Toward AI-Enabled Battery Management and Mission Decision Support for Autonomous Maritime Defense Systems

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***Abstract*—Autonomous maritime systems depend on electric propulsion and software that must perform well during long, safety-critical operations. For such platforms the battery management system (BMS) does more than just monitor energy; its predictions influence endurance planning, payload scheduling, fault response and the decision to return to base. This paper presents the architecture and prototype of an AI-enabled BMS for autonomous maritime defense systems, organized around three integrated layers: 1) a maritime battery system that feeds voltage, current, and temperature telemetry; 2) an AI-enabled BMS pipeline covering acquisition, state estimation (SoC, SoH, SoE, RUL), explainable AI, and core BMS functions; and 3) a mission decision support layer that surfaces estimates through an operator dashboard, a data-scientist XAI dashboard, and energy-risk advisories. The current prototype is simulation-based, combining a physics-based lithium-ion battery model with two complementary interfaces: an operator view of battery state, mission status, and alerts, and a data-scientist view for analyzing model behavior and understanding the variables that drive each estimate. The paper defines eight operational requirements, presents the three-layer architecture and dual-interface dashboard prototype, and discusses the design choices, namely physics-informed constraints, feature attribution, and rule-based alerts, that make AI estimates auditable within a mission control loop.**

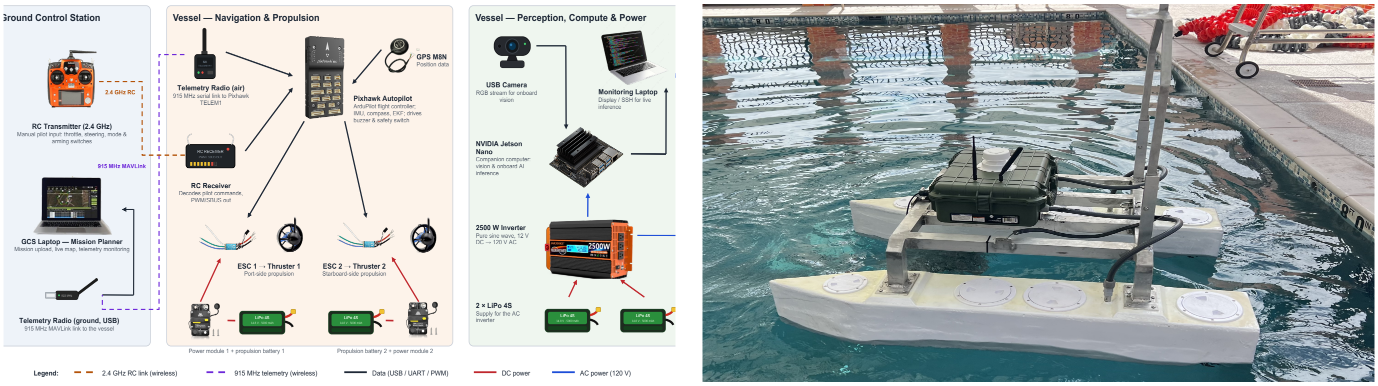
***Index Terms*—battery management system, mission decision support, maritime autonomy, explainable AI, digital twin, real-time monitoring, situational awareness**

I. Introduction

Autonomous maritime systems are moving from controlled demonstrations towards persistent operations that require robust sensing, navigation, propulsion, communications, and payload management. For defense-oriented missions, availability of energy is a first-order operational constraint that limits the duration of patrol, loitering time, sensor duty cycle, communication windows, and the ability to return safely after a disruption [1]. Such platforms need a Battery Management System (BMS) that is far more than a simple voltage or current display. It must diagnose hidden battery states, detect incipient failures, report energy risk to mission control software and operators, and facilitate operational decision-making under uncertainty [2], [3].

Lithium-ion battery packs have been applied to small and medium unmanned surface vessels due to their high power density and operational flexibility [4]. But their behavior depends on loading history, temperature, age, and cell-to-cell variation. A good BMS should include real-time sensing, state estimation, protection, fault detection, data logging, and mission critical decision support. This work estimates and tracks important variables such as state of charge, health, energy, remaining useful life, pack and cell voltages, current, temperature, alert status, mission time, platform position, movement status, and longer-term energy-risk indicators [2], [5]. In maritime autonomy, errors in mission planning can result from bad projections of the battery state, or delayed alerts of faults: a route may appear to be feasible when it is not, or an overly conservative decision to return can reduce useful mission time. Mission planning errors will also be greatly affected by environmental factors such as weather changes (wind, wave height and periodicity, temperature variations, etc.); weather and proper navigation planning in particular are among the biggest risks to mission success, as errors here consume the safety margin in power estimation required for safe return-to-base. Issues of maritime traffic congestion in harbors and coastal regions that impose additional restrictions on vehicle maneuverability and mission planning are also important. Autonomous maritime systems must also abide by the U.S. Coast Guard Rules of the Road (International Regulations for Prevention of Collisions at Sea, 1972 (COLREGS) and U.S. Inland Navigation Rules) [6], which are rules for safe navigation in shared waterways, creating additional complexity to the problem of mission planning and energy allocation.

Classical BMS approaches employ similar circuit models, physics-based models, Kalman filtering, Coulomb counting, and threshold-based protection [2], [7]. These techniques are still valuable because they encode known electrical behavior and are computationally cheap; but, solely model-based solutions are difficult to calibrate across various batteries, sur-



(a) Hardware Architecture of the Autonomous Surface Vessel.

(b) The surface vessel prototype.

Fig. 1. Autonomous surface vessel platform: (a) hardware architecture showing the ground control station and the vessel's navigation/propulsion and perception/compute/power domains, including the RC and MAVLink telemetry links, GPS-based positioning, ESC-driven thrusters, onboard compute, and DC/AC power distribution; (b) physical prototype (HydraCat) used to define the operational context and signal structure for the BMS and digital twin.

roundings, and aging regimes. Modern machine learning (ML) can learn nonlinear patterns from voltage, current, temperature, and capacity data [5], [8], [9]. However, black-box forecasts are challenging to trust in safety-critical installations. This encourages a hybrid approach: physics-informed AI models with predictions constrained by battery degradation principles [3], [10], paired with explainable AI (XAI) interfaces that make estimates understandable to operators and mission-control logic [11]–[14].

This paper presents the architecture and prototype of an AI-enabled BMS for an autonomous maritime digital twin. Real-world data collection from the surface vessel and ML model development are ongoing in parallel; this paper documents the system design and the simulation-based dashboard prototype that forms the foundation for that work. Recent battery-management literature emphasizes the need to connect physical models, measured data, and learning algorithms for reliable operational decisions [3], and recent work on digital twins for battery energy storage systems (BESS) highlights the role of virtual representations in monitoring, prediction, and decision support [15], [16]. This work makes three contributions. First, a three-layer system architecture is defined, covering the maritime battery system, the AI-enabled BMS pipeline, and the mission decision support layer, with explicit design requirements for real-time awareness, physics compliance, interpretability, deployability, and security. Second, a simulation-based prototype demonstrates the dual-interface dashboard (operator view and data-scientist XAI view), validating the interface design and dataflow before real sensor data and trained models are available. Third, a staged deployment roadmap is presented that connects the current prototype to the ongoing data collection and ML development, and ultimately to validated AI-driven mission decision support; full model benchmarking and evaluation results will be reported in the extended journal paper.

II. System Requirements for Maritime Defense BMS

A BMS has to work in the real world, not the laboratory environment of a controlled test. The defense-oriented autonomous surface vessel will be subject to variable propulsion loads, saltwater exposure, vibration, intermittent communications, and mission goals that can change during deployment [1], [17]. Because energy management is coupled with guidance and payload control, a bad state estimate or missed fault propagates to mission planning rather than staying isolated in the BMS [2]. From this context, eight requirements follow.

Real time state awareness: The mission software must continuously read SoC, SoH, SoE, RUL, pack voltage, current, temperature, fault indicators, platform position and mission time with low latency [2], [18]. Berger et al. [18] show update rates lower than 10 s for high power platforms. However, the discharge trajectory changes can be faster due to propulsion and payload decisions.

Predictive ability: The present situation alone cannot do it. The BMS must predict future energy availability and degradation risk to support endurance planning, return-to-base decisions, and payload scheduling [2], [3], [8]. The route that looks viable in the present SoC may not survive the thermal load of the last leg. We also want a confidence bound or prediction interval on each estimate so operators can tell a good prediction from a degraded or out-of-distribution prediction [3], [7].

Robustness: the estimation should be valid in the presence of sensor noise, measurement offsets, cell-to-cell variance, temperature swings and progressive aging [18]. As noted by Berger et al., the industry always prefers robustness over model complexity; a good algorithm that fails in noisy field conditions is of little operational value. *Physics compliance:* estimates should be physically consistent. For a normal aging capacity, the recovery between cycles should not be observed, the internal resistance should increase monotonically with usage, and high temperature should accelerate degradation [3]. It is hard for operators to detect violations and they can

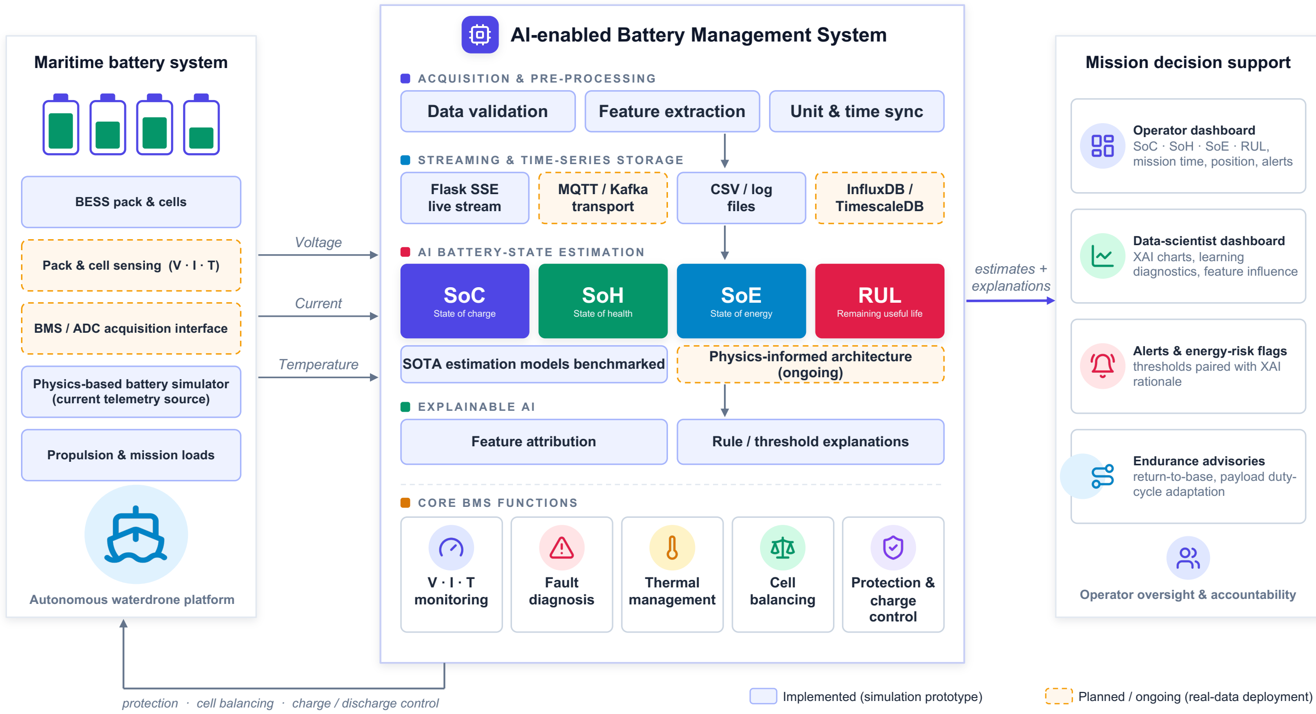


Fig. 2. Workflow of the AI-enabled maritime BMS and mission decision support platform.

insidiously corrupt mission planning.

Fault diagnosis and detection: The BMS must be able to detect cell over-voltage, over-current, abnormal temperature rise, isolation faults, and sensor failure, and differentiate between a true battery fault and a load transient or sensor artifact [2], [3]. In the defense context, the cost of a false positive (mission abort) and a missed fault (loss of propulsion) is high. The system should fallback to conservative estimations in case of failures in the BMS pipeline itself instead of stopping, because silent failure is more dangerous than degraded output [1], [18].

Interpretability: commanders need to know the cause of a risk flag, not just that a risk flag was raised. A useful explanation points to the dominant driver: temperature increase, high discharge current, abnormal voltage sag, or accumulated cycle throughput [11], [13]. Cheung and Ho [19] show that the quality of explanation directly influences operator trust calibration in dynamic monitoring tasks. Operators should also be able to override or reject any AI-generated alerts, with all decisions logged for post-mission accountability [11], [19].

Deployability: the onboard companion computer constrains model size, memory, and inference latency [2], [18]. The BMS must support low-latency streaming inference and remain updatable without full retraining when new operational data is collected.

Security and resilience: the RC, telemetry, and mission-control links shown in Fig. 1(a) are exposed to jamming, spoofing, and unauthorized access [20]. The BMS must validate incoming sensor data, flag estimates that depend on implausible or tampered readings, enforce role-based dashboard access, and maintain tamper-evident logs for post-mission audit.

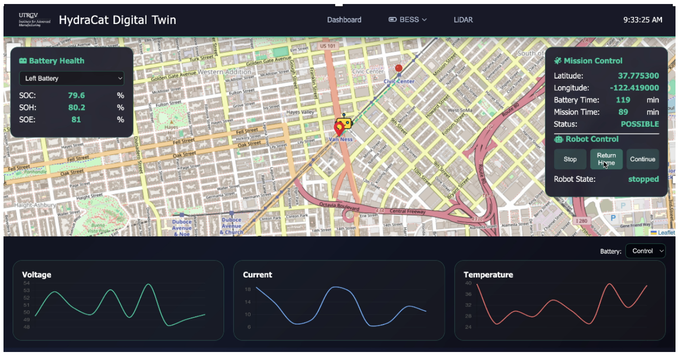
Reliability and repeatability: the consistency and repeatability of system evaluations increase the operator confidence in the AI-driven estimates and support robust decision-making. The BMS must deliver reliable, repeatable measurements and predictions across multiple operational cycles and conditions, with documented performance metrics that operators can use to assess the reliability of any given estimate or alert.

These requirements guide the architecture in Section III and the AI/XAI design choices in Section IV. The prototype is built with simulated telemetry as a conscious engineering decision, which enables the testing of the dashboard, pipeline, and alert logic without depending on sensor availability and hardware integration.

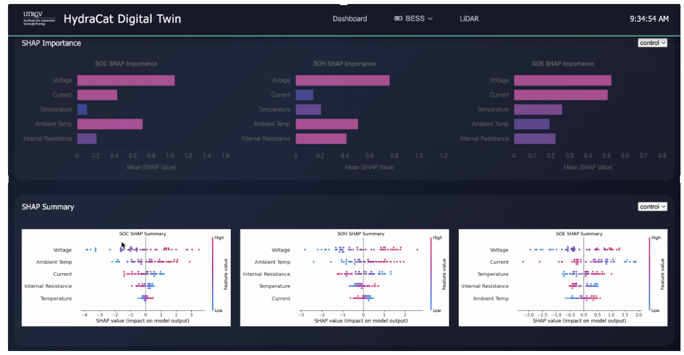
III. Autonomous Maritime Digital Twin: BMS and Mission Decision Support

A. Prototype Architecture

The current BESS prototype is built around the autonomous surface vessel platform shown in Fig. 1. As illustrated in Fig. 1(a), the hardware architecture spans three functional domains. The Ground Control Station consists of an RC transmitter, a GCS laptop running Mission Planner for telemetry monitoring and mission upload, and a ground-side 915 MHz MAVLink telemetry radio. The vessel Navigation and Propulsion domain integrates a Pixhawk autopilot with an onboard GPS receiver for position data, an air-side telemetry radio, an RC receiver, and two ESC-driven thrusters for differential



(a) Operator dashboard: battery health, mission control, boat control, and V/I/T trends.



(b) Data-scientist dashboard: SHAP importance and SHAP summary for SoC, SoH, and SoE.

Fig. 3. HydraCat digital-twin dashboards generated from simulated lithium-ion telemetry: (a) operator dashboard combining BMS state (battery health), mission control (position, mission time, status), boat control, and voltage/current/temperature time histories; (b) data-scientist dashboard showing SHAP feature-importance rankings and SHAP summary (beeswarm) plots for the SoC, SoH, and SoE estimators across voltage, current, temperature, ambient temperature, and internal resistance.

(port/starboard) propulsion, each powered through its own power module by a dedicated LiPo 4S battery pack. The Perception, Compute, and Power domain includes a USB camera for onboard vision, an NVIDIA Jetson Nano as the companion computer for AI inference, a monitoring laptop for live SSH access, and a 2500 W pure sine-wave inverter (12 V DC to 120 V AC) supplied by two further LiPo 4S packs. Communication between domains relies on a 2.4 GHz RC link, 915 MHz MAVLink telemetry, USB/UART/PWM data lines, and DC/AC power buses. All dashboard data used at this stage are simulated; the physical platform shown in Fig. 1(b) defines the operational context and signal structure for the BMS and digital twin under development.

Fig. 2 traces the full workflow from the battery to mission decisions.

Maritime Battery System (left panel of Fig. 2) comprises the BESS pack and cells, the pack/cell voltage-current-temperature sensing layer, the BMS/ADC acquisition interface, and the propulsion and mission loads on the autonomous surface vessel platform; in the current prototype, a physics-based battery simulator stands in as the source of these voltage, current, and temperature signals. The system architecture enables monitoring of both the collective battery parameters (pack level voltage, current and temperature) and the individual battery cell level parameters distributed across port and starboard sides of the platform for high fidelity data collection and accelerated AI model development. This dual-side and multi-level monitoring strategy improves the spatial and temporal resolution of battery system understanding, enabling the AI models to capture asymmetric loading effects and cell-to-cell variation that mimic real operational conditions.

AI-enabled BMS (center panel of Fig. 2) receives these signals at its acquisition and pre-processing stage, where data validation, feature extraction, and unit/time synchronization are performed. The streaming and time-series storage stage currently uses a Flask/SSE live stream and CSV/log files, with MQTT/Kafka transport and InfluxDB/TimescaleDB storage planned for the real-data deployment. The AI battery-state estimation stage produces the SoC, SoH, SoE, and RUL estimates: state-of-the-art models are targeted for this stage, and a physics-informed architecture is being designed alongside them; model benchmarking results will be reported in the extended paper. An explainable-AI stage then turns these estimates into feature-attribution and rule/threshold explanations, and a core BMS functions stage covers voltage/current/temperature monitoring, fault diagnosis, thermal management, cell balancing, and protection/charge control, feeding a control loop back to the battery system.

Mission Decision Support (right panel of Fig. 2) connects the resulting estimates and explanations to four mission-facing outputs: the operator dashboard (SoC, SoH, SoE, RUL, mission time, position, and alerts), the data-scientist dashboard (XAI charts, learning diagnostics, feature influence), alerts and energy-risk flags paired with XAI rationale, and endurance advisories for return-to-base and payload duty-cycle adaptation, all under operator oversight and accountability.

Fig. 3 shows the two views of this dashboard, both generated from simulated telemetry. The operator view, Fig. 3(a), combines a Battery Health panel (cell battery level, SoC, SoH, SoE, RUL), a Mission Control panel (latitude, longitude, mission time, and platform status), a Boat Control panel (start/stop command and moving/stopped status), and time-series plots of voltage, current, and temperature, giving mission operators a single monitoring surface. The data-scientist view, Fig. 3(b), reports SHAP-based feature attribution [12] for the SoC, SoH, and SoE estimators: a SHAP Importance panel ranks voltage, current, temperature, ambient temperature, and internal resistance by their mean impact on each estimate, and a SHAP Summary panel shows the corresponding beeswarm plots, indicating both the magnitude and the direction of each feature's effect on the model output.

B. Deployment Roadmap

As a first planned step, the prototype uses simulated telemetry. The alert logic, dataflow, and interface design are validated separately from sensor availability and model readiness, so that neither the dashboard nor the pipeline need be redesigned when real hardware is connected. Chart rendering, boundary behavior, alert triggering, mission-control widgets and live streaming were exercised under representative conditions using the simulation backend.

The dashboard has been built so you can swap the telemetry source without changing the interface. Now data acquisition from the surface vessel is being performed; the acquired signals will replace the simulator by connecting a sensor-acquisition layer to the BMS/ADC interface and checking the signals' names, units, sampling frequency and time synchronization. Once the acquisition is stable, the streaming and storage layers can be upgraded to deployment-grade transports such as MQTT or Kafka, and time-series databases such as InfluxDB or TimescaleDB, to support long missions and post-mission analysis.

IV. AI and XAI System Design

The AI layer aims at SoC, SoH, SoE, RUL, and mission-level energy-risk estimation from voltage, current, temperature, accumulated throughput, and recent trend features. In parallel to data-driven models, a physics-informed architecture is developed to impose battery-domain constraints by model structure, loss terms, or post-processing checks [3], [10]. This is directly motivated by the physics compliance requirement of Section II: purely data-driven models risk implausible outputs, e.g., SoH recovery between cycles or temperature insensitive capacity fade, which would propagate silently into mission decisions. The maritime context imposes additional constraints: Differential thruster loading leads to highly variable discharge rates, exposure to outdoor temperatures increases degradation compared to lab conditions, and the multi-pack architecture introduces cell-to-cell variability that is not captured by single-cell models [5], [8]. The extended journal paper will concentrate on model selection, benchmarking and evaluation against these conditions.

The XAI layer builds on the two-dashboard design of Fig. 3 and has two natural forms of output that directly map to the two user roles. The feature importance bars give the operators a quick, ranked explanation of what caused an alert (meeting the interpretability requirement of Section II). The beeswarm plots give data scientists directional, per-sample attribution over the entire dataset for model diagnostics [12], [13]. We keep rule-based alert thresholds and feature attribution to ensure that safety-critical notifications are transparent and auditable without relying on post-hoc model explanations [11]. Together, these mechanisms are meant to make AI estimates usable in the mission control loop, while maintaining a human accountable for consequential energy decisions.

V. Discussion

The eight requirements of Section II pull in different directions and the design has to make reasonable compromises. Interpretability favors simpler, more transparent models; predictive capability favors expressive models; deployability constrains both by ruling out models too large for the Jetson Nano. The tie-breaker on this platform is physics compliance: an estimate that violates known battery behavior is less trustworthy than one that is slightly less accurate but respects it. Operators cannot easily see a physically impossible but plausible prediction. Therefore, the design decision of integrating physics-informed constraints with explanations based on feature attribution and rule based alerts is not just an engineering decision but a straightforward reply to the accountability requirement that safety-critical energy decisions should be auditable. A black-box range estimate that cannot distinguish high temperature and sensor drift from real capacity fade provides no basis for operator review and no evidence trail for post-mission analysis.

The next phases follow the roadmap of Section III-B. Data collection from the surface vessel and ML model development are actively ongoing; AI/XAI model evaluation on the collected maritime datasets, validation of the physics-informed architecture, and operator studies of the XAI explanations will be reported in the extended journal paper. Security and resilience hardening of the telemetry and control links [20] is scoped for the real-sensor integration phase, once the communication links are physically in place and the attack surface is fully defined. Confidence bounds and prediction intervals for AI estimates, graceful-degradation fallback modes for sensor dropout and inference failures, and operator override logging with audit trails are likewise deferred to that phase, where they can be validated under live operational conditions.

VI. Conclusion

This paper presented the architecture and prototype of an AI-enabled BMS and mission decision support system for autonomous maritime defense platforms. The three-layer design, covering the maritime battery system, the AI-enabled BMS pipeline, and the mission decision support layer, is grounded in eight operational requirements and demonstrated through a dual-interface dashboard prototype that decouples interface validation from sensor and model availability. The prototype confirms that the human-machine interface, alert logic, and dataflow are sound. Future work will focus on integrating the real sensor data currently being collected from the surface vessel, training and benchmarking the AI/XAI models on maritime duty cycles, validating the physics-informed architecture, conducting operator studies of the XAI explanations, implementing confidence bounds on AI estimates, validating graceful-degradation fallback behavior, and deploying operator override logging. These results will be reported in the extended journal paper. The long-term goal is a trustworthy BMS that predicts energy risk, respects battery physics, explains its estimates, and helps autonomous maritime platforms make safer, endurance-aware decisions.

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Declarations

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