Digital Twin Architectures for Maritime Microgrids: Toward Resilient and Intelligent Port Operations

Muhammad Sadiq
Department of electrical engineering
University of Malta, Malta
muhammad.sadiq@um.edu.mt

John Licari
Department of electrical engineering
University of Malta, Malta
john.licari@um.edu.mt

Maurice Apap
Department of electrical engineering
University of Malta, Malta
mauric.apap@um.edu.mt

Cyril Spiteri Staines
Department of electrical engineering
University of Malta, Malta
cyril.spiteri-staines@um.edu.mt

Alexander Micallef
Department of electrical engineering
University of Malta, Malta
alexander.micallef@um.edu.mt

Abstract—The transition toward intelligent and sustainable port operations requires advanced tools to manage the complexity of maritime microgrids. These systems must enable real-time coordination between hybrid vessels and port-side infrastructure while adapting to variable renewable generation, uncertain berthing schedules, and mission-critical loads. This paper presents a focused review of digital twin (DT) technologies as a foundation for data-driven predictive control, diagnostics, and energy optimization in maritime environments. Key architectural elements are analyzed, including multi-source sensing, data modeling, forecasting, and secure communication. Representative DT applications such as cold ironing scheduling, DER coordination, propulsion monitoring, and AIS-based demand prediction are discussed. A unified framework is proposed to illustrate how a centralized Energy Management System (EMS) integrates port and shipboard DTs, enabling dynamic interaction, load forecasting, and synchronized control. The paper also identifies major challenges and research directions to support scalable, secure, and low-emission digital twin deployments for resilient port electrification.

Keywords—Digital Twin, Energy Management System, Maritime Microgrids, Port Electrification, Ship-Port Coordination.

I. INTRODUCTION

Decarbonization of maritime infrastructure has become a strategic priority in global efforts to reduce greenhouse gas emissions from the transportation sector. With increasing regulatory mandates and sustainability targets set by the International Maritime Organization (IMO) and European Union, ports are transitioning toward low-emission and fully electrified operational models [1]. One of the most promising enablers of this transformation is the maritime microgrid, an autonomous energy system that integrates renewable generation, energy storage, and smart control infrastructure for port-side and ship-side operations, transitioning ports to energy hubs [2]. Several studies have shown that microgrids embedded with photovoltaic (PV) panels, battery energy storage systems (BESS), and cold ironing stations can reduce emissions by up to 40% in medium-scale ports while improving operational flexibility [3].

Despite these benefits, the effective management of maritime microgrids remains technically challenging. Port environments are inherently dynamic and are characterized by variable berthing schedules, irregular load profiles, uncertain

renewable outputs, and mobile energy demands from hybrid or electric vessels. These conditions result in high variability in the load behavior and often lead to mismatches between energy supply and demand. In particular, mission-critical systems such as quay cranes, reefer containers, propulsion drives, and cold ironing terminals require uninterrupted power, involving precise coordination across ship—port interfaces. The existing Supervisory Control and Data Acquisition (SCADA) and Energy Management Systems (EMS) in ports are typically rule-based and with predefined responses, which limit their ability to model uncertainty, anticipate failures, or optimize dispatch under fast-changing conditions. As a result, renewable generation assets are often underutilized, and load prioritization becomes reactive rather than predictive [4],[5].

Digital twins (DTs) offer a compelling solution to these limitations. A DT is not merely a static model, but its a dynamic, continuously updated, representation of a physical asset or system that enables real-time monitoring, simulation, and optimization. Originally conceived for aerospace systems to monitor and simulate mission-critical components in real time [6], DTs have since gained adoption in power systems [7], industrial automation [8] and transportation sectors due to their ability to synchronize virtual models with physical systems. For instance, in power systems, DTs have been successfully used for transformer health diagnostics, distributed energy resources (DER) scheduling under uncertainty, and grid topology identification and monitoring [9],[10]. As demonstrated in [11], a machine learningenhanced digital twin was used to forecast building-level demand in a campus microgrid, showing robust performance under volatile load conditions. In [12], a physics-informed digital twin was developed to model battery degradation, supporting predictive dispatch strategies aimed at improving reliability and extending asset lifespan.

Nevertheless, the application of DTs in maritime microgrids remains unexplored. Although prior studies have utilized Automatic Identification System (AIS) data to model ship-to-shore energy interactions and forecast berthing schedules [13], most lack integration with real-time control mechanisms, multi-scenario simulation environments, and closed-loop feedback architectures essential for coordinated energy dispatch in maritime microgrids.

The authors in [14] have developed co-simulation platforms integrating ship propulsion models with port-side energy systems, while Micallef et al. [15] developed a framework for forecasting electricity demand in cruise port microgrids using advanced machine learning models. However, these approaches often lack validation using real-

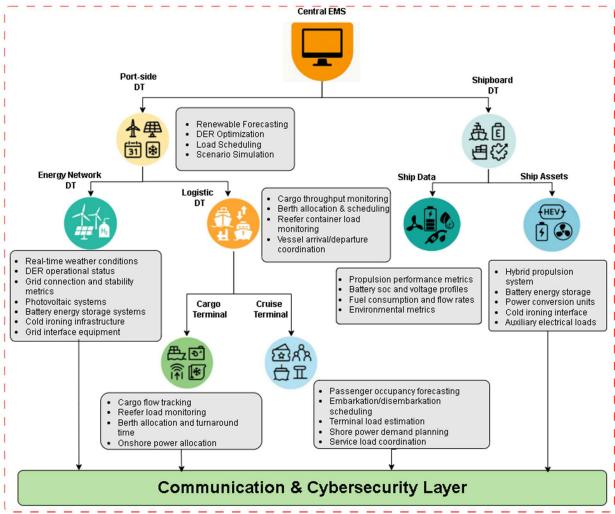


Fig. 1 Conceptual overview of a digital twin in a maritime microgrid.

time data streams or fail to incorporate synchronization mechanisms necessary for dynamic maritime operations. Unlike stationary terrestrial microgrids, maritime systems require DTs capable of adaptive modeling that responds to both spatial and temporal variability, particularly when coordinating distributed energy resources with shipboard systems.

Moreover, while some progress has been made in developing DT architectures, an integrated framework that synchronizes shipboard and port-side DTs within a real-time EMS remains underexplored. Existing modular DT platforms designed for electric vehicle infrastructure or isolated microgrids have shown promising results [16], yet their application to maritime systems is constrained by operational diverse operations, intermittent connectivity, cybersecurity risks. As seaports evolve into multi-functional energy hubs catering to both stationary infrastructure and mobile assets, the ability to simulate, coordinate, and control hybrid systems in real time is increasingly recognized as a critical enabler for enhancing resilience and reducing emissions.

To address these gaps, this paper provides a targeted review and conceptual framework for the deployment of digital twins in maritime microgrids.

The remainder of this paper is organized as follows. Section II introduces the digital twin architecture for maritime microgrids, detailing port-side, shipboard, and logistics DT domains along with the communication and cybersecurity layer. Section III presents a layered data flow hierarchy that supports predictive modeling, control, and cyber-physical coordination. Section IV outlines the unified maritime DT framework centered around the EMS, enabling real-time shipport synchronization and optimization. Section V discusses key technical challenges, including sensors' reliability, cybersecurity, and computational scalability. Section VI concludes the paper by summarizing insights and highlighting future research directions for secure, interoperable, and scalable DT deployment in maritime microgrids.

II. MARITIME TWIN ARCHITECTURE

DT architectures play a transformative role in maritime microgrids by enabling synchronized high-resolution virtual models of complex physical systems. These architectures support continuous simulations, forecasting, and adaptive control under various operational and environmental conditions. Unlike conventional SCADA-based systems, DTs facilitate data-driven coordination of DERs, hybrid propulsion systems, and critical port loads, such as cranes, reefer containers, and cold ironing stations [17].

A. Digital Twin Architecture for Maritime Microgrids

Fig. 1 presents a modular architecture for maritime microgrids centered around a centralized EMS, which integrates interoperable DT domains: port-side DT, shipboard

DT, and logistics DT. These domains are digitally coupled to enable synchronized control, real-time diagnostics, and predictive optimization of energy flows between the port infrastructure and docked vessels.

Port-side DT focuses on static infrastructure within the harbour, capturing DERs through a dedicated energy network DT. This subdomain monitors the PV generation, battery energy storage systems (BESS), cold ironing systems, and grid interfaces. Real-time and historical data such as irradiance levels, battery state-of-charge (SoC), grid voltage fluctuations, and DER availability are utilized for renewable forecasting, DER optimization, load scheduling, and contingency-based scenario simulations.

The shipboard DT models onboard systems, including hybrid propulsion modules, energy storage units, and auxiliary electrical loads. It integrates vessel/fleet telematics, combining onboard diagnostics such as propulsion torque, SoC, fuel consumption, and exhaust temperature to support predictive maintenance, dynamic power allocation, and coordinated onshore power supply (OPS). Diagnostic outputs such as the estimated remaining battery life and real-time power profiles are relayed to the EMS for optimal resource dispatch during the berthing, loitering, and departure phases.

The logistics DT serves as a coordination layer between vessel traffic, terminal operations, and energy dispatch. This is divided into two operational sub-domains. The cargo terminal DT manages cargo throughput monitoring, berth allocation, turnaround scheduling, reefer container tracking, and onshore power-sharing. The cruise terminal DT captures the dynamics of passenger-centric activities, including occupancy forecasting, embarkation/disembarkation scheduling, terminal power demand estimation, and lighting loads. These models are essential for managing intermittent but high-intensity demand from cruise vessels, which differs significantly from freight ship operations.

All DTs communicate through a communication and cybersecurity layer, which ensures secure and standardized real-time data exchange across physical and digital domains. Lightweight telemetry data from distributed sensors (e.g., temperature readings from PV panels or occupancy levels at terminals) are transmitted using MQTT [18], while critical grid control signals are exchanged through the IEC 61850 protocol. Embedded cybersecurity mechanisms such as encryption [19], authentication, and gateway isolation are implemented to protect against spoofing, intrusion, and unauthorized command injection, which are critical in maritime operational contexts.

This integrated framework connects the physical port infrastructure and physical ship infrastructure, which serve as the source of real-world telemetry and execution endpoints for EMS-issued commands. Examples of physical telemetry include the hybrid tugboat engine RPM, BESS voltage levels, cold ironing load transfer, and occupancy sensor data. The EMS uses these data to issue control commands, such as initiating battery charging, adjusting the PV inverter output, or redistributing the berth power allocation, thereby enabling a closed-loop control strategy.

Through this hierarchical, multidomain architecture, the EMS synthesizes digital forecasts, operational priorities, and real-time system states to coordinate load balancing, and energy resilience across the entire maritime microgrid. This configuration supports both cargo and cruise operations and lays the foundation for decarbonized intelligent port ecosystems.

B. Data Flow Hierarchy for Maritime Microgrid Digital Twins

Fig. 2 illustrates a five-layer DT architecture that governs data flow and operational synchronization within a maritime microgrid environment [20]. This structure facilitates predictive modeling, supervisory control, and cyber-physical coordination across both the port infrastructure and shipboard energy systems. The vertical alignment of the layers, from physical assets to user-facing applications, ensures continuous feedback loops for real-time decision-making. Each layer processes or routes data, generating outputs that flow upwards for analysis and downward for control. The hybrid tugboat, considered as a representative asset, helps ground this architecture, as it functions as both a generator and consumer of energy, interacting with the port's microgrid to request power (via the OPS) or providing telemetry to forecast propulsion needs. Its participation exemplifies how physical devices are digitized and managed within this DT-based control framework.

1) Physical Layer

The physical layer comprises all tangible maritime assets that generate, store, or consume energy within the port ecosystem. These include hybrid tugboats, BESS, PV arrays, wind turbines, cold ironing terminals, and grid interface hardware, and other marine vessels, etc. Each system is equipped with sensors that measure real-time parameters, such as battery SoC, propulsion torque, fuel flow, voltage levels, PV irradiance, wind speed, and shore-side power loads. For instance, a hybrid tugboat batteries system may report SoC values as it approaches the port, enabling the system to prepare a cold ironing berth with an adequate DER supply. These raw sensor data streams are routed into the data infrastructure for preprocessing and interpretation.

2) Data Layer

Sensor telemetry is first transmitted to the data layer, where the raw values are filtered, synchronized, and integrated with historical and simulated datasets. This layer performs essential preprocessing, such as timestamp alignment, noise filtering, and normalization. The resulting fusion dataset supports both short- and long-term degradation analyses. For example, the battery temperature profiles from the tugboat can be merged with the historical discharge curves and ambient temperature readings to infer potential thermal aging. Preprocessed outputs such as normalized voltage datasets or aggregated load demands are passed to the model layer for high-level forecasting and diagnostic analytics.

3) Model Layer

The model layer forms the core analytical engine of the digital twin framework. It comprises three subcomponents: physical models, data-driven system models, and a decision model. Physical models replicate deterministic behavior, such as the DC-DC converter efficiency or cold ironing cable losses. System models include machine learning approaches to forecast terminal energy consumption based on AIS schedules and weather inputs, as well as Kalman filters for real-time SoC estimation in shipboard batteries using measured voltage and current data [21].

The decision model uses the outputs from these analytical engines to generate optimized schedules, battery management strategies, and DER prioritization plans. For instance, based on the predicted DER availability and ship demand, the model might determine whether the tugboat should be connected immediately or delayed until the PV output increases.

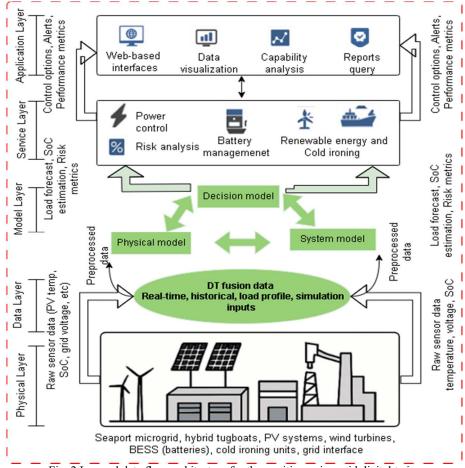


Fig. 2 Layered data flow architecture for the maritime microgrid digital twin.

4) Service Layer

The service layer operationalizes insights from the model layer into specific system actions. This includes automated power dispatch, cold ironing activation, battery charge scheduling, and fault response strategies. For instance, if the model layer forecasts a potential SoC drop during a tugboat's approach, the service layer can initiate prioritised battery charging using renewable sources such as wind or solar power, or shedding of nonessential terminal loads. Risk metrics, emissions thresholds, and grid balancing objectives are also processed to enable dynamic system adjustment. These services maintain bidirectional links with the application layer (for operator feedback) and model layer (for continuous optimization based on the live system response).

5) Application Layer

At the top of the architecture, the application layer provides the human-machine interface and external system coordination functions. This includes EMS dashboards, SCADA portals, and analytics panels displaying the system KPIs, forecasts, etc. Operators interact with live energy flow maps, historical efficiency curves, and predictive maintenance alerts, and may issue direct commands such as initiate tugboat charging, reduce BESS discharge, or allocate cold ironing power for cruise terminal. The application layer also links stakeholders such as national grid control centers and port logistics systems by transmitting forecasted DER output, berth schedules, or energy flexibility bids. These interactions close the loop, with top-down commands flowing through the

service and model layers to reconfigure operations at the physical level.

III. MARITIME DIGITAL TWIN FRAMEWORK

The maritime DT framework offers an integrated, real-time coordination environment between the shipboard and port-side energy systems. As shown in Fig. 3, the port and vessel are modeled not as independent entities, but as interdependent nodes within a unified cyber-physical energy network. At the center of this configuration is the EMS, which links distributed physical assets to virtual representations and data-driven decision making processes.

A key advancement of the DT-based approach over traditional SCADA lies in its capacity for continuous synchronization and reconfiguration. SCADA systems typically rely on fixed rules and time-based schedules and lack responsiveness to dynamic events such as unscheduled vessel arrivals, renewable generation variability, or equipment degradation. In contrast, the DT framework enables continuous real-time feedback loops, in which sensor-derived data and forecast models continuously influence operational strategies. For example, a hybrid tugboat transmitting propulsion torque, battery SoC, and auxiliary power demand in real time allows the EMS to adjust cold ironing schedules or redistribute the DER output based on actual vessel readiness and energy availability.

The EMS does not only aggregate information; it also acts as a coordination and optimization layer that interprets fused data streams from the DTs, translates them into actionable

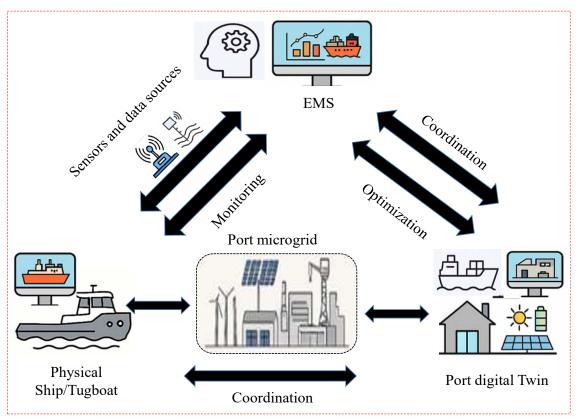


Fig. 3 Unified digital twin framework linking ship and port systems to EMS for real-time maritime microgrid coordination and optimization.

insights, and issues control commands that shape microgrid behavior.

It synthesizes environmental inputs (e.g., weather and sea conditions), infrastructure states (e.g., PV output, grid voltage, and OPS load), and vessel-specific forecasts (e.g., departure and auxiliary energy consumption trends) to prioritize energy flows and minimize differences between competing loads.

For instance, if a cruise vessel is expected to experience a surge in energy demand during passenger boarding while solar output declines, the EMS may trigger controlled OPS battery discharge while deferring less urgent charging for a departing tugboat.

This dynamic interplay between the port and ship twins is maintained through shared time horizons, scenario coordination, and bidirectional communications. The port DT provides the shipboard twin with up-to-date berth energy availability and DER constraints, whereas the shipboard twin sends forward-looking demand forecasts, enabling the EMS to execute joint optimization. Consequently, the charging profiles, dispatch schedules, and maintenance events are cooptimized across the system.

The coordination mechanism within the EMS is based on decision models that leverage both physical- and system-level simulations. Physical models summarize component-level behavior (e.g., BESS degradation curves and engine thermal dynamics), whereas system models predict aggregate effects (e.g., port load curves and grid stability margins). Decision logic may include model predictive control, heuristic optimization, or multi-objective solvers depending on the application. These models are continuously updated using DT data that combine real-time telemetry with historical baselines and simulation inputs.

By treating ship and port operations as functionally coupled domains, this DT framework unlocks flexibility, reliability, and decarbonization potential that are not achievable with siloed energy control. Its layered design allows for the secure integration of predictive analytics, adaptive control, and scenario-driven planning, thereby laying the groundwork for zero-emission maritime operations.

IV. TECHNICAL CHALLENGES

Implementing DTs in maritime microgrids remains constrained both by the reliability of sensor telemetry and the need for minimal latency in real-world port conditions. Continuous exposure to salt spray, humidity, vibration, and thermal drift degrades sensor fidelity and can disrupt critical data streams. Such interruptions not only impair real-time forecasting and scheduling but also introduce instability into predictive energy dispatch if not promptly addressed. Advanced estimation strategies such as adaptive Kalman filtering and robust observers help reconstruct missing signals; however, they remain sensitive to sensor drift and long-term degradation without redundant sensing or self-diagnosing edge architectures. Maritime systems often lack physical redundancy or rapid calibration cycles, particularly during vessel traffic, further amplifying operational vulnerability.

Cyber-physical security presents a growing threat to shipboard DT ecosystems, where continuous multi-protocol data exchange spans both operational technology and IT domains. Lightweight telemetry protocols like MQTT and maritime standards like NMEA 2000 lack native encryption, making spoofing, packet manipulation, and time-delay attacks

feasible even under localized network access. Such disruptions can cause the EMS to initiate a grid-unstable dispatch or unscheduled cold ironing.

Finally, achieving computational scalability and semantic interoperability remains a core barrier to deploying real-time DT coordination across ship and port domains. High-fidelity simulations such as propulsion response modeling, transient grid stability analysis, and battery health prediction are often infeasible to execute at the edge without reduction techniques. Emerging approaches such as physics-informed neural networks and dynamic surrogate models demonstrate strong potential [22], but they demand extensive, high-quality training datasets and thorough validation within maritime operational contexts. Simultaneously, many ship and port control systems operate on proprietary platforms with incompatible data schemas and communication protocols.

V. CONCLUSION

This paper presents a modular DT architecture for maritime microgrids, enabling real-time synchronization between shipboard and port-side systems under the supervision of a centralized EMS. The proposed framework adopts a structured five-layer hierarchy to facilitate predictive load forecasting, optimal dispatch of DERs, and coordinated energy exchange. Use cases such as SoC-aware hybrid tugboat charging and adaptive cold ironing scheduling highlight the system's capability to improve flexibility, operational continuity, and emission mitigation across dynamic port environments.

However, several technical barriers remain to be resolved. These include sensor degradation under harsh maritime conditions, cybersecurity risks due to continuous data exchange, computational limitations for real-time DT execution, and lack of interoperability with legacy infrastructure. Overcoming these challenges is essential to enable scalable, robust, and secure DT deployment in operational port settings.

Future research will focus on the development of lightweight modeling techniques suitable for embedded and edge-level deployment, secure and interoperable communication protocols tailored for maritime microgrids, and EMS coordination strategies leveraging ML-based forecasting and decision support. Additional efforts will explore lifecycle assessment optimization and validation across multi-terminal port infrastructures to facilitate the transition toward fully digitalized and decarbonized maritime ecosystems.

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