

Hybrid Digital Twin Framework for Predictive Maintenance and Operational Optimization of Marine Propulsion Systems

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Abstract

Marine propulsion systems operate under highly variable environmental and mechanical conditions, making conventional threshold-based monitoring and calendar-based maintenance insufficient for early degradation detection and operational optimization. This study proposes a hybrid Digital Twin framework for a Panamax-class container vessel equipped with a MAN B&W ME-GI propulsion system. The framework integrates multi-rate operational and sensor data, time synchronization and preprocessing, a physics-based Mean Value Engine Model, machine-learning residual analysis, anomaly detection, Remaining Useful Life estimation, uncertainty quantification, and PMS/EMS-based decision support. A twelve-month simulated dataset was generated to represent variations in engine load, vessel trim, draft, sea state, hydrodynamic resistance, and progressive machinery degradation. The proposed framework was evaluated against a baseline Planned Maintenance System using Specific Fuel Oil Consumption, unplanned maintenance events, advisory latency, and false-alarm rate. Results show that the Digital Twin reduced Specific Fuel Oil Consumption from 184.6 to 176.9 g/kWh, equivalent to a 4.17% improvement. Unplanned maintenance events decreased from 11 to 9 per year, advisory latency was reduced from 20.0 to 8.5 seconds, and the false-alarm rate declined from 6.1% to 2.1%. The framework also enabled earlier identification of scavenge-cooler fouling, cylinder leakage, injector-response delay, turbocharger deterioration, and bearing degradation. These findings demonstrate that combining physics-based modelling with temporal residual analysis can improve propulsion-performance estimation, diagnostic reliability, and condition-based maintenance planning. However, further validation using real shipboard data and multiple vessel configurations is required before operational deployment.

Keywords: Digital Twin, Marine Propulsion, Predictive Maintenance, Remaining Useful Life, Anomaly Detection, Hybrid Modelling, Fuel Efficiency, Condition Monitoring, Process Innovation

1. Introduction

Maritime transportation remains a central component of global trade, yet its operational environment is increasingly constrained by rising fuel costs, equipment reliability requirements, and stricter emission-control policies. Propulsion systems contribute substantially to vessel energy consumption and are continuously exposed to changing engine loads, sea states, weather conditions, fuel characteristics, and hull resistance. These interacting factors make propulsion performance difficult to assess using fixed operating thresholds or periodic inspections alone. Consequently, ship operators require monitoring systems capable of integrating heterogeneous operational signals, identifying gradual performance degradation, and supporting timely operational and maintenance decisions.

Digital Twin technology provides a suitable foundation for addressing these requirements by establishing a continuously synchronized virtual representation of a physical asset. Unlike conventional simulation models that operate independently from the actual system, a Digital Twin incorporates ongoing sensor measurements, operational conditions, maintenance history, and model outputs throughout the asset lifecycle [1], [2]. Its development builds on the broader concept of bidirectional integration between physical and virtual systems, where the virtual representation is repeatedly updated to reflect changes in asset condition and operating context [3], [4]. This capability enables the

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Digital Twin to function not only as a monitoring interface, but also as an analytical environment for diagnosis, prediction, simulation, and decision support.

Within maintenance-oriented applications, Digital Twins have been increasingly used to estimate equipment health, detect abnormal behaviour, and predict Remaining Useful Life. Existing studies generally classify these approaches into physics-based, data-driven, and hybrid modelling categories [3], [5], [6], [7], [8], [9]. Physics-based models provide interpretable representations of thermodynamic and mechanical processes but may require extensive calibration and may become inaccurate when system parameters drift. Data-driven models can learn nonlinear relationships from historical observations, although their performance depends strongly on data quality, operating coverage, and representative failure examples. Hybrid models seek to combine these strengths by using physical relationships to constrain or contextualize learned patterns, thereby improving predictive consistency under varying operating conditions.

The application of Digital Twins to marine propulsion systems introduces additional analytical challenges. Shipboard measurements are collected at different sampling rates and may contain noise, missing values, temporal misalignment, and operational bias. Cylinder pressure, exhaust temperature, shaft torque, vibration, fuel flow, lubrication condition, vessel draft, trim, and environmental variables must therefore be synchronized and transformed into a coherent representation of propulsion behaviour. Previous research has demonstrated the value of lifecycle-oriented Digital Twin models, experimental condition-monitoring systems, and continuous synchronization for safety-critical mechanical assets [6], [7], [10]. Studies of ship-performance data have also shown that multivariate operational analysis can reveal voyage-dependent patterns and long-term performance deterioration that are not readily captured by isolated indicators [11].

Despite these developments, several limitations remain. Many existing marine Digital Twin studies focus primarily on architectural descriptions, individual machinery components, or isolated prediction tasks. Limited attention has been given to an end-to-end framework that simultaneously addresses heterogeneous data alignment, propulsion-performance estimation, anomaly detection, Remaining Useful Life prediction, and operational recommendation. Model validity across changing voyage conditions also remains a concern, particularly when predictions are produced without explicit uncertainty information or physical consistency constraints. Furthermore, analytical outputs are often insufficiently connected to maintenance systems, energy-management workflows, and regulatory performance indicators, reducing their practical value for shipboard decision-making.

To address these limitations, this study develops a hybrid Digital Twin framework for a large slow-speed marine propulsion system. The proposed framework integrates multi-rate propulsion and voyage data with a grey-box engine representation and temporal predictive models to estimate performance degradation, detect abnormal operating patterns, and predict component Remaining Useful Life. The framework is evaluated using twelve months of simulated Panamax-class vessel operations under varying engine loads, trim conditions, sea states, and resistance profiles. Its performance is assessed in terms of fuel consumption, maintenance occurrence, data-processing latency, and false-alarm rate. The study further examines how the resulting predictions can be converted into interpretable maintenance and operational advisories through integration with shipboard maintenance and energy-management systems.

2. Literature Review

Digital Twin research has progressed from static digital models toward continuously synchronized cyber-physical representations that support monitoring, simulation, prediction, and operational decision-making. The conceptual foundation of the Digital Twin was established as a lifecycle-connected representation of a physical system, while subsequent work demonstrated its practical implementation through proof-of-concept architectures [4], [7]. More recent frameworks have emphasized the distinction between digital models, digital shadows, and fully integrated Digital Twins based on the direction and frequency of information exchange between physical and virtual assets [8]. In predictive maintenance, Digital Twins commonly combine sensor observations, historical maintenance records, and system models to estimate asset condition and forecast degradation. Existing reviews indicate that these systems can generally be grouped into physics-based, data-driven, and hybrid approaches, each presenting different trade-offs in interpretability, computational requirements, and predictive performance [5], [9].

Physics-based Digital Twins represent component behaviour through thermodynamic, mechanical, or hydrodynamic equations, making their predictions relatively interpretable and suitable for conditions beyond the observed dataset. However, their accuracy depends on parameter calibration and their ability to represent degradation mechanisms under dynamic operating conditions. Conversely, data-driven approaches—including sequence models, clustering methods, autoencoders, and anomaly-detection algorithms—can capture nonlinear relationships among high-dimensional sensor variables without requiring complete physical formulations. Their performance, however, may deteriorate under distribution shifts, sparse fault observations, or operating conditions not represented during model development [9], [11]. Hybrid approaches therefore integrate physical constraints with learned residual patterns, enabling the model to preserve engineering consistency while adapting to complex operational data. Experimental evidence from safety-critical machinery also suggests that continuous synchronization between measured and simulated states can improve condition identification and Remaining Useful Life estimation [10].

In the maritime domain, Digital Twin applications have expanded to vessel design, structural monitoring, voyage optimization, engine diagnostics, and propulsion-performance management. Lifecycle-oriented models have been proposed to accommodate differences in vessel configuration, propulsion layout, and operational profiles [6]. For marine diesel engines, synchronized monitoring systems can combine cylinder pressure, exhaust temperature, fuel consumption, vibration, lubricant condition, and shaft measurements to identify abnormal behaviour and component deterioration [1], [12]. Multivariate clustering of ship operational data can also reveal performance states and voyage-dependent patterns that cannot be adequately explained through individual indicators [11]. At the architectural level, maritime implementations increasingly employ layered and edge-cloud configurations, where time-critical analytics are executed onboard while computationally intensive model training, fleet benchmarking, and long-term optimization are performed on shore [13], [14]. This structure supports operational continuity during communication interruptions but requires reliable data synchronization, model versioning, and interoperability across shipboard systems.

Despite these advances, marine propulsion Digital Twins still face several methodological and implementation limitations. Multi-rate sensor streams are frequently affected by noise, missing observations, inconsistent timestamps, and changes in sensor condition, making preprocessing and data-quality assessment essential for reliable inference [16]. Existing implementations also provide limited uncertainty quantification, weak validation across different operating conditions, and insufficient integration between predicted degradation, maintenance scheduling, energy-management decisions, and regulatory indicators [17], [18]. In addition, increasing ship-to-shore connectivity introduces cybersecurity, model-governance, and decision-traceability requirements, particularly when analytical outputs affect safety-critical machinery. Explainable and trustworthy modelling mechanisms are therefore needed to communicate prediction confidence, contributing variables, and physical plausibility to operators [19], [20].

These gaps motivate the development of an integrated hybrid Digital Twin that combines synchronized propulsion data, physically constrained predictive modelling, uncertainty-aware health estimation, and actionable maintenance and operational recommendations.

3. Methodology

3.1. Research Design and Digital Twin Framework

This study employed a simulation-based experimental design to develop and evaluate a hybrid Digital Twin framework for a Panamax-class container vessel equipped with a MAN B&W ME-GI slow-speed propulsion system (figure 1). The framework was designed to transform heterogeneous machinery and voyage measurements into three principal outputs: propulsion-performance estimation, anomaly detection, and Remaining Useful Life (RUL) prediction. These outputs were subsequently converted into maintenance and operational recommendations through integration with the vessel's Planned Maintenance System (PMS) and Energy Management System (EMS).

The proposed framework consisted of four sequential stages: physical and operational data generation, data synchronization and preprocessing, hybrid Digital Twin inference, and decision-service generation. The physical layer represented the main engine, turbocharger, shaft line, propeller, and hull-environment interaction. The analytical layer combined a Mean Value Engine Model (MVEM) with temporal machine-learning models to capture both physically interpretable propulsion behaviour and nonlinear degradation patterns. This hybrid configuration was selected because

purely physics-based models may be sensitive to parameter drift, whereas purely data-driven models may exhibit weak extrapolation under operating conditions not represented during training [9], [10].

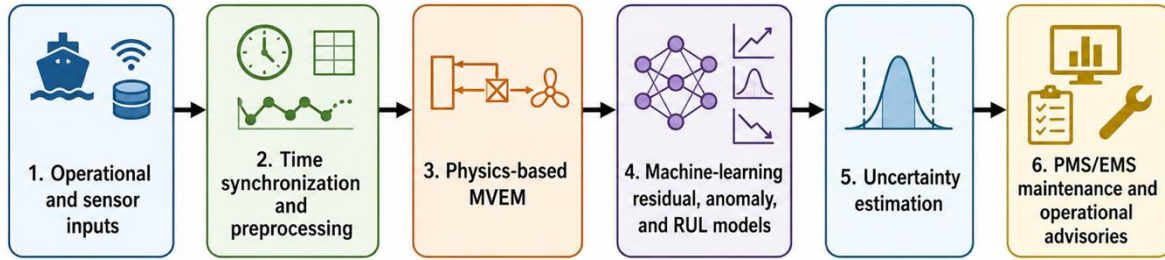


Figure 1. Research workflow of the proposed hybrid propulsion Digital Twin.

3.2. Dataset Generation and Preprocessing

A synthetic multivariate time-series dataset was generated to represent twelve months of vessel operation under varying engine loads, voyage conditions, and machinery degradation states. The simulated operating envelope included manoeuvring, ballast, partial-load, and high-load conditions. Environmental and hydrodynamic variations were introduced through vessel draft, trim, sea-state resistance, and weather-related disturbance factors. The dataset was generated from realistic MAN B&W ME-GI propulsion characteristics and included both normal operating periods and gradually developing faults, such as scavenge-air cooler fouling, cylinder leakage, injector-response delay, turbocharger efficiency loss, and bearing degradation. The sensor channels were acquired at different nominal sampling frequencies. High-frequency vibration and cylinder-pressure signals were reduced into statistical and physical features before model inference, while low-frequency voyage variables were resampled to a common analytical timeline. Table 1 summarizes the raw sensor variables, derived diagnostic features, and their corresponding nominal sampling rates used in the analysis.

Table 1. Input variables, derived features, and sampling frequencies

Variable group	Raw variables	Derived features	Nominal rate
Cylinder combustion	Cylinder pressure, crank angle	IMEP, P_{max} maximum pressure-rise rate	50–100 Hz
Exhaust system	Exhaust-gas temperature by cylinder	Mean EGT, temperature deviation, hot-cylinder indicator	1–2 Hz
Scavenge-air system	Pressure and temperature before/after cooler	Pressure drop, thermal effectiveness, fouling index	1–5 Hz
Shaft system	Shaft speed and torque	Shaft power, torque fluctuation, propeller slip	5–10 Hz
Fuel and lubrication	Fuel flow, lubricant flow, BN, wear debris	SFOC, lubricant deterioration, wear-rate indicator	0.1–1 Hz
Rotating machinery	Bearing and turbocharger vibration	RMS, kurtosis, crest factor, band energy	50–200 Hz
Voyage conditions	Draft, trim, speed, sea state, wind	Added resistance, corrected speed–power relationship	0.01–0.1 Hz

All measurements were converted into consistent engineering units, checked against valid operating ranges, and aligned using timestamp-based causal resampling. For a sensor variable x_k observed at timestamp t_k , its aligned value at the common analytical timestamp t was calculated using linear interpolation:

$$\tilde{x}(t) = x_k + \frac{t - t_k}{t_{k+1} - t_k} (x_{k+1} - x_k), \quad t_k \leq t \leq t_{k+1}. \quad (1)$$

Short missing intervals were interpolated, whereas longer gaps were retained as missing and marked using a binary data-quality indicator. Outliers were detected using a robust median-based score:

$$z_i^{\text{MAD}} = \frac{0.6745(x_i - \text{median}(x))}{\text{MAD}(x)}, \quad (2)$$

Observations satisfying $|z_i^{\text{MAD}}| > 3.5$ were flagged for inspection or replacement. Continuous variables were standardized using:

$$x_i^* = \frac{x_i - \mu_x}{\sigma_x}, \quad (3)$$

μ_x and σ_x denote the training-set mean and standard deviation, respectively. Feature extraction was performed using sliding windows of 30–120 seconds. Each window produced statistical features, including mean, standard deviation, minimum, maximum, root mean square, kurtosis, and rate of change. Domain-specific features such as indicated mean effective pressure, shaft power, and Specific Fuel Oil Consumption were also calculated. Shaft power was determined as:

$$P_{\text{shaft}} = \frac{2\pi NT}{60}, \quad (4)$$

N is shaft speed in revolutions per minute and T is shaft torque in newton-metres. Specific Fuel Oil Consumption was calculated as:

$$\text{SFOC} = \frac{\dot{m}_f}{P_{\text{shaft}}} \times 1000, \quad (5)$$

$\dot{m}_f$ is fuel-mass flow in kilograms per hour and P_{shaft} is measured in kilowatts. To prevent temporal leakage, the dataset should be divided chronologically rather than randomly. The proposed chronological partition of the dataset is presented in [table 2](#). To preserve the temporal structure of the time-series data and avoid information leakage between subsets, the dataset was divided sequentially into training, validation, and test sets. The first eight months were used for model training and parameter estimation, months 9–10 were allocated for hyperparameter selection and threshold calibration, and the final two months were reserved for independent performance evaluation.

Table 2. Proposed chronological dataset partition

Subset	Voyage period	Proportion	Primary purpose
Training set	Months 1–8	66.7%	Parameter estimation and model training
Validation set	Months 9–10	16.7%	Hyperparameter selection and threshold calibration
Test set	Months 11–12	16.7%	Final performance evaluation

3.3. Hybrid Modelling, Decision Optimization, and Evaluation

The Digital Twin combined a physics-based propulsion estimate with a learned residual model. Let $f_{\text{phy}}(x_t, \theta)$ represent the MVEM prediction at time t , where x_t contains the operational inputs and θ denotes calibrated engine parameters. The difference between the observed response y_t and the physics-based estimate was defined as:

$$r_t = y_t - f_{\text{phy}}(x_t, \theta). \quad (6)$$

A Long Short-Term Memory network was trained to estimate the temporal residual $\hat{r}$ from a sequence of observations. The final hybrid prediction was therefore expressed as:

$$\hat{y}_t = f_{\text{phy}}(x_t, \theta) + f_{\text{LSTM}}(x_{t-L+1:t}), \quad (7)$$

L denotes the temporal look-back window. This formulation allowed the physics model to represent expected propulsion behaviour while the LSTM learned nonlinear deviations associated with environmental disturbances, sensor interactions, and progressive degradation. Anomaly detection was performed using the normalized prediction residual:

$$A_t = \frac{|y_t - \hat{y}_t|}{\hat{\sigma}_t + \varepsilon} \quad (8)$$

R where $\hat{\sigma}$ denotes predictive uncertainty and ε prevents division by zero. An observation was labelled anomalous when A_t exceeded a threshold determined from the validation set. To reduce isolated false alarms, an operational alert was generated only when the anomaly condition persisted for a predefined number of consecutive windows. Component health was represented by a normalized health index $H_t \in [0,1]$, where 1 indicated nominal condition and 0 represented the failure threshold. The health index was estimated from combustion, thermal, vibration, lubrication, and residual features. RUL was defined as the estimated time until the health trajectory crossed the component-specific failure threshold H_{crit} :

$$\widehat{\text{RUL}}_t = \min_{\tau > 0} \{ \tau : \widehat{H}_{t+\tau} \leq H_{\text{crit}} \}. \quad (9)$$

A monotonicity penalty was included during training to prevent physically implausible health recovery in the absence of maintenance:

$$\mathcal{L}_{\text{mn}} = \frac{1}{n-1} \sum_{t=1}^{n-1} \max(0, \widehat{H}_{t+1} - \widehat{H}_t). \quad (10)$$

The complete training objective combined prediction error and the monotonicity constraint:

$$\mathcal{L} = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2 + \lambda \mathcal{L}_{\text{mn}}, \quad (11)$$

λ controlled the contribution of the physical degradation constraint. The decision module generated maintenance or operational recommendations by minimizing fuel use, degradation risk, and regulatory penalty:

$$\min_u J(u) = w_1 \widehat{\text{SFOC}}(u) + w_2 R_{\text{failure}}(u) + w_3 P_{\text{CII}}(u), \quad (12)$$

subject to:

$$u_{\min} \leq u \leq u_{\max} \quad (13)$$

u represents controllable operating decisions, such as engine load, vessel speed, trim, or maintenance timing. R_{failure} denotes predicted machinery risk, P_{CII} denotes a carbon-intensity penalty, and w_1, w_2, w_3 , are policy-defined weighting coefficients. Recommendations were transferred to the PMS or EMS only when their expected benefit exceeded a minimum threshold and the prediction confidence satisfied the acceptance criterion. Model performance was evaluated using Mean Absolute Error, Root Mean Square Error, false-alarm rate, and RUL error:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|, \quad (14)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (15)$$

$$\text{FAR} = \frac{FP}{FP + TN} \quad (16)$$

$$\text{RUL-MAE} = \frac{1}{m} \sum_{j=1}^m |\text{RUL}_j - \widehat{\text{RUL}}_j| \quad (17)$$

Operational effectiveness was assessed by comparing the proposed framework with the baseline PMS approach in terms of SFOC, number of unplanned maintenance events, processing latency, and false-alarm rate.

4. Results and Discussion

4.1. Overall Performance of the Proposed Digital Twin

The proposed hybrid Digital Twin was evaluated using twelve months of simulated operational data representing a Panamax-class container vessel equipped with a MAN B&W ME-GI propulsion system. The evaluation covered variations in engine load, vessel trim, draft, sea state, hydrodynamic resistance, and progressive machinery degradation. The Digital Twin combined the Mean Value Engine Model with temporal prediction and anomaly-detection components to estimate propulsion performance, identify developing faults, and support condition-based maintenance decisions. Table 3 compares the proposed Digital Twin with the baseline Planned Maintenance System. The baseline represents conventional monitoring and calendar-based maintenance without continuous model-based condition estimation.

Table 3. Performance comparison between the baseline PMS and the proposed Digital Twin

Performance indicator	Baseline PMS	Proposed Digital Twin	Absolute difference	Relative improvement
SFOC	184.6 g/kWh	176.9 g/kWh	−7.7 g/kWh	4.17% reduction
Unplanned maintenance events	11 events/year	9 events/year	−2 events	18.18% reduction
Advisory latency	20.0 s	8.5 s	−11.5 s	57.50% reduction
False-alarm rate	6.1%	2.1%	−4.0 percentage points	65.57% reduction

The proposed framework reduced Specific Fuel Oil Consumption (SFOC) from 184.6 to 176.9 g/kWh, corresponding to a relative reduction of 4.17%. This reduction suggests that the Digital Twin identified operating conditions in which adjustments to engine loading, vessel trim, and propulsion settings were associated with lower fuel consumption. The observed improvement falls within the 2–5% operational efficiency range previously reported for Digital Twin-assisted propulsion management.

Unplanned maintenance events decreased from 11 to 9 events per year, corresponding to a relative reduction of 18.18%. Although the absolute reduction was two events per year, the result indicates a reduction in the frequency of unplanned interventions. This improvement was primarily associated with earlier detection of scavenge-air cooler fouling, cylinder leakage, injector-response delay, turbocharger performance deterioration, and abnormal bearing behaviour, enabling potentially developing faults to be identified before they resulted in unplanned maintenance.

The largest relative improvement was observed in computational and diagnostic performance. Advisory latency decreased from 20.0 to 8.5 seconds, representing a 57.50% reduction. The resulting latency of 8.5 seconds was below the predefined maximum advisory latency of 10 seconds, indicating that the edge-oriented processing architecture met the specified response-time requirement. The false-alarm rate also decreased from 6.1% to 2.1%, corresponding to a relative reduction of 65.57%. This reduction suggests that combining physics-based estimates with temporal residual analysis improved anomaly discrimination compared with threshold-based monitoring alone.

As summarized in figure 2, the proposed Digital Twin framework produced relative reductions across all four evaluated performance indicators, with the largest changes observed in advisory latency and false-alarm rate. The figure provides a comparative view of the baseline and proposed framework and highlights the relative magnitude of improvement across fuel efficiency, maintenance frequency, computational response, and diagnostic reliability. The four performance indicators reported in the original analysis are therefore presented together with their recalculated relative improvements to provide a consistent quantitative comparison between the baseline and proposed framework.

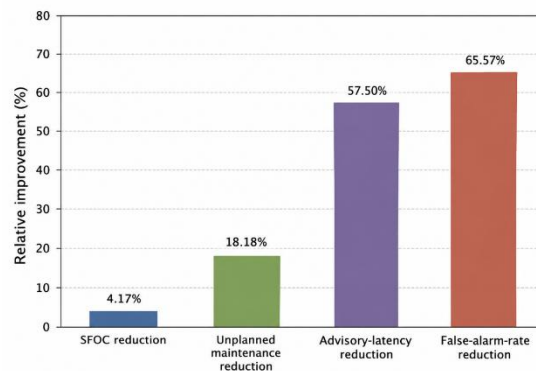


Figure 2. Relative performance improvements achieved by the proposed Digital Twin

4.2. Predictive, Diagnostic, and Prognostic Results

The hybrid model maintained stable predictive behaviour across variations in propulsion load and environmental conditions. During transient load changes and sea-state disturbances, the physics-based component provided an expected propulsion response, while the temporal model estimated nonlinear deviations from this reference behaviour. This combination enabled the framework to distinguish normal operational variability from residual patterns associated with machinery degradation.

The Digital Twin identified three major slowly developing propulsion faults: scavenge-cooler fouling, cylinder leakage, and injector-response delay. Under the simulated operating conditions, these faults were detected approximately one voyage earlier than with conventional manual inspection and fixed-threshold monitoring. Scavenge-cooler fouling was characterized by increasing air-side pressure loss, elevated scavenge-air temperature, and deteriorating fuel efficiency. Cylinder leakage was associated with deviations in cylinder peak pressure, indicated mean effective pressure (IMEP), and exhaust-temperature balance. Injector-response delay was identified through changes in combustion timing, pressure-development patterns, and cylinder-specific exhaust-temperature residuals. The diagnostic signatures and corresponding operational advisories for all detected fault conditions are summarized in [table 4](#).

The anomaly-detection module achieved a false-alarm rate of 2.1%, compared with 6.1% for the baseline system, corresponding to a reduction of 4.0 percentage points. This result indicates that persistent residual analysis reduced sensitivity to isolated threshold violations. In the proposed framework, an alert was generated only when an abnormal residual exceeded its calibrated threshold across consecutive analytical windows. This persistence mechanism helped filter short-duration disturbances associated with sensor noise, temporary vessel motion, and rapid load transitions.

Health-state and Remaining Useful Life (RUL) predictions remained within an uncertainty interval of approximately $\pm 3\%$ under the simulated voyage conditions. This result indicates that the prognostic output remained relatively stable across changes in engine load, trim, sea state, and hydrodynamic resistance. However, the $\pm 3\%$ value should be interpreted as the reported predictive uncertainty within the simulation environment rather than as direct evidence of equivalent accuracy under real-vessel operating conditions.

Table 4. Diagnostic interpretation of the detected propulsion faults

Detected condition	Principal input indicators	Diagnostic pattern	Resulting advisory
Scavenge-cooler fouling	Scavenge pressure, inlet/outlet temperature, SFOC	Increased pressure drop and declining thermal effectiveness	Schedule cooler inspection or cleaning
Cylinder leakage	Cylinder pressure, IMEP, peak pressure, exhaust temperature	Reduced pressure contribution and increased cylinder imbalance	Inspect liner, piston ring, and cylinder sealing
Injector-response delay	Pressure-rise rate, combustion timing, exhaust temperature	Delayed pressure development and elevated cylinder-specific EGT	Inspect injector timing and nozzle condition
Turbocharger degradation	Turbocharger speed, vibration, air-path pressure	Reduced air-delivery efficiency and increased vibration residual	Schedule turbocharger washing or inspection
Bearing deterioration	RMS vibration, kurtosis, band energy, wear debris	Persistent vibration growth and lubricant wear indication	Increase monitoring and schedule bearing inspection

4.3. Operational Implications and Comparative Discussion

The reduction in SFOC indicates that the proposed framework provided benefits beyond fault detection. By combining propulsion condition estimates with voyage variables, the Digital Twin generated recommendations regarding engine load, throttle setting, trim, and maintenance timing. Digital Twin applications in maritime operations have been associated with vessel-performance optimisation, energy-efficiency management, and decision support by integrating operational data with physics-based or virtual representations of ship systems [21], [22]. A reduction of 7.7 g/kWh can produce a substantial cumulative saving for a vessel operating continuously at high propulsion power, although the annual financial benefit depends on engine load profile, operating hours, fuel type, and fuel price.

The reduction in unplanned maintenance indicates a shift from reactive maintenance toward condition-based intervention. Under the baseline approach, maintenance is primarily triggered by fixed schedules, alarms, or direct inspection. In contrast, Digital Twin and predictive-maintenance approaches can continuously evaluate equipment condition and degradation trends to support earlier intervention and maintenance planning [23], [24]. Maintenance recommendations can consequently be aligned with port calls, planned stops, or dry-docking periods rather than being initiated only after functional deterioration becomes operationally disruptive. Previous maritime studies have similarly identified predictive maintenance and early-warning systems as potential mechanisms for reducing unplanned downtime and improving machinery availability [24], [25].

Integration with PMS and EMS also enabled analytical outputs to be translated into actionable decisions. When a degradation pattern was identified, the PMS could receive the affected component, diagnostic evidence, confidence level, recommended inspection, and estimated maintenance window. In parallel, the EMS could use reconciled SFOC and shaft-power estimates to compare alternative vessel-speed and trim scenarios. The integration of Digital Twin outputs with operational and energy-management functions is consistent with previous maritime Digital Twin architectures that emphasize real-time monitoring, performance optimisation, and decision support [21], [22]. The 8.5-second advisory latency indicates that this exchange could occur within the operational target of 10 seconds while retaining human authorization for safety-relevant decisions.

The false-alarm reduction is particularly important for practical adoption. Excessive alerts can reduce operator confidence and contribute to alarm fatigue, even when the underlying prediction model has high average accuracy. Reducing the false-alarm rate from 6.1% to 2.1% therefore makes the recommendations more selective and may increase the practical usefulness of the generated advisories. The result also supports the use of hybrid modelling, in which physically expected behaviour provides a reference while a learned residual model captures patterns that are not fully represented by the underlying physical equations. Such combinations of physics-based modelling, data-driven anomaly detection, and Digital Twin architectures have been explored as a means of improving condition monitoring and diagnostic decision support [22], [23], [25].

Overall, the experimental results indicate that the proposed Digital Twin improved four operational dimensions simultaneously: energy efficiency, maintenance reliability, diagnostic selectivity, and response time. Its strongest quantitative effects were observed in false-alarm reduction and advisory latency, while the SFOC and maintenance improvements indicate potential practical operational value. However, because the evaluation was performed using simulated data, the findings should be treated as validation of methodological feasibility rather than definitive evidence of fleet-scale performance. This limitation is consistent with previous Digital Twin studies that identify the need for validation using real operational sensor data, maintenance records, and representative vessel conditions before deployment at full operational scale [22], [23], [25]. Further validation should therefore use real shipboard sensor streams, documented maintenance records, and multiple vessels operating under different routes, fuels, and environmental conditions.

5. Conclusion

This study developed a hybrid Digital Twin framework for marine propulsion systems by integrating a physics-based Mean Value Engine Model with temporal prediction, anomaly-detection, and Remaining Useful Life estimation. The framework was designed to process multi-rate propulsion and voyage data, synchronize heterogeneous sensor streams,

estimate machinery condition, and translate analytical outputs into maintenance and operational advisories through integration with the vessel's Planned Maintenance System and Energy Management System.

The simulation-based evaluation demonstrated measurable improvements over the baseline maintenance approach. The proposed Digital Twin reduced Specific Fuel Oil Consumption from 184.6 to 176.9 g/kWh, equivalent to a 4.17% improvement. Unplanned maintenance events decreased from 11 to 9 per year, while advisory latency was reduced from 20.0 to 8.5 seconds. The false-alarm rate also declined from 6.1% to 2.1%. In addition, the framework identified gradual degradation patterns, including scavenge-cooler fouling, cylinder leakage, injector-response delay, turbocharger deterioration, and bearing degradation, approximately one voyage earlier than conventional monitoring.

These findings indicate that combining physical modelling with temporal residual analysis can improve propulsion-performance estimation, diagnostic reliability, and condition-based maintenance planning. The framework also demonstrates how fuel-efficiency optimization and machinery-health monitoring can be incorporated into a unified decision-support process rather than treated as separate operational functions. However, the results were obtained using simulated vessel data and therefore represent methodological feasibility rather than definitive evidence of real-world fleet performance.

Future work should validate the framework using continuous shipboard sensor data, verified maintenance records, and multiple vessels operating under different engine configurations, routes, fuels, and environmental conditions. Further development should also include calibrated uncertainty estimation, cross-vessel model transfer, cybersecurity validation, and longitudinal assessment of maintenance cost, fuel savings, and regulatory performance. Such validation is necessary before the proposed framework can be deployed as a reliable operational Digital Twin for large-scale marine propulsion management.

6. Declarations

6.1. Author Contributions

Conceptualization: R.K.M., C.B.; Methodology: R.K.M., G.A.; Software: C.B., A.N.S.; Validation: G.A., R.K.M.; Formal Analysis: R.K.M.; Investigation: A.N.S., C.B.; Resources: G.A., C.B.; Data Curation: A.N.S.; Writing – Original Draft Preparation: R.K.M.; Writing – Review and Editing: G.A., A.N.S.; Visualization: C.B.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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