inbound transit.

Table 1. Electrical system parameters for a 3 GT electric fishing boat

Subsystem	Parameter dan nilai
Battery	LiFePO ₄ 16S1P, 51,2 V, 200 Ah; 10,24 kWh (9,6 kWh at 48 V); R ₀ = 30 mΩ at 25 °C; R ₁ = 12 mΩ; τ = 90 s; charging efficiency 0,98; BMS SoC protection 15%; taper charging above the SoC 92%
Photovoltaic	860 Wp; η _{MPPT} = 0,96; soiling factor 0,97; power temperature coefficient -0,38 %/°C
Propulsion	BLDC Motor rating 10 kW; throttle 0,205 (left), 0,031 (catching fish), 0,108 (return)
Hotel load	110 W continuous; intermittent peak 420 W
Mission	8 hours; 1-minute resolution (480 points per voyage)

LiFePO₄ Battery Model

The cell is modeled using an OCV-R₀-R₁C equivalent circuit, following the findings of Tran et al. (2021) demonstrating that a single RC branch is sufficient for LiFePO₄ chemistry. The terminal voltage of the pack is expressed in Equation (1), where V_{OCV} is a non-linear function of the SoC derived from the interpolated cell characteristic curve multiplied by the number of series cells.

$$V_t(k) = V_{OCV}(SoC(k)) - I(k)R_0(SoC, T, SOH) - V_1(k) \quad (1)$$

Ohmic resistance is not constant; it increases at low SoC, low temperatures, and as the state of health (SOH) degrades, as shown in Equation (2).

$$R_0 = R_{0,nom} [1 + 0,75e^{-SoC/11}] [1 + 0,013(25 - T)] [1 + 2,2(1 - SOH)] \quad (2)$$

The polarization voltage is updated recursively following a first-order discretization in Equation (3), with Δt = 60 s and τ = 90 s.

$$V_1(k + 1) = e^{-\Delta t/\tau} V_1(k) + (1 - e^{-\Delta t/\tau}) I(k) R_1 \quad (3)$$

The reference or ground-truth SoC is calculated via Coulomb counting on noise-free current according to Equation (4), where Q represents the effective capacity in ampere-hours and η is the coulombic efficiency, set to 1 during discharge and 0.98 during charge.

$$SoC(k + 1) = SoC(k) - \frac{100 \eta I(k) \Delta t}{3600 Q} \quad (4)$$

Photovoltaic and Load Models

Array plane irradiance is modeled as a clear-sky sinusoidal daily curve multiplied by a cloud transmission factor formulated as a smoothed random walk accompanied by random thick cloud passages. The output power follows Equation (5), with cell temperature derating from the NOCT model in Equation (6), aligning with the photovoltaic array modeling practices on ships by Karatuğ and Durmuşoğlu (2020).

$$P_{PV} = P_{Wp} \frac{G}{1000} [1 + \gamma(T_{sel} - 25)] \eta_{MPPT} \eta_{soil} \quad (5)$$

$$T_{sel} = T_{amb} + \frac{G}{800} \times 26 \quad (6)$$

The electrical input power for the propulsion is calculated from the shaft power using a classical loss model in Equation (7), encompassing constant, load-proportional, and quadratic copper losses. The parameters are calibrated so that the drivetrain efficiency ranges from 0.84 at light loads to 0.91 at medium loads, consistent with the characteristics of BLDC motors for boat propulsion reported by Mandasari et al. (2024). The hotel load encompasses navigation, fish finder, radio, and lighting at 110 W continuously, with intermittent surges up to 420 W representing bilge pumps and net haulers.

$$P_{in} = P_{poros} + 60 + 0,060P_{poros} + 0,090 \frac{P_{poros}^2}{P_{rating}} \quad (7)$$

Dataset Synthesis and Feature Engineering

The dataset is generated across 60 independent voyages, each lasting 480 minutes, totaling 28,800 samples. Six parameters are varied across voyages, as presented in Table 2, to enable the model to learn generalization. Sensor noise is added to the simulated measurements, namely voltage (0.022 V), current (0.35 A with a fixed bias per voyage), and temperature (0.12 °C), while the reference SoC is calculated from the noise-free current.

Table 2. Range of parameter variation between voyages

No	Parameter	Range	Physical meaning
1	Cloud level	0,05 – 0,85	Daily weather conditions
2	Ambient temperature	27 – 32 °C	Tropical climate
3	Early SoC	65 – 100%	Conditions at the time of departure
4	Sea state factor	0,88 – 1,18	Waves, currents, and loads
5	State of health (SOH)	0,94 – 1,00	Battery pack aging
6	Hotel load factor	0,85 – 1,25	Variety of active equipment

Features are constructed exclusively from quantities measurable by the battery management system: terminal voltage, current, motor power, photovoltaic power, battery temperature, and ambient temperature. These are augmented with sliding-window statistics of 5, 15, and 30 minutes, derivatives of voltage and current, and one physical feature representing the estimated open-circuit voltage in Equation (8), yielding a total of 27 features.

$$V_{OCV}(k) = V_t(k) + I(k)R_{0,nom} \quad (8)$$

Two specific quantities are intentionally excluded: cumulative current integration is omitted because it is mathematically equivalent to the target variable (which would yield an artificial near-zero error), and absolute time is excluded to prevent the model from memorizing the mission curve shape. This restriction is a direct consequence of the covariate shift warning by Tian et al. (2021). The first thirty minutes of each voyage are discarded as the sliding windows are not yet fully populated, leaving 27,000 training-ready samples.

Model Architecture, Data Splitting, and Metrics

Two paradigms are compared. Random Forest is selected due to its robustness to noise and suitability for real-time computation with limited sensor inputs, as demonstrated by Lipu et al. (2023). LSTM is chosen based on Chemali et al. (2017), directly mapping measurement sequences to SoC. The configurations for both models are presented in Table 3.

Table 3. Configuration of the two models

Aspect	Random forest	LSTM
Input	27 tabular features	8 channels × 30-minute sequence
Structure	300 trees, maximum depth of 22	LSTM(96) – Dropout(0,10) – LSTM(48) – Dense(32) – Dense(1)
Regularization	min_samples_leaf 3; max_features sqrt	Dropout 0,10; early stopping patience 20

Aspect	Random forest	LSTM
Optimization	—	Adam, learning rate 2×10^{-3} , batch 64, 120 epochs (max)
Normalization	Not required	Input standardization; scaling to the [0, 1] range

Data splitting is performed per voyage rather than randomly per sample, allocating 42 voyages for training, 6 for validation, and 12 for testing. Random splitting on time-series data would leak temporal neighborhood information and artificially inflate performance. LSTM sequences are constructed separately for each voyage to avoid crossing mission boundaries. Since LSTM truncates the first 29 samples of each voyage, the metrics for both models are recalculated on a shared set of 5,052 test samples for an equitable comparison. Performance is evaluated using four metrics (Equations 9 to 12): Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R^2).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (9)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (10)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \frac{|\hat{y}_i - y_i|}{y_i} \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (12)$$

RESULTS AND DISCUSSION

Dataset Characteristics and Mission Energy Balance

Figure 1 presents the operational profile of a representative voyage featuring a median photovoltaic harvest of 3.35 kWh. Panel (a) illustrates the three mission phases: a plateau of approximately 2.5 kW in the first hour, a low-power period with maneuvering surges during fishing, and a 1.4 kW plateau during the inbound transit. Panel (b) shows the current reaching 64 A during the heaviest maneuvers and turning negative multiple times when photovoltaic power exceeds the load. Panel (d) reveals that the SoC drops 55 percentage points from 69.2% to 14.2%, concluding the voyage exactly at the protection threshold. Panel (c) highlights the core problem of this study: for such a significant SoC drop, the terminal voltage only fluctuates within a 3.4 V range, and during the 30–65% SoC plateau, this range shrinks to 1.98 V—or even 0.86 V when considering only low-current samples. With a sensor noise of 0.022 V, the signal-to-noise ratio in this plateau region renders direct voltage-based estimation inadequate.

The energy audit in Table 4 reveals a narrow operational margin. Out of the 10.24 kWh of installed energy, only 8.70 kWh is available before reaching the protection threshold, whereas total consumption reaches 9.12 kWh. The deficit is covered by the photovoltaic array, which harvests 2.68 kWh, or 29.4% of the mission's energy requirement—higher than the 22.7% contribution reported by Yuan et al. (2018) for a much larger vessel. This aligns with Karatuğ and Durmuşoğlu's (2020) finding that the ratio of deck area to power demand dictates the photovoltaic contribution. Out of 60 voyages, 8 touch the 15% protection threshold under a combination of cloudy conditions and high waves, reinforcing Kim et al.'s (2022) argument that the control layer provides irreplaceable benefits beyond hardware replacement.

Table 4. Eight-hour mission energy audit (representative voyage)

No	Energy balance components	Value
1	Installed/available energy up to the 15% protection threshold	10,24 / 8,70 kWh
2	Energy harvesting	2,68 kWh
3	Propulsion consumption / hotel load	7,61 / 1,50 kWh
4	Total consumption; photovoltaic contribution to the load	9,12 kWh; 29,4%
5	End of 60 voyages SoC (min/avg/max)	13,0 / 29,7 / 51,1%

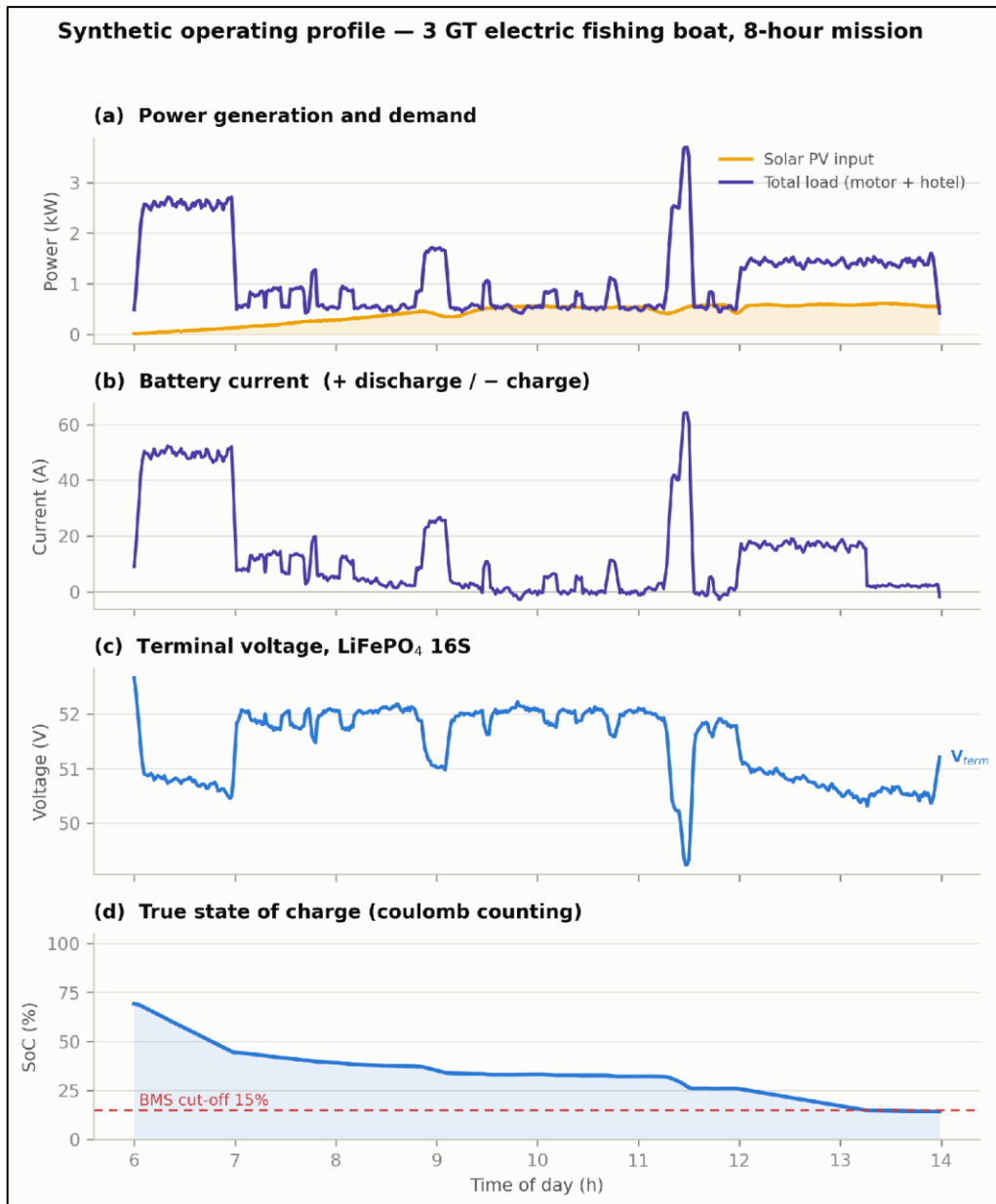


Figure 1. Representative voyage operational profile: (a) generation power and demand, (b) battery current, (c) terminal voltage, (d) reference SoC

State of Charge Estimation Accuracy

Table 5 summarizes the performance of both models on the 5,052 shared test samples from 12 unseen voyages during training. LSTM achieves an RMSE of 0.587 and a coefficient of determination of 0.9970, outperforming Random Forest (which records 0.696 and 0.9958) by approximately 16%. The superiority of LSTM is more pronounced in the maximum error, registering 2.543 compared to 3.974, indicating that the recurrent model is less prone to extreme deviations. Conversely, Random Forest requires only 10.3 seconds of training time versus 339.8 seconds, making it approximately 33 times faster.

Figure 2 illustrates the SoC curve tracking on the test voyage with the widest range. Both models closely track the reference curve throughout the mission, including the fishing phase where the current is low and the voltage remains nearly static. The residual panel reveals their behavioral differences: Random Forest errors fluctuate rapidly between samples because each prediction is calculated independently, whereas LSTM errors are smoother and temporally correlated due to the utilization of the previous 30-minute context. For an EMS, the latter characteristic is more advantageous, as control decisions are less likely to be triggered by momentary estimation spikes.

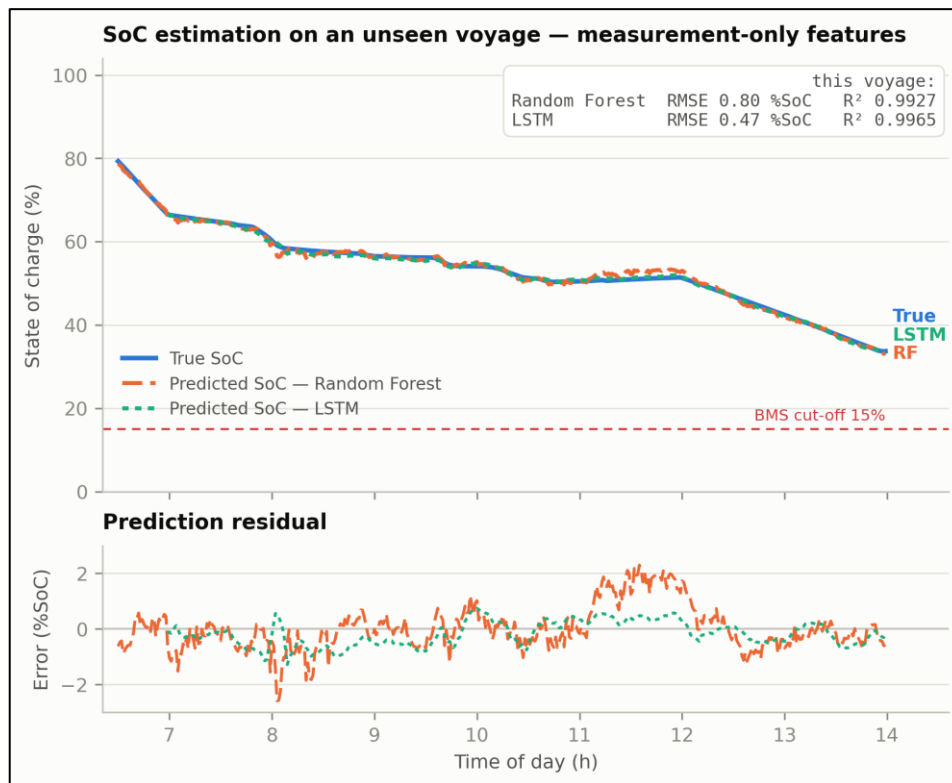


Figure 2. Comparison of reference SoC and predicted SoC during a single test voyage, along with the residuals

Table 5. Combined SoC estimation performance across 5,052 test samples

Model	RMSE	MAE	Max error	MAPE (%)	R ²	Training time (s)
Random forest	0,696	0,526	3,974	1,128	0,9958	10,3
LSTM	0,587	0,463	2,543	0,989	0,9970	339,8

Error Distribution and Feature Contribution

Figure 3 presents the parity diagrams for both models alongside their error distributions. The scatter points align closely with the identity line across the entire range covered by the test set (21.7% to 73.8%), exhibiting no systematic bias dependent on the SoC level. The error histogram shows that the LSTM distribution is narrower and centered around zero, whereas the Random Forest distribution possesses a thicker right tail in the 1 to 2 range, consistent with the maximum error difference in Table 5.

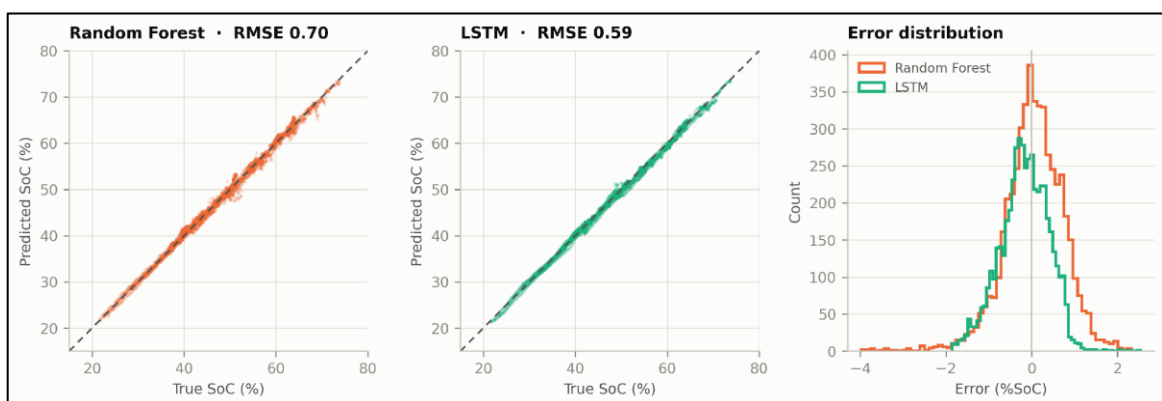


Figure 3. Parity diagram of both models and error distribution across the entire test sample

Figure 4 displays the fifteen most significant features contributing to the Random Forest model. The top four ranks are entirely occupied by the estimated open-circuit voltage and its moving

averages over 30, 15, and 5-minute windows, contributing a combined 0.750 or about 75%. The physical interpretation is straightforward: compensating for the ohmic voltage drop in Equation (8) restores the measured voltage to a value correlating with the SoC, while the sliding window smoothing suppresses the 0.022 V sensor noise—which, on the LiFePO₄ plateau, equates to roughly 0.76 SoC percentage points. Conversely, instantaneous terminal voltage contributes only 0.027, about one-ninth of the 30-minute OCV estimate mean. This finding empirically validates Tian et al.'s (2021) assertion that raw voltage is an inadequate predictor for LiFePO₄ chemistry and explains why model-based filters relying on voltage error feedback struggle with this battery type.

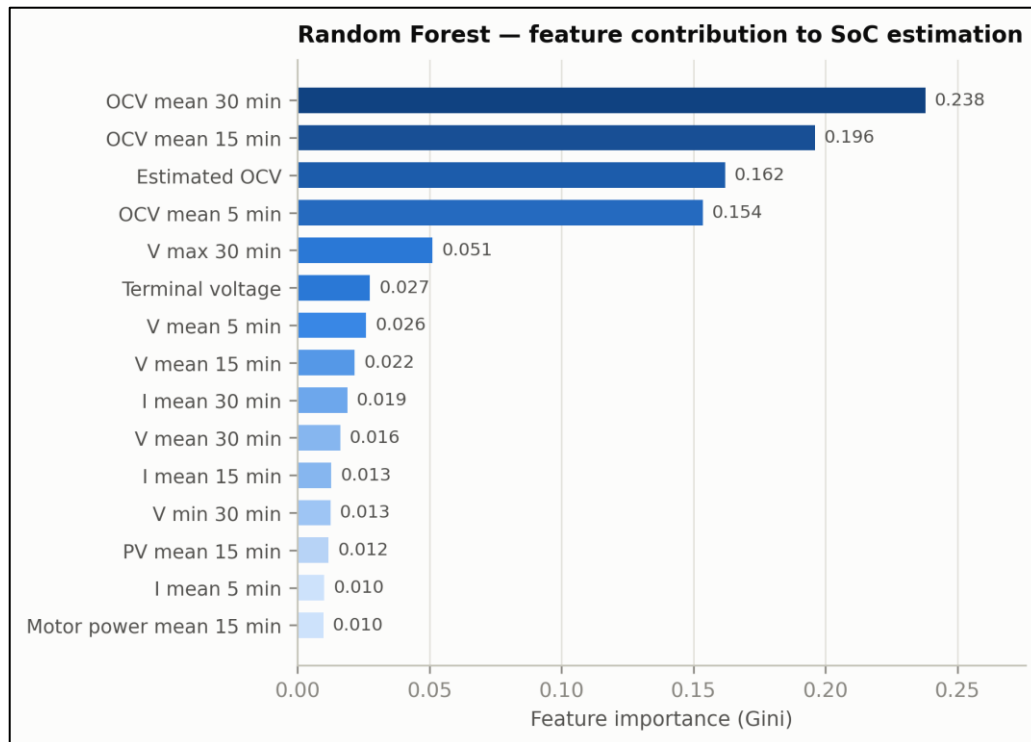


Figure 4. Contribution of the top fifteen features in the random forest model

Positioning Against Previous Research and Implications

Compared to previous studies, the RMSE of 0.587 achieved by the LSTM model is lower than the 0.978% reported by Tian et al. (2021) for fresh LiFePO₄ cells, and comparable to the 0.573% in Chemali et al. (2017) and 0.382% in Lipu et al. (2023), both of which utilized standardized laboratory current profiles. The 0.25% value obtained by Fu et al. (2022) using an adaptive Kalman filter on an underwater vehicle is indeed lower, but it was achieved under a much more regular load profile. This comparison is not entirely equivalent: the benchmark studies used standardized one-way, repetitive profiles such as DST, FUDS, or UDDS. In contrast, the dataset in this study contains bidirectional currents due to opportunistic charging, as well as variations in weather, sea state, and battery health. Achieving comparable error rates under more diverse conditions demonstrates robust generalization capabilities.

Three practical implications can be drawn. First, an error of 0.6 to 0.7 corresponds to roughly 0.06 kWh on a 10.24 kWh pack, substantially smaller than the operational margin in Table 4, making it safe to support threshold-based EMS decisions. Second, the 0.109 accuracy improvement in LSTM comes at the cost of 33 times longer training duration and the need for deep learning libraries during inference; thus, for mid-range shipboard microcontrollers, Random Forest remains a rational choice. Third, the estimation accuracy fully realizes its benefits only when integrated with solar generation and load forecasting modules (Antonopoulos et al., 2021; Singh et al., 2024).

Three limitations must be stated. The dataset is synthetic and generated from physical models; thus, the reported errors represent an upper bound on performance, assuming the physical model accurately represents the real system. Validation with direct acquisition data on operational boats is a mandatory subsequent step. The SoC range in the shared test set is limited to 21.7%-73.8%, leaving performance at very low SoC uncharacterized. Furthermore, battery aging is modeled solely as a

static inter-voyage variation rather than longitudinal degradation, despite Kolodziejski and Michalska-Pozoga (2023) emphasizing degradation as a primary consideration in ship energy storage.

CONCLUSION

This study established a simulation framework and a machine learning-based SoC estimation for a 3 GT electric fishing boat powered by a LiFePO₄ battery and photovoltaic hybrid system. A synthetic dataset of 60 voyages or 28,800 samples at one-minute resolution, successfully represented the dynamics of an eight-hour fishing mission, including bidirectional currents from opportunistic solar charging. The energy audit showed that the 860 Wp array covered 29.4% of the mission energy requirement; however, 8 out of 60 voyages still hit the battery protection threshold under adverse weather and sea conditions, proving that accurate SoC estimation is a strict operational prerequisite.

On 5,052 test samples from unseen voyages, the LSTM achieved an RMSE of 0.587, MAE of 0.463, and a coefficient of determination of 0.9970, outperforming Random Forest (RMSE of 0.696, MAE of 0.526, and R² of 0.9958) but requiring about 33 times longer training. Feature contribution analysis indicated that the estimated open-circuit voltage and its moving averages accounted for approximately 75% of the predictive capability. Consequently, compensating for ohmic voltage drops and providing temporal context are proven keys to accuracy in flat-curve LiFePO₄ chemistry. Future developments will be directed toward validation with direct operational boat data, expanding the SoC coverage to deep discharge regions, and integrating this estimator with solar and load forecasting modules into a single predictive EMS ready for deployment on shipboard embedded devices.

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