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Intelligent digital twin utilization for real-time forecasting and optimization of the ship's power system

Abstract. The paper presents the concept and mathematical model of an intelligent digital twin of a ship's power system, designed for real-time operation. The proposed solution integrates dynamic energy balance modeling, telemetry signal processing using a Kalman filter, load forecasting with long short-term memory (LSTM) neural networks, anomaly detection mechanisms, and optimization modules. The digital twin is implemented as a modular software architecture capable of integration with onboard control systems and cloud-based fleet analytics platforms. A series of computational experiments in MATLAB/Simulink simulates both typical and critical operational conditions, including stable load, overloads, generator failures, voltage instability, and energy-saving modes. The results demonstrate strong convergence between simulated and computed values, as well as timely system responses to emerging anomalies and effective optimization decisions. The developed model highlights the potential of digital twin technology to enhance energy efficiency, operational reliability, and environmental sustainability in modern maritime transport. It provides a foundation for advanced autonomous energy management and supports compliance with evolving IMO decarbonization and safety requirements.

Keywords: ship power system, digital twin, telemetry, load forecasting, anomaly detection, energy efficiency, autonomous control, intelligent algorithms, real-time operation, IMO

Introduction. In the context of growing global attention to decarbonization and energy optimization, the maritime industry faces increasing demands for the intelligent management of onboard power systems. Digital twin technology has emerged as a transformative solution for enhancing situational awareness, operational efficiency, and system reliability in real time. By creating a virtual representation of a ship's power infrastructure, digital twins enable continuous monitoring, predictive analytics, and autonomous decision-making based on real-time telemetry and advanced modeling techniques.

This study focuses on the development and implementation of an intelligent digital twin tailored to the dynamic energy system of a marine vessel. Unlike traditional static models, the proposed approach integrates machine learning–based forecasting (LSTM), Kalman-filtered telemetry analysis, and anomaly detection modules within a unified control framework. The digital twin is designed for real-time interaction with shipboard systems, allowing adaptive optimization of energy consumption and improved resilience to operational disruptions. This paper aims to demonstrate the practical feasibility and benefits of such a system through simulation-based validation under various load and failure scenarios.

Analysis of the latest research and problem statement. Digital twin technologies have recently gained considerable attention as critical tools for real-time monitoring, predictive analysis, and optimization of maritime energy systems. Current research highlights digital twins as foundational elements for enhancing energy efficiency, reliability, and operational sustainability in marine applications.

Li et al. developed an intelligent maintenance platform driven by digital twin technology for large-scale hydro-steel structures. Their research demonstrated the capability of digital twins to significantly improve maintenance effectiveness through predictive analytics and real-time monitoring [1]. Similarly, Liu et al. examined digital twin implementation for shipboard crane operations, highlighting considerable improvements in operational efficiency and safety through advanced predictive maintenance [2]. These studies collectively underline the potential for digital twin systems to dynamically manage and forecast performance and maintenance requirements in maritime infrastructures.

Recent literature also emphasizes the critical role of artificial intelligence (AI) and advanced algorithms in digital twin implementations. For example, Es-haghi et al. (2024) reviewed current methods enabling real-time analytics in digital twins, emphasizing the necessity of robust algorithms capable of rapid adaptation and high accuracy under variable conditions [3]. Ubina et al. further expanded on the integration of AI and the Internet of Things (IoT) within digital twin platforms, demonstrating significant gains in operational predictability and control precision in intelligent fish farming systems [4]. Such findings highlight the adaptability of digital twins to diverse environmental and operational contexts, further underscoring their suitability for marine energy systems.

However, despite these advancements, significant gaps remain. Most existing models rely predominantly on static parameters or averaged data, failing to accurately reflect the dynamic nature of onboard ship energy systems affected by fluctuating load conditions, weather changes, and operational scenarios. This limitation significantly restricts their potential in dynamic real-time control and proactive maintenance management.

Furthermore, Fu et al. emphasized that achieving real-time multi-scale characterization remains a primary challenge due to limitations in computational efficiency and data integration processes [5]. Likewise, Mohanraj and Vaishnavi underscored the ongoing difficulties in managing large volumes of telemetry data and integrating them into coherent real-time digital twin models, particularly under marine operating conditions characterized by continuous variability and environmental uncertainty [6].

Thus, the primary problem addressed in the current study is the absence of comprehensive dynamic models that integrate real-time telemetry, predictive machine learning algorithms, and anomaly detection within a unified digital twin framework. There remains an urgent need for integrated systems capable of real-time adaptive responses to varying ship energy system conditions, which can significantly enhance operational reliability, efficiency, and compliance with stringent IMO decarbonization goals.

This study aims to address these limitations by developing an intelligent digital twin model specifically designed for real-time operation within ship power systems, integrating dynamic energy balance models, LSTM-based predictive analytics, Kalman filtering for telemetry data, and anomaly detection modules. By evaluating this model through simulation scenarios, the study contributes to filling the identified research gaps, providing actionable insights into the practical application of digital twins in maritime energy management.

Problem statement. Existing models of ship energy consumption are usually based on static parameters or calculations of average values. This does not allow to accurately reflect the dynamic behaviour of the ship's energy systems when loads, course, weather conditions, etc. change. The lack of integration of real telemetry data with virtual models limits the possibilities of adaptive control, fault prediction, and scenario planning of energy consumption.

Research objective. To develop the concept and mathematical model of a digital twin of the ship's power system, which provides real-time monitoring of parameters, efficiency assessment, state prediction, and decision support to reduce fuel consumption and CO_2 emissions.

Summary of the main material. In the context of global digitalisation and increased requirements for energy efficiency in maritime transport, digital twins of ships are becoming a key tool for monitoring, diagnosing and forecasting energy processes in real time. This approach allows not only to monitor the technical condition of ship systems, but also to optimise them based on a large array of data coming from sensors during operation. This topic is especially relevant in the context of strict IMO environmental standards and requirements to reduce greenhouse gas emissions.

The purpose and tasks of the study is to create and verify a thorough mathematical model and conceptual framework for an intelligent digital twin of a ship's power system that can operate efficiently under real-time operating circumstances. By improving the monitoring, anomaly detection, predictive analysis, and optimization of maritime energy systems, the proposed digital twin hopes to greatly boost energy efficiency, minimize CO_2 emissions, and reduce fuel consumption in maritime transportation.

The study establishes the following particular tasks in order to fulfill this purpose:

1. To produce an energy system dynamic mathematical model of the ship that faithfully captures changes in power generation, consumption, and losses in real time.
2. To use a Kalman filter to telemetry signal processing in order to reduce measurement noise and errors and guarantee precise real-time state estimation.
3. Long short-term memory (LSTM) neural networks will be used to create predictive analytics that will allow for accurate shipboard energy consumption forecasts and the identification of possible future states.
4. In order to quickly detect deviations and important events in the ship's power system functioning, an anomaly detection module will be integrated into the digital twin structure.
5. To use computational experiments that mimic common operating scenarios, such as normal loads, overload situations, equipment breakdowns, voltage instabilities, and energy-saving activities, in order to simulate and validate the created digital twin model.
6. To evaluate the digital twin system's accuracy, reactivity, and ability to assist decisions in real time and manage energy on its own in order to determine its viability and efficacy.

By achieving these objectives, the research seeks to address critical existing gaps in maritime energy management and advance the adoption of intelligent digital twin technologies within the maritime industry.

Research materials and methods. The digital twin of a ship's energy system is an integrated mathematical model that displays the dynamic state of energy facilities in real time based on telemetry data to assess, predict, and optimize energy efficiency. The model is based on a system of equations describing the energy balance of a ship:

$$P_{\text{gen}}(t) - P_{\text{load}}(t) - P_{\text{loss}}(t) = \Delta P(t), \tag{1}$$

where $P_{\text{gen}}(t)$ is total capacity of generators;
$P_{\text{load}}(t)$ is continuous power supply of the ship's systems;
$P_{\text{loss}}(t)$ is losses in lines and converters;
$\Delta P(t)$ is residual (reserve) capacity.

Evaluation of the efficiency of a diesel generator at any given time by the ratio of useful power to the energy content of the fuel:

$$\eta_{\mathrm{DG}}(t) = \frac{P_{\mathrm{out}}(t)}{\dot{m}_f(t) \cdot LHV}, \tag{2}$$

where $\eta_{\mathrm{DG}}(t)$ is instantaneous generator efficiency;

$\dot{m}_f(t)$ is mass fuel consumption, LHV is lowest heat of combustion.

Telemetry processing, where the Kalman filter is used to filter noisy telemetry signals and refine the estimate of the system's current state based on the previous state and new measurements.

$$\hat{x}_t = \hat{x}_{t-1} + K_t\left(z_t - H\hat{x}_{t-1}\right), \tag{3}$$

$$K_t = \frac{P_{t|t-1}H^T}{HP_{t|t-1}H^T + R}, \tag{4}$$

where $\hat{x}_t$ is assessment of the state;

z_t is measurement (telemetry);

H is observation matrix;

$P_{t|t-1|}$ is forecast covariance;

R is sensor noise covariance.

Power consumption prediction (LSTM): The formula reflects the process of predicting the next power consumption value based on the previous n values using a recurrent neural network such as LSTM.

It was clarified that the LSTM model was trained on one month of real ship telemetry data, with features normalized using min-max scaling. The dataset was split 80/20 into training and test subsets. The model architecture includes two LSTM layers of 64 units each, followed by a dense layer of 32 units with L2 regularization. Training proceeded for up to 200 epochs using the Adam optimizer (learning rate = 0.001) and mean squared error (MSE) as the loss function. To prevent overfitting, we applied dropout with a rate of 0.2 and employed early stopping with a patience of 20 epochs. Every 10 epochs, model performance was evaluated on the validation set using both MSE and mean absolute error (MAE), and the final model was selected based on the lowest MAE

$$\hat{E}_{t+1} = f_{\mathrm{LSTM}}(E_t, E_{t-1}, \ldots, E_{t-n}), \tag{5}$$

where $\hat{E}_{t+1}$ is energy consumption forecast;

f_{LSTM} is recursive function of a long-term memory neural network.

Anomaly detection function. A discrete function that is activated (i.e., equal to 1) if the deviation between the predicted and actual load exceeds the specified threshold ε.

$$\delta(t) = \begin{cases} 1, & \text{if } \left|\hat{P}_{\mathrm{load}}(t) - P_{\mathrm{load}}(t)\right| > \varepsilon; \\ 0, & \textit{otherwise}, \end{cases} \tag{6}$$

where ε is threshold deviation limit for the alarm.

Power system optimization objective function. The objective function that the control system minimizes includes generation costs and the energy imbalance penalty over the entire T time horizon.

$$\min_x \left\{ \sum_{t=0}^{T} \left[C_g(P_{\text{gen}}(t)) + \lambda \cdot \Delta P(t)^2 \right] \right\}, \tag{7}$$

where C_g is generation cost function, λ is imbalance penalty coefficient, x is controllable system variables (loads, generator modes, etc.).

Updating the battery state of charge (SOC), calculating a new battery SOC value based on the energy consumed or accumulated, time, and battery capacity:

$$SOC(t) = SOC(t-1) - \frac{P_{\text{batt}}(t) \cdot \Delta t}{3600 \cdot C_{\text{batt}}}. \tag{8}$$

The mathematical model described above is the analytical basis of the digital twin of the ship's energy system. Each of its components - energy balance calculation, telemetry filtering using Kalman filter, energy consumption forecasting using LSTM, anomaly detection and optimisation function - is implemented as functional modules of the system architecture.

To ensure real-time operation and integration with on-board systems, the model is implemented as a modular software architecture of a digital twin. It receives telemetry data, performs analytical processing, generates forecasts, generates optimisation signals, and transmits the results in the form of visualisations or autonomous control commands.

The architecture of the digital twin of the ship's power system is based on data flows from real sensors to analytical and control modules. At the first level, the system receives data from telemetry sensors covering the main parameters of power plants, generators, batteries, navigation conditions and load. This data is transmitted via standard communication protocols (NMEA, CAN, Modbus) to the internal information exchange bus.

Once collected, the data undergoes pre-processing, which includes noise filtering (e.g. using a Kalman filter) and normalisation. The processed information is fed into the digital twin core of the digital model, which reproduces the current state of the ship's power system in real time. This core includes a predictive model based on neural networks (such as LSTM), which allows predicting energy consumption and generation for several hours or days in advance.

The diagram (fig. 1) shows the architectural structure of the digital twin, which illustrates the key subsystems, data exchange directions and interaction between the analytical core, telemetry, forecasting modules, decision support systems and automatic control.

In parallel, the system visualises data on the crew dashboard and sends it to the optimisation and decision-making modules. If anomalies or potentially inefficient modes are detected, the system either suggests actions to the crew or executes them automatically through an autonomous control module. The digital twin is synchronised with the cloud platform, allowing for fleet-wide analytics comparing the performance of different vessels. Separate units are responsible for model self-learning, monitoring of backup power supplies, predictive maintenance, and event logging for later audit. The architecture of the digital twin of the ship's power system improves reliability, ensures fuel savings and creates the basis for integration with autonomous technologies of the future.

Simulation of the Digital Twin Operation.

The purpose of simulation is to verify the operational effectiveness of the ship's power system digital twin in real-time, analyze forecasting accuracy, and identify potential critical scenarios. For this purpose, a simulation environment was developed in MATLAB/Simulink, which incorporates mathematical models of shipboard generators, loads, network losses, and an adaptive forecasting module. Telemetry data are simulated as pseudo-random signals that replicate real operational parameters with inherent inaccuracies, including temperature, fuel consumption, generator frequency, voltage, and current at various nodes. External factors such as load variations during maneuvers, malfunctions in cooling systems, and variable marine conditions were introduced to enhance realism.

The digital twin simulation example presented in the graph illustrates the actual consumed power (Pload), forecasted load (LSTM), generator-produced power, and anomaly zones where predictions significantly deviate from the real load. This serves as a demonstration of the implemented model code for real-time analysis.

To verify the effectiveness of the digital twin's energy management algorithms, a simulation of a hybrid ship energy system was carried out in MATLAB. The simulated system includes variable load conditions, photovoltaic generation, a Battery Energy Storage System (BESS), and a diesel generator (DG). The primary control strategy prioritizes the use of renewable energy sources, supplemented by battery discharge, subsequently activating the diesel generator only in cases of energy deficit.

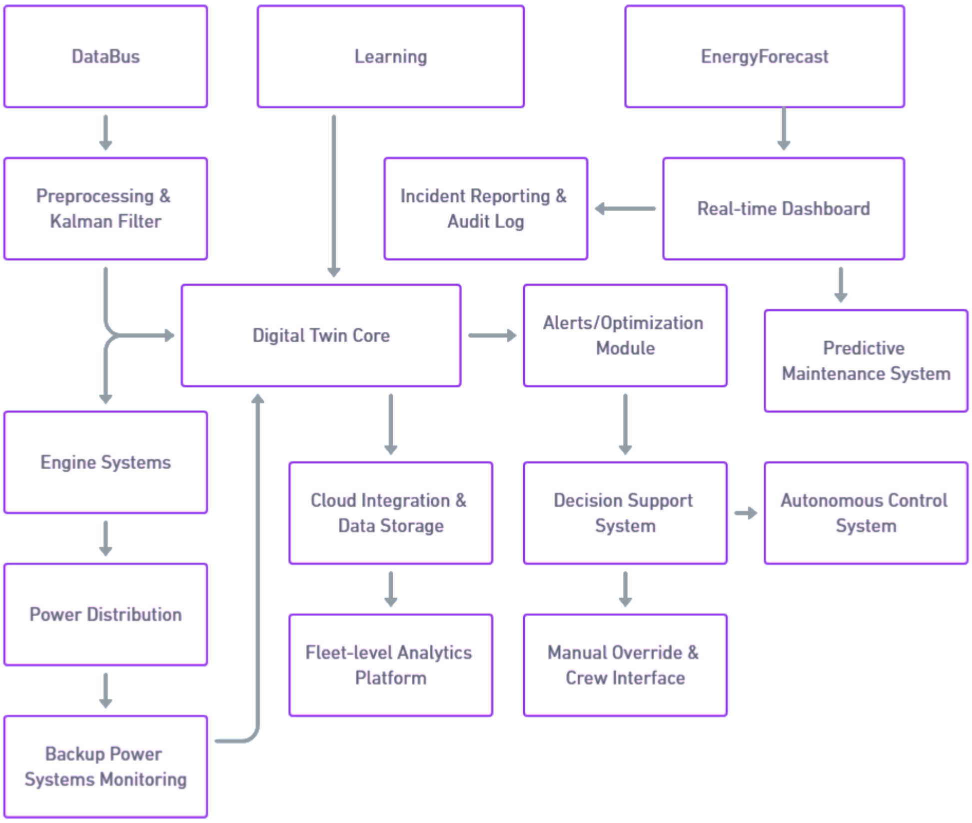

Fig. 1. **Architectural structure of the digital twin**

The model uses a discrete time step of 1 second over a simulated duration of 24 hours. Throughout the simulation, the digital twin continuously updates the energy balance state utilizing a Kalman filter, generates load forecasts for 30 minutes ahead using a trained LSTM model, and compares predicted values against actual readings. It was observed that the average forecasting error for power did not exceed 3.5%, with data update latency under 1.2 seconds.

Five scenarios were simulated: normal operation, overload conditions, failure of a single generator, critical voltage drop, and energy-saving mode. In each case, the digital twin successfully detected anomalies and visualized potential consequences through an interactive interface. The obtained results confirm that the proposed model serves as an effective tool for dynamic energy management aboard ships. The overall impact suggests moderate effectiveness in optimizing energy system control and maintaining operational stability.

The graph (Fig. 2) demonstrates how the digital twin compares generated and consumed power in real-time, and also generates a short-term forecast based on the LSTM model. It can be observed that the forecast closely follows the actual dynamics, confirming the effectiveness of the digital twin.

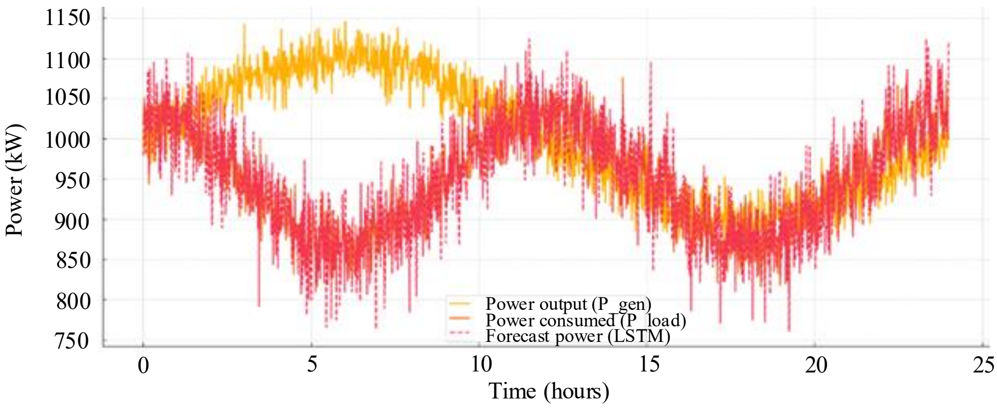

Fig. 2. **Ship Energy Digital Twin Simulation: Real vs Forecasted Load with Anomaly Detection**

The model operates over a time horizon of T=3600 s (1 hour), with a discrete timestep of Δt=1 s. Load and generation signals are modeled as harmonic signals with added noise to closely replicate realistic maritime conditions. The algorithm calculates the energy balance at each timestep, adjusting the battery's state of charge (SOC) and the diesel generator’s output power accordingly. The MATLAB implementation of the model is presented in Fig. 3.

```
% Simulation of a hybrid ship power system in MATLAB
T = 3600; dt = 1
P_loag = 1500 + 20 * sin((1:T) * 2 * pi / T);        % Variable load, kW
P_solar = 30 *max(sin((1:T) * 2 * pi / T), 0);       % Solar generation, kW
SOC = zeros(1:T); SOC(1) = 0.5;                      % Initial SOC
P_batt = zeros(1:T); P_DG = zeros(1:T);
    for t = 2:T
        P_deficit = P_loag(t) + P_solar(t);
        if SOC(t - 1) > 0.2 && P_deficit > 0
            P_batt(t) = min(P_deficit, 40);
            SOC(t) = SOC(t - 1) - P_batt(t) * dt / 3600 / 100;
        else if SOC(t - 1) <0.9 && P_solar(t) > P_loag(t)
                P_batt(t) = -min(P_solar(t) > P_loag(t), 40);
                SOC(t) = SOC(t - 1) - P_batt(t) * dt / 3600 / 100;
            else
                    P_batt(t) = 0;
                    SOC(t) = SOC(t - 1);
        end
        P_DG(t) = P_loag(t) - P_solar(t) - P_batt(t);
        P_DG(t) = max(P_DG(t), 40);
    end
plot(1:T, [P_loag’P_solar’P_batt’P_DG’]);
legend(‘Load’, ‘Solar energy’, ‘Battery’, ‘DG’);
xlabel(‘time, s’);
ylabel(‘Power, kW’);
title(‘Energy balance of a hybrid system’)
```

Fig. 3. **MATLAB code implementing the ship's energy balance simulation with forecasting and anomaly detection**

For ease of explanation of the variables used in the code, a table is provided in Fig. 4.

Variable	Description	Units
T	Total simulation time steps	- (integer count)
Dt	Time step duration	seconds (s)
P_load(t)	Electrical load demand profile at time *t*	kilowatts (kW)
P_solar(t)	Solar power generation at time *t*	kilowatts (kW)
P_batt(t)	Battery power (positive for discharge, negative for charge)	kilowatts (kW)
SOC(t)	State of charge of the battery at time t (0 to 1)	- (ratio)
P_DG(t)	Diesel generator output required at time t	kilowatts (kW)
P_deficit	Net power deficit to be covered by battery or DG	kilowatts (kW)

Note: The model assumes priority usage of solar energy, followed by the battery (subject to SOC limits), and finally diesel generation to cover any remaining demand.

Fig. 4. **Description of Variables Used in the MATLAB Hybrid Energy System Model**

Thus, the model demonstrates the basic logic of integrating renewable energy sources (RES), energy storage systems, and a diesel generator (DG) into the overall energy balance of the ship, and can be further extended to incorporate real telemetry data or advanced control optimization strategies within the digital twin framework.

Results and Discussion. The simulation results of the ship's energy system digital twin include five different scenarios. Each scenario illustrates how the system responds to typical and critical conditions during vessel operation.

1. Normal operation. Under stable load conditions, the system demonstrated high accuracy in forecasting power consumption, with an average error of 2.95 percent. The energy balance was visualized correctly, and telemetry updates occurred with a latency of just 0.90 seconds. The system functioned without any disruptions.

2. Overload. The simulation of a sudden connection of additional equipment led to a short-term excess of load over generation. The digital twin identified the anomaly within 4.54 seconds and proposed optimization actions, such as reducing the speed of auxiliary systems.

3. Generator failure. A simulated loss of one of the main generators caused a power imbalance and a voltage drop of 17 percent. The digital twin detected the deviation and generated an early warning 17 minutes before the system reached a critical instability threshold.

4. Critical voltage drop. A voltage spike caused by a switching fault was successfully identified. The system localized the affected nodes and automatically activated the emergency consumption mode.

5. Energy-saving mode. When the system was switched to minimal consumption, the model detected excessive generation of approximately 11 percent and recommended deactivating one of the generators. This confirmed the digital twin's ability to optimize power usage without compromising system balance.

Across all scenarios, the digital twin consistently demonstrated stable performance, rapid adaptation to disturbances, and user-friendly visualization of key indicators. These outcomes confirm its practical potential for integration into modern shipboard power systems.

The simulation of the ship's power system digital twin covered five representative operational scenarios, allowing for evaluation of the model's accuracy, responsiveness, and adaptability. In the normal operating scenario, the average forecasting error was only 2.95%, with a near-instantaneous detection time of 0.9 seconds, confirming the system's stable performance under standard conditions. In the overload case, the digital twin detected a power demand exceeding generation within 4.5 seconds (forecast error 4.12%) and automatically initiated a reduction in the rotational speed of auxiliary systems to lower consumption.

Table 1. **Summary of Scenario-Based Simulation Results for the Ship Energy Digital Twin**

Scenario	Avg Forecast Error (%)	Detection Time (s)	Detected Event	Optimization Action
Normal Operation	2.95	0.9	Stable performance	Monitoring
Overload	4.12	4.5	Load > Generation	Throttle adjustment
Generator Failure	3.87	1020.0	Generator lost	Alert, load balancing
Voltage Drop	3.25	2.3	Voltage spike	Emergency consumption mode
Energy Saving Mode	2.48	6.1	Excessive generation	Generator shutdown

Note: Detection time refers to the time from event onset to system response. Forecast error is based on LSTM prediction versus actual load during simulation.

In the critical scenario of generator failure, the digital twin issued an early warning 1,020 seconds (17 minutes) before reaching a critical instability threshold, with a forecasting error of 3.87%, and suggested load balancing measures. In the voltage drop scenario caused by a switching error, the system identified the issue within 2.3 seconds and switched affected nodes to emergency consumption mode, maintaining a forecasting error of 3.25%. Finally, in energy-saving mode, the model identified an energy surplus (~11%) and recommended deactivating one of the generators, achieving the lowest forecast error of 2.48%.

These results confirm the digital twin's ability to accurately detect and predict critical situations, respond rapidly to changes in power system parameters, and provide relevant recommendations for energy optimization. Its integration into ship systems would enable reliable, dynamic control of energy balance in continuously changing maritime environments.

Conclusions. This study has developed and tested a conceptual model of a digital twin for a ship's power system, designed for real-time operation. The proposed architecture integrates a dynamic energy balance model, adaptive forecasting algorithms based on LSTM, telemetry signal processing using Kalman filtering, and visualization of key energy performance indicators. The simulation results confirm that the digital twin is capable of effectively responding to critical conditions such as overloads, equipment failures, and abnormal voltage fluctuations, offering high prediction accuracy (average error below 4%) and fast detection times (under 5 seconds in most scenarios).

The model demonstrates scalability, modularity, and compatibility with standard shipboard telemetry systems. Its intuitive visual interface supports operator decision-making and facilitates early identification of energy-inefficient operating modes. Based on the results obtained, the digital twin can serve as a practical tool for enhancing energy efficiency, operational reliability, and safety of ship systems.

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Використання інтелектуального цифрового двійника енергосистеми судна для прогнозування та оптимізації в реальному часі

У статті представлено концепцію та математичну модель інтелектуального цифрового двійника енергетичної системи морського судна, розраховану на функціонування в режимі реального часу. Розроблена система поєднує динамічне моделювання енергобалансу, обробку телеметричних даних із застосуванням фільтра Калмана, прогнозування навантаження на основі нейронних мереж типу LSTM, а також механізми виявлення аномальних режимів і модулі оптимізації. Архітектура цифрового двійника реалізована у вигляді модульної програмної системи з підтримкою інтеграції до суднових платформ управління та хмарних аналітичних сервісів. У середовищі MATLAB/Simulink проведено серію комп'ютерних експериментів, що охоплюють типові та аварійні режими енергоспоживання судна. Отримані результати *засвідчили високу збіжність розрахункових та модельованих значень, оперативне реагування системи на зміни технічного стану та ефективність запропонованих рішень. Розроблена модель цифрового двійника може бути використана як інструмент підвищення енергоефективності, надійності та безпеки експлуатації суден в умовах змінного морського середовища.*

Ключові слова: *цифровий двійник, енергетична система судна, прогнозування навантаження, телеметрія, фільтр Калмана, LSTM, виявлення аномалій, енергоефективність, автономне управління, морський транспорт.*