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TOWARDS THE DIGITAL TWIN-ENABLED V2I MONITORING OF SHIP POWER PLANTS UNDER REAL OPERATING CONDITIONS

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Resume

In this paper is presented an ITS-oriented framework for monitoring and predictive assessment of ship power plants based on V2I communication and digital twin principles. The framework integrates onboard sensor data with environmental and operational information in a unified cyber-physical environment. A mathematical model and structured algorithm support state estimation, prediction, diagnostics, and decision-making under non-stationary conditions. The distributed architecture combines onboard systems, communication networks, and infrastructure-level processing. Validation using real operational data demonstrates that the framework captures variations in vessel speed, fuel consumption, and engine performance while providing reliable parameter estimates. The results confirm its feasibility for maritime monitoring, digital twin development, and predictive maintenance.

Article info

Received 10 May 2026
Accepted 21 July 2026
Online 20 August 2026

Keywords:

intelligent transport systems
V2I communication
digital twin
remote monitoring
maritime transport
condition monitoring
cyber-physical systems

Available online: https://doi.org/10.26552/com.C.2026.047

ISSN 1335-4205 (print version)
ISSN 2585-7878 (online version)

1 Introduction

The rapid digitalization of maritime transport has stimulated the development of intelligent monitoring systems aimed at improving operational efficiency, safety, and sustainability. Modern vessels operate under dynamically changing conditions where the technical, environmental, and operational factors continuously interact. Under such non-stationary conditions, traditional onboard monitoring systems remain limited due to their reliance on isolated data sources and insufficient situational awareness.

The evolution of Intelligent Transport Systems (ITS) has enabled the integration of communication, control, and information technologies across transport domains. In maritime applications, Vehicle-to-Infrastructure (V2I) communication supports continuous data exchange between the vessels and shore-based infrastructure, enabling real-time monitoring and decision-making. However, existing maritime V2I approaches remain constrained by fragmented data integration, limited consideration of operating conditions, and communication instability.

At the same time, Digital Twin technologies have emerged as an effective approach for representing physical systems in virtual environments. By continuously synchronizing physical assets with digital counterparts, digital twins support predictive analytics,

anomaly detection, and operational optimization. Nevertheless, the integration of digital twin principles with V2I-enabled maritime monitoring systems remains insufficiently explored.

In this study is proposed an ITS-oriented framework for remote monitoring and predictive assessment of ship power plants based on V2I communication and digital twin principles. The proposed approach integrates onboard, environmental, and infrastructure-level data into a unified cyber-physical monitoring environment capable of operating under constrained communication conditions.

The main contributions of this paper include:

- development of a unified V2I-based information model for ship power plant monitoring;
- integration of environmental, transport, and human-related operating conditions into the monitoring process;
- formulation of a mathematical model for state estimation and prediction under non-stationary conditions;
- development and experimental validation of an ITS-oriented monitoring architecture using real operational data.

The remainder of the paper is organized as follows. In Section 2, related work on maritime monitoring, V2I communication, and digital twin technologies is reviewed. In Section 3, the proposed monitoring architecture is presented. In Section 4, the mathematical model is described, while in Section 5, the monitoring algorithm is introduced. In Section 6, the system implementation is discussed. In Section 7, the experimental validation results are presented, whereas in Sections 8 and 9, the discussion and conclusions are provided, respectively.

2 Related work

Ship condition monitoring is a key component of reliable maritime operation. Traditional approaches mainly rely on onboard sensor data and predefined diagnostic thresholds; however, their effectiveness is limited under the non-stationary operating conditions [1-3]. Existing systems often depend on static models and offline analysis, reducing their ability to detect unexpected faults and respond to dynamically changing conditions [3].

Recent studies indicate that insufficient integration of environmental and operational factors significantly affects monitoring accuracy [4].

In addition, measurement uncertainty, variable load conditions, and limited operational data complicate the condition assessment and predictive maintenance implementation [5]. Moreover, limited availability of detailed usage data and operational profiles restricts the effectiveness of predictive maintenance strategies.

To improve monitoring performance, recent research has explored multivariate modelling, intelligent diagnostics, and advanced sensor configurations [6-7]. Nevertheless, subsystem-level diagnostics and vibration-based monitoring still face limitations under the variable operating conditions [8-9]. As a result, the integration of heterogeneous data sources for reliable real-time monitoring remains an open research problem.

The development of ITS has enabled new approaches to maritime monitoring through distributed communication and data processing technologies. Modern maritime systems increasingly rely on IoT networks, multi-sensor data fusion, and advanced situational awareness tools to support real-time decision-making [10-14].

However, the majority of existing studies focus on individual aspects of maritime monitoring, including visualization [15], satellite-based analysis [16], or onboard situational awareness systems [17-18], rather than integrated vessel-infrastructure interaction. Although the role of interconnected sensor networks and real-time data exchange was emphasized in several studies [11-12], the comprehensive V2I-enabled monitoring architectures for maritime ITS applications remain insufficiently developed.

Digital twin technologies have emerged as an effective approach for monitoring, prediction, and optimization in maritime transport systems. By continuously synchronizing physical assets with virtual models, digital twins support predictive maintenance and operational decision-making [19-21].

Recent studies demonstrated the integration of artificial intelligence, IoT technologies, and data-driven analytics into digital twin frameworks to improve prediction accuracy and operational efficiency [22]. Several researchers also highlighted the potential of combining digital twins with communication technologies, including V2I systems, to enhance situational awareness and distributed monitoring capabilities.

Despite these advances, the majority of existing approaches addressed the digital twins and communication infrastructures separately. Therefore, integrated frameworks combining digital twin methodologies with V2I-enabled ITS architectures for real-time maritime monitoring and prediction remain insufficiently explored.

The analysis of existing studies shows that the ship condition monitoring, ITS technologies, and digital twin applications are still largely developed independently. Current approaches lack comprehensive integration of onboard and external data, reliable operation under non-stationary conditions, and unified predictive capabilities.

In this study are addressed these limitations by proposing an ITS-oriented monitoring framework that integrates V2I communication and digital twin principles for remote monitoring and predictive assessment of ship power plants under real operating conditions.

3 System concept and ITS architecture

The proposed monitoring framework is developed as a cyber-physical component of an Intelligent Transport System (ITS), enabling continuous interaction between the vessel, onboard systems, and transport infrastructure through V2I communication. The ship is considered as an integrated system combining the power plant, onboard information systems, operators, operating conditions, and maritime infrastructure.

The general interaction scheme of the proposed ITS-based monitoring framework is presented in Figure 1.

The core of the proposed framework is a V2I communication layer that enables the data exchange between the onboard and infrastructure-level systems. The monitoring architecture consists of three interconnected levels:

- onboard level, including sensors and local processing modules;
- V2I communication level responsible for data

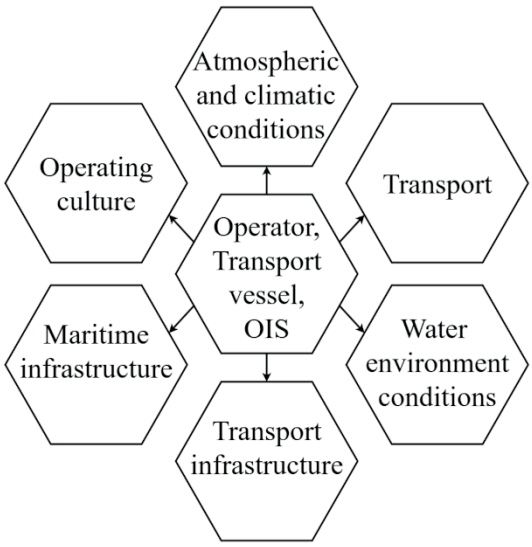

Figure 1 *General scheme of system interaction in the ITS-based monitoring framework*

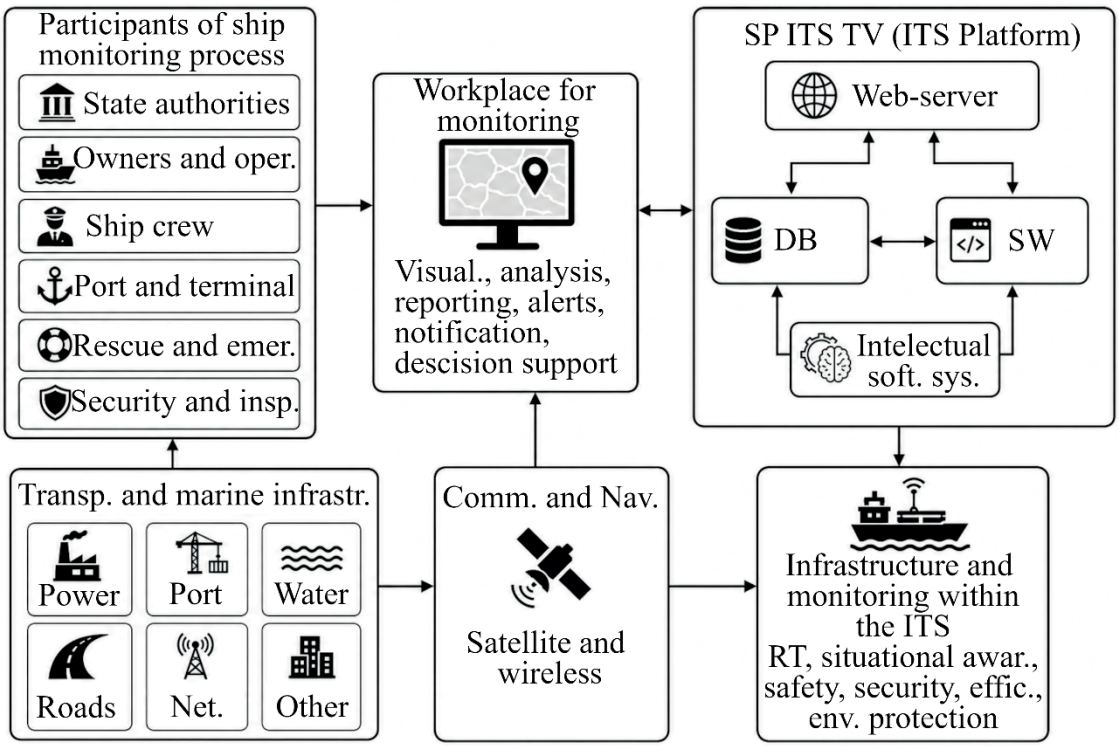

Figure 2 *The V2I-based information exchange between onboard systems and transport infrastructure*

transmission;

- infrastructure level, including servers, databases, and analytical tools.

This distributed architecture enables the continuous monitoring under limited communication bandwidth by allocating processing tasks between onboard and shore-based components. The information exchange structure is shown in Figure 2.

A key feature of the proposed approach is the integration of operating conditions into the monitoring process. The framework considers environmental, transport, atmospheric, and human-related factors affecting the ship power plant performance, including sea state, traffic density, climatic conditions, and operator-related influences.

The classification of operating conditions and their integration into the monitoring framework are summarized in Table 1.

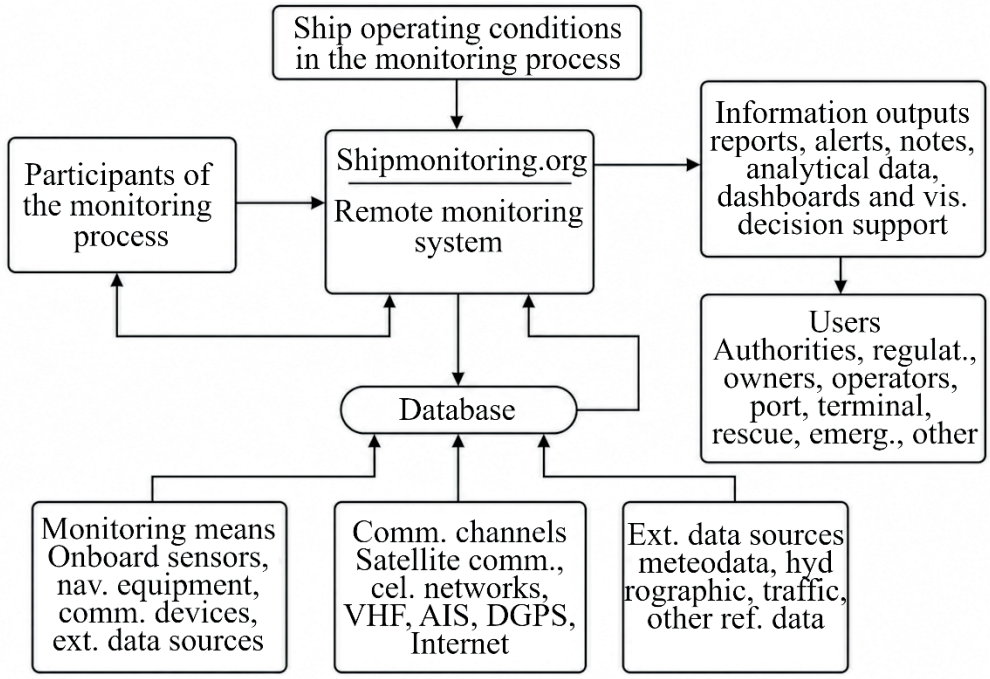

Figure 3 *Data flow diagram of the ITS-based ship monitoring system*

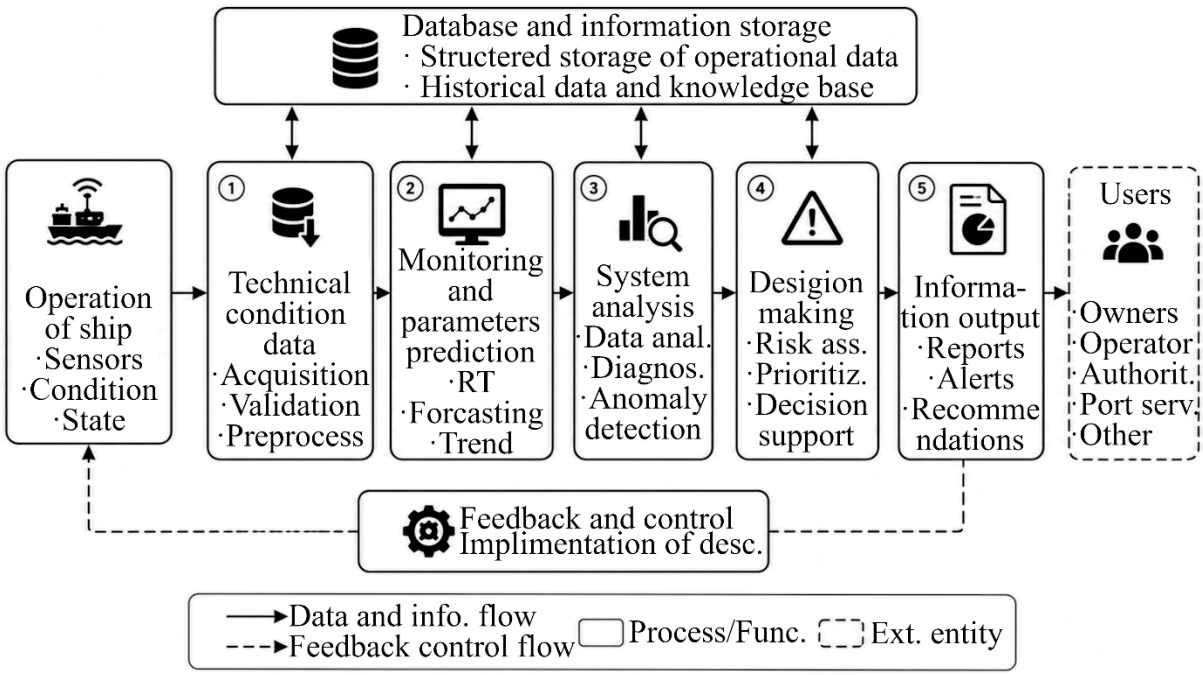

Figure 4 *Structured V2I-based information model of the transport ship monitoring system*

Table 1 *Classification of operating conditions and their integration within the ITS monitoring framework*

Main classification features of the operating conditions		ITS Information opportunities		Notes
		OIS	Maritime and transport infrastructure	
Water environment conditions	Seawater temperature	+	+ (-)	*
	Seawater density	+ (-)	- (+)	*
	Presence of undercurrents	-	+ (-)	*
	Altitude	+	+	
	Depth under the vessel keel	+	-	
	Fairway Width	-	+	
	The presence of resistance to movement (physical objects of artificial and natural origin)	- (+)	+ (-)	*
	Ship's hull fouling	- (+)	+ (-)	
Transport conditions	Type of cargo carried	+	- (+)	*
	Ship traffic density	- (+)	+	*
	Driving mode	+	- (+)	*
	Movement speed	+	+	
Atmospheric and climatic conditions	Air temperature	+	+	
	Air pressure	+	-	
	Air humidity	+	+	
	Precipitation	-	+	
	Visibility	-	+	
Operating culture	Level of work organization and management	- (+)	+	*
	Operator(s) qualifications and diligence	- (+)	-	*
	Compliance with the provisions of technical regulations and rules of technical operation	- (+)	+	*
	Repair and maintenance material and technical base of the vessel and transport infrastructure	+ (-)	+	
	Quality of shipboard maintenance materials	- (+)	- (+)	*

The monitoring framework is implemented as a distributed information system combining onboard data acquisition modules, communication subsystems, databases, and data processing tools. Information exchange between the system components is represented using a data flow approach, as illustrated in Figure 3.

The monitoring process includes vessel identification, acquisition of technical parameters, integration of operating conditions, state prediction, diagnostics, and decision support. The structured V2I information model describing these interactions is presented in Figure 4.

The proposed framework forms a basis for the development of a digital twin of the ship power plant. Continuous acquisition and processing of real-time data enable synchronization between physical and digital system states, supporting predictive analysis and operational optimization.

Thus, the proposed ITS-oriented architecture provides a foundation for the future integration of advanced digital twin technologies into maritime transport systems.

4 Mathematical model of monitoring and prediction

The monitoring of a ship power plant under the real operating conditions is considered as a dynamic process within a cyber-physical transport system integrating onboard, environmental, and infrastructure-level data through V2I communication.

The technical state of the ship power plant is represented as a multidimensional vector:

$$Y(t) = \{y_1(t), y_2(t), \ldots, y_m(t)\}, \tag{1}$$

where $y_i(t)$ denotes measurable parameters such as engine speed, fuel consumption, exhaust gas temperature, and load characteristics.

Operating conditions are represented as:

$$O(t) = \{o_1(t), o_2(t), \ldots, o_p(t)\}, \tag{2}$$

including environmental, transport, and human-related factors.

The monitoring process is defined as the integration

of technical and operating condition data into a unified system representation:

$$Y_{TCP,VOP}(t) = A_{TCP}(Y_{TCP}(t)) \circ A_{VOP}(Y_{VOP}(t)), \quad (3)$$

where: Y_{TCP} - technical condition parameters, Y_{VOP} - operating condition parameters, A_{TCP}, A_{VOP} - transformation operators, $\circ$ - composition operator.

The estimated technical state is obtained as:

$$\hat{Y}(t) = f(S(t), O(t)), \quad (4)$$

where: $S(t)$ - onboard sensor data, $O(t)$ - operating conditions, $f(\cdot)$ - estimation function.

Future system behavior is predicted using the historical and current state data:

$$\hat{Y}(t + k\Delta t) = F(\hat{Y}(t), H(t - n : t)), \quad (5)$$

where: $H(t - n : t)$ - historical data, k - prediction horizon, Δt - time step.

The system operates within a distributed information environment:

$$I = \{C, L, N\}, \quad (6)$$

where: C - cloud-based infrastructure, L - local onboard data sources, N - networked databases.

The proposed model forms a functional basis for a digital twin of the ship power plant. The estimated state $\hat{Y}(t)$ represents the digital counterpart of the physical system, while the prediction model supports forward simulation and scenario analysis.

5 Monitoring algorithm and data processing

Algorithm 1: V2I-Based Monitoring and Prediction of Ship Power Plant State

Input:

- Onboard sensor data $S(t)$
- Operating conditions data $O(t)$
- Historical data $H(t - n : t)$;

Output:

- Estimated technical state $\hat{Y}(t)$
- Predicted technical state $\hat{Y}(t + k\Delta t)$.

Step 1: Data Acquisition.

Acquire the real-time onboard sensor and navigation data together with external information obtained via V2I communication.

Step 2: Data Synchronization and Preprocessing.

Synchronize the heterogeneous data streams, remove outliers, filter noise, and normalize parameters.

Step 3: Feature Extraction.

Generate derived indicators describing the current operating state of the ship power plant.

Step 4: State Estimation.

Integrate onboard and external data to estimate the current technical state of the power plant:

$$\hat{Y}(t) = f(S(t), O(t)). \quad (7)$$

Step 5: Prediction of Technical State.

Use historical observations and current state estimates to predict future system behavior:

$$\hat{Y}(t + k\Delta t) = F(\hat{Y}(t), H(t - n : t)). \quad (8)$$

Step 6: Diagnostics and V2I Exchange.

Detect anomalies, generate diagnostic indicators, and exchange processed data with infrastructure-level systems.

Step 7: Visualization and Decision Support.

Present monitoring results and operational recommendations to the operator.

6 Implementation of the V2I monitoring system

The proposed monitoring framework is implemented as a distributed cyber-physical system within an ITS environment, integrating onboard subsystems, communication channels, and infrastructure-level components. The system includes onboard data acquisition and diagnostic modules, an onboard information system (OIS), V2I communication interfaces, infrastructure-level servers and databases, and data visualization tools.

The monitoring framework operates as a distributed telecommunications network supporting continuous data collection, transmission, storage, and analysis under real operating conditions.

The system integrates heterogeneous onboard and external data sources obtained through the V2I communication, including:

- onboard sensor data (engine parameters, fuel consumption, diagnostics);
- navigation data (GPS-based position and speed);
- environmental data (weather conditions, sea state);
- infrastructure-based data (traffic conditions, maritime information systems).

These data sources form a unified information environment for monitoring and predictive analysis. Additional information sources include ship geolocation data, maritime infrastructure models, weather services, and ship tracking systems.

The data processing architecture is designed for operation under limited communication bandwidth by distributing computational tasks between onboard and infrastructure-level components.

The primary processing, including filtering, aggregation, and preliminary diagnostics, is performed onboard, while advanced analysis and storage are executed within infrastructure-level systems. This approach reduces communication load while preserving monitoring continuity.

6.1 Functional capabilities of the monitoring system

The implemented system supports: real-time monitoring of ship power plant parameters; integration of operating conditions into diagnostics; anomaly detection and diagnostic code generation; prediction of system behavior based on historical data; decision support for operational adjustments.

The framework also enables continuous archiving and visualization of monitoring results.

Within the ITS framework, the proposed system functions as a distributed monitoring node enabling interaction between vessels and transport infrastructure through V2I communication.

Continuous data acquisition and processing provide the basis for a digital twin of the ship power plant, supporting the state estimation, prediction, and scenario analysis. This enables the transition from reactive monitoring toward predictive and prescriptive maintenance strategies.

7 Experimental results and validation

Experimental validation of the proposed V2I-based monitoring framework was performed using the real operational data obtained from a transport vessel operating under varying environmental and transport conditions. The onboard information system collected time-series data from the key ship power plant subsystems, including engine rotational speed, exhaust gas turbocharger (EGT) parameters, auxiliary generator load, fuel consumption, and GPS-based vessel speed.

The initial data acquisition frequency was 1 s and it was later aggregated to 60 s intervals for stable analysis. External weather and navigation data were integrated via V2I communication channels. The dataset corresponds to a voyage segment of approximately 497 nautical miles (921 km) and contains more than 40,000 measurement points.

The dataset includes synchronized onboard and external data streams representing technical, operational, and environmental conditions. The monitored variables were grouped into technical parameters (engine speed, fuel consumption, EGT characteristics), operational parameters (vessel speed and load conditions), and environmental influences affecting system behavior.

The temporal variation of the key operational parameters is presented in Figures 5-7. The obtained results demonstrate: a strong dependency of fuel consumption on vessel speed and engine load; observable variations in engine performance under changing operating conditions; the capability of the monitoring system to capture transient behavior in non-stationary environments.

In Figure 8 are compared the measured and estimated fuel consumption values, demonstrating the consistency of the proposed monitoring model.

The performance of the proposed framework was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the correlation

Table 2 *Comparison of measured and estimated parameters*

Parameter	Measured (avg)	Estimated (avg)	MAE	RMSE	R
Vessel speed (knots)	9.8	9.5	0.32	0.41	0.96
Fuel consumption (kg/h)	1850	1790	65	82	0.94
EGT speed (rpm)	9200	9050	110	145	0.92

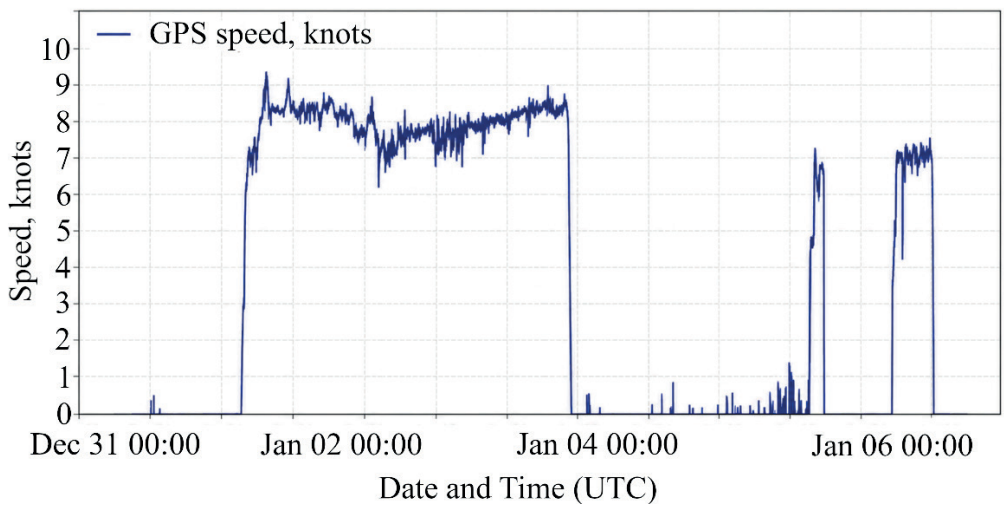

Figure 5 *Temporal variation of the vessel speed during the monitored voyage segment*

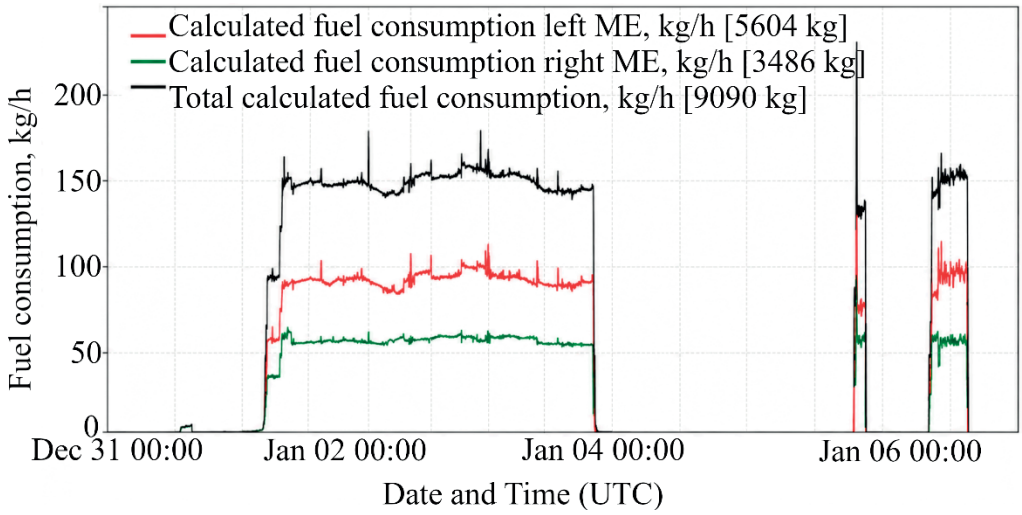

Figure 6 *Temporal variation of the fuel consumption during the monitored voyage segment*

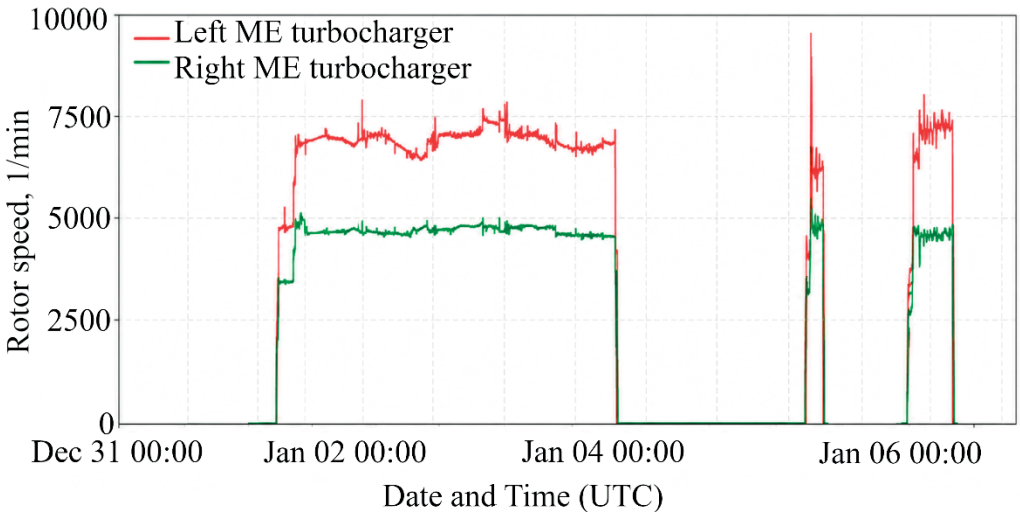

Figure 7 *Temporal variation of the main engine turbocharger rotor speed during the monitored voyage segment*

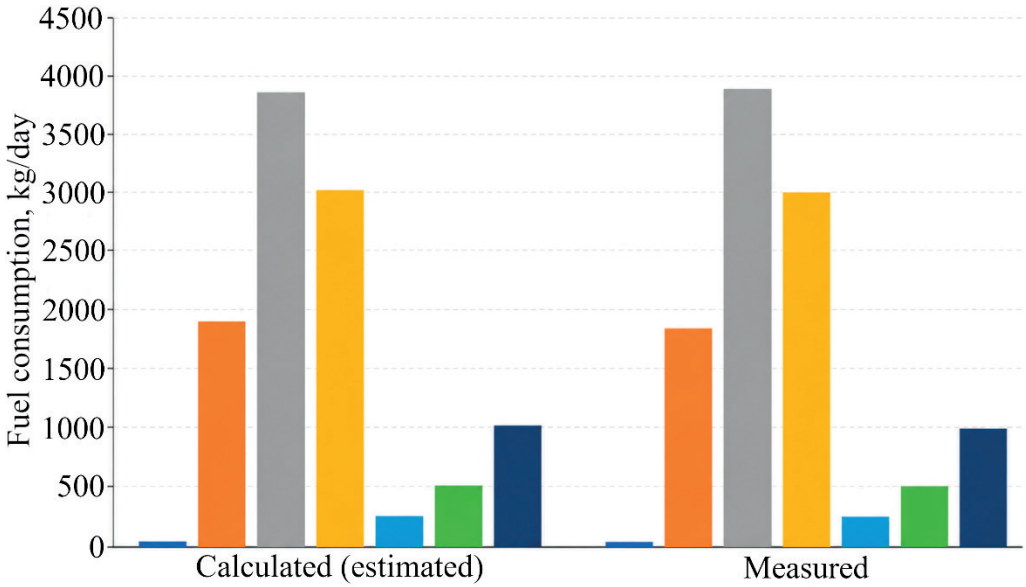

Figure 8 *Comparison of measured and model-estimated daily fuel consumption*

coefficient (R):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Y_i - \hat{Y}_i|, \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}, \tag{10}$$

$$R = \frac{\sum(Y_i - \bar{Y})(\hat{Y}_i - \bar{\hat{Y}})}{\sqrt{\sum(Y_i - \bar{Y})^2 \sum(\hat{Y}_i - \bar{\hat{Y}})^2}}. \tag{11}$$

The calculated metrics are summarized in Table 2.

The results show a close agreement between the measured and estimated values, confirming the adequacy of the proposed model for representing the system behavior under real operating conditions. The results demonstrate the strong agreement between the measured and estimated values, with correlation coefficients exceeding 0.9 for all analyzed parameters. The results obtained confirm the capability of the proposed framework to integrate heterogeneous data sources and provide reliable estimation of ship power plant performance under non-stationary operating conditions.

From an ITS perspective, the proposed approach demonstrates the feasibility of distributed monitoring systems supporting real-time interaction between vessels and transport infrastructure.

8 Discussion

The obtained results demonstrate the feasibility of integrating V2I communication with onboard monitoring systems to create an ITS-oriented framework for maritime applications. The proposed approach enables continuous interaction between vessels and transport infrastructure while integrating onboard and external data into a unified monitoring environment.

A key advantage of the framework is its ability to operate under the non-stationary conditions and limited communication bandwidth through distributed onboard and infrastructure-level processing. In addition, the proposed approach introduces digital twin elements that support real-time monitoring and predictive assessment of ship power plant behavior.

However, the proposed model has several limitations. The prediction framework is based on simplified functional relationships and does not yet incorporate advanced machine learning methods. Moreover, experimental validation was conducted using data from a specific vessel and operational scenario, which may limit the generalizability of the results. System performance also depends on the availability and quality of the sensor data.

From an ITS perspective, the proposed framework contributes to the development of distributed cyber-physical maritime transport systems supporting situational awareness and data-driven decision-making. The approach can be further extended towards the fleet-level monitoring and integration with broader maritime transport infrastructures.

Future research should focus on integrating machine learning techniques, developing full-scale digital twin implementations, and extending the framework to multi-vessel and large-scale maritime transport systems.

9 Conclusions

In this paper is presented an ITS-oriented framework for the remote monitoring and predictive assessment of ship power plants based on V2I communication and digital twin principles. The proposed approach integrates onboard and external operating data into a unified cyber-physical monitoring environment.

A mathematical model for the state estimation and prediction under non-stationary operating conditions was developed together with a structured monitoring algorithm supporting real-time data acquisition, diagnostics, and decision-making. The monitoring architecture was implemented as a distributed system combining onboard subsystems, communication networks, and infrastructure-level components.

Experimental validation using real operational data demonstrated the capability of the proposed framework to capture variations in vessel speed, fuel consumption, and engine performance parameters under real operating conditions. Quantitative analysis confirmed strong agreement between the measured and estimated values, indicating the adequacy of the proposed model.

From an ITS perspective, the framework supports the development of distributed maritime monitoring systems that improve situational awareness and enable data-driven operational decision-making. In addition, the proposed approach provides a functional basis for the development of digital twins of ship power plants, supporting predictive analysis and advanced maintenance strategies.

Future work should focus on the integration of machine learning methods and the extension of the proposed framework to multi-vessel and large-scale maritime transport systems.

Acknowledgment

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

Conflicts of 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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