



Digital Twins for Marine Engine-Room Systems: A Classification Framework for Training and Predictive Maintenance

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ABSTRACT

Within the current context and with the changes that have taken place in recent years, the maritime sector is facing a set of transformations that may lead to the adoption of complex cyber-physical systems. These developments facilitate high operational reliability for vessel's critical elements, including both the power generation plant and the safety of navigation systems, while simultaneously enhancing energy efficiency and environmental sustainability. Until now, traditional maintenance models (corrective, preventive, predictive and static predictive) have been the main resource. These models face several limitations, the statistical sense being the foremost. These operations also require experienced personnel; yet, a shortage of specialized personnel combined with generational turnover creates significant recruitment bottlenecks. Additional challenges include increasing technological complexity and the growing demand for continuous availability on ships' operation with minimal downtime. The methodology follows an exploratory and verification-oriented approach, combining a review of the technical literature and up-to-date information on the state of the art in this domain with the development of functional digital architectures. These architectures integrate data acquisition and communication, simulation of outcomes, dynamic modelling, and predictive analysis based on machine learning, together with the use of realistic physical systems. Preliminary analyses suggest that implementing a modular architecture makes it possible to supervise the installation at different levels of complexity. Moreover, detailed models are already showing the ability to detect minor deviations in machinery performance. This should make possible to identify not only the root causes of failures that will occur in the installation if no countermeasures are taken, well before they become irreversible, but also to estimate the remaining time before such failures, and to support decisions that prevent unplanned shutdowns. Further on, this technology has the potential to complement the existing training software. The results obtained and the data analysed provide indications of the viability of the modular approach, although they also show that it significantly increases the complexity. It is, however, a technology rooted in solid foundations, such as the physical twins historically used by some space agencies. The findings likewise reveal major challenges, particularly in managing on time the large volumes of data generated on board and in addressing potential vulnerabilities to cyberattacks on these data. It has been observed that the effectiveness of these tools is closely tied to the correct modelling of the twin and to the availability of high-quality, on time data that are properly labelled, segmented and updated at an appropriate frequency. This last aspect, related to temporal resolution and synchronization frequency, is still not always explicitly considered in digital twin classifications, although it is essential for practical implementation. For this reason, this paper proposes a classification scheme to support the selection of the appropriate type of model according to their purpose, required fidelity, data demand and synchronization needs. The technology is promising, but its implementation at plant level entails a degree of complexity that calls for progressive development and rigorous validation across multiple operational scenarios.

1. Introduction.

Digital twin technology is an innovation with multiple applications across a wide range of sectors. A digital twin is not merely a 3D image of a real-world object, but a digital representation of the state of an element or a process. Useful digital twins are not a static image or representation of the reality in one point of time, but they must be able to use real-

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world data to generate a synchronized copy of reality. Normally, digital twins combine IoT (Internet of Things) with functioning/working rules, machine learning or physics/engineering-based simulators.

Digital twins come in many forms, ranging from those used to monitor health and create a digital image of a person's physical condition to those that make it possible to track maintenance and logistics in large companies.

The usefulness of digital twins lies in the ability of connecting real systems with digital models. Evolution of digital models can be computed easily, and this opens up many possibilities as, monitoring in real time a process or an asset, predicting future events related with the real state of the system and their operation conditions, and detecting abnormal behaviour, allowing for predictive maintenance lowering the costs of future operation of an installation.

1.1. Maritime digital twins.

Maritime digital twins might apply the concepts of terrestrial digital twins to on-board systems, ports, offshore structures and fleet operations. Depending on the proposed use, the physical element to be monitored may be a complete vessel, a propulsion plant, an engine-room system, a cargo operation, a port terminal or even a fleet of ships. For this purpose, the digital twin must receive real data from sensors, automation systems, navigation equipment, maintenance records and external sources such as weather, sea state or traffic information.

A maritime digital twin can therefore represent both the technical status of a vessel and its operational environment. Within the engine room, a digital twin can monitor energy flows, operational outputs, (temperatures, pressures, vibration signals), fuel and lubricating oil conditions, cooling and seawater dynamics, and alarm logs [Sun et al., 2025]. A fleet-level digital twin may include vessel positions, voyage plans, fuel efficiency, port waiting times, maintenance windows and operational KPIs (Key Performance Indicators). Those distinct scopes require varying levels of fidelity, real time data update, frequencies and real data architectures. Furthermore, ensuring vessel security demands, adapted security protocols and data validation mechanism.

The maritime sector is especially suitable and very demanding for digital twin technology because ships are complex, expensive and have safety-critical systems. They operate under variable conditions, often far from shore-based technical support. Additionally, limited or unstable communications (internet connectivity) may affect the reliability and continuity of the digital twin. Failures can have serious economic, environmental and safety consequences. For this reason, a maritime digital twin can become a useful tool to improve reliability, reduce downtime, optimize fuel consumption and support predictive maintenance. However, digital twins may face significant barriers to adoption not only by companies but also by workers in the maritime sector.

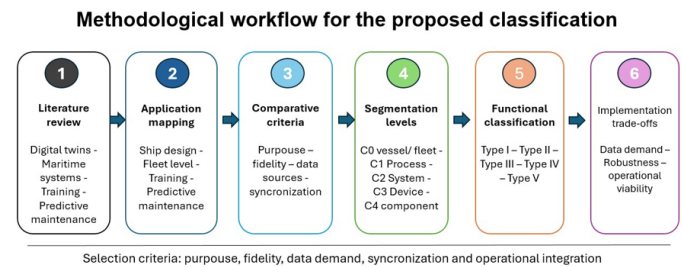
However, maritime digital twins are not all at the same stage of maturity, as is generally the case across the broader digital twin field. Some applications are mainly 3D models or simulations used during design [Mao et al., (2023)]. Others are digital

“follow-on” or shadows, where real data flows from the ship to the model but the model does not strongly influence the physical system. The most advanced digital twins combine real-time data, simulation, diagnostics and prediction to support operational decisions.

2. Methodology.

The methodology applied in this study consists of a life-cycle assessment and a comparative analysis of maritime digital twins. The framework categorizes and examines the technology across four core operational stages: ship design, fleet operations, crew training, and predictive maintenance. For each stage, we evaluate its functional scope, ranging from basic digital shadows to complex real-time decision-support environments. Furthermore, the analysis investigates the specific data requirements of each application, distinguishing between the need for synchronized, real-time data and the viability of unsynchronized or synthetic data, to identify the technical trade-offs, limitations, and operational advantages of this technology, see Fig. 1:

Figure 1: Methodological workflow for the proposed classification.



Source: Authors.

2.1. Applications in the Maritime.

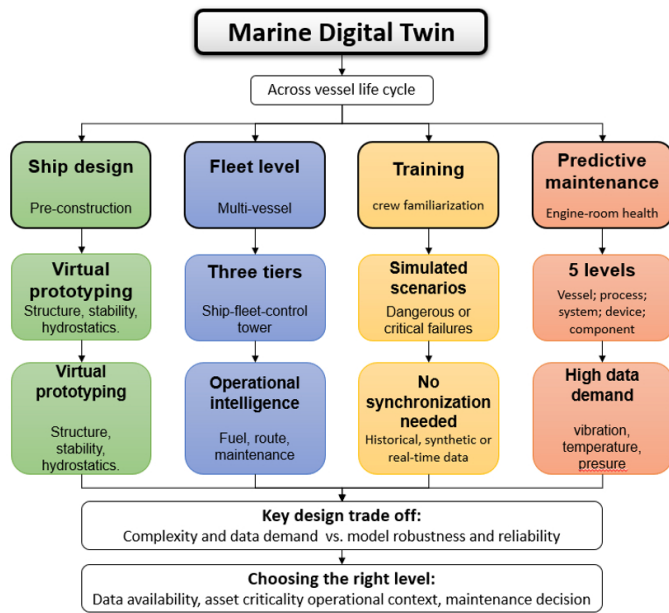
Maritime digital twins can become a useful tool in different phases of the vessel life cycle, where manufacturing and service are treated as distinct data-integration regimes rather than as a single temporal mode, see Fig. 1. [Tao F. et al., (2018)], from the early design, training of the crew and predictive maintenance. However, the scope of the twin, changes significantly depending on the use or application. Each of the following applications demonstrates both the advantages and implementation limitations of this technology, see Fig 2.

– Ship Design.

During the design phase, 3D and simulation tools can be used to analyse the structure, virtual prototypes can be used instead of real models making cheaper and easier to test alternative designs before any construction. These tools are used to assess structural soundness, hydrostatics and stability performance, for instance.

Design oriented Digital twins, can help the companies to compare different configurations, they can evaluate the impact of the different equipment working in the ship if machinery

Figure 2: Application areas.



Source: Authors.

spaces are accessible for a properly maintenance, or whether the propulsion system is correctly dimensioned for the expected operating profile.

In this sense, the digital twin is a decision-support tool for improving the technical quality, safety and operational efficiency of the future vessel. [Hasan et al., (2024); Khaled, I., Bennebach, M., Vasiukov, D., Shakoor, M., & Chaki, S. (2025)]

– Fleet level.

At fleet level, digital twins can support voyage planning, fuel optimization, port-call coordination and maintenance scheduling. Instead of analysing each ship separately, the operator can compare the condition, location and performance of several vessels at the same time. This approximation is similar to the use of digital twins on land-based **logistics**, when digital twins are now a reality and can represent long supply chains, simulate scenarios and update the schedules based on real time data.

This digital twins at fleet level are nowadays a reality, they are being used not as a full physical model, but as a digital shadow in a more complex system, the maritime sector is progressively moving from conventional operations for more automated, remote and integrated approaches [Kanashiro et al. (2026)]. This type of digital twin can be understood at different levels.

At ship level, the twin represents the macroscopic overall technical and operational state of a single vessel. At fleet level, the twin connects several vessels and compares their performance, availability and operational constraints. At control tower level, the digital twin becomes part of a shore - based decision-support environment, where operators can monitor the fleet, anticipate disruptions and coordinate actions between ships, ports and maintenance teams. This links to the logistics chains.

If we combine these digital twins with real data, it can pro-

vide operational intelligence. As we have seen in the land-based logistics, their main advantages could include better fleet status visibility, improved coordination, fuel and route optimisation, more efficient maintenance planning and faster response to operational disruptions.

– Training and familiarisation.

Training of the crew is a relevant application of digital twins in the maritime sector, especially when this crew needs to understand the dynamic behaviour of the systems aboard the ship rather than memorize isolated procedures, and short-term scenarios that are a good way to avoid alarms, accidents or failures; this could become even more valuable when operators could observe how different system variables interact during the development of critical failures and the degradation of the systems.

As it happens with the simulators nowadays, synthetic data and simulated scenarios can be used to reproduce operational situations that are rare, dangerous or difficult to observe during normal service.

To create these digital twins for simulation, we could need access to historical data, synthetic data or real time data, but this approach does not need to rely on synchronized data.

Not needing real time data or historical data is particularly valuable when operational data are scarce, expensive because of data transfer and communications, or difficult to obtain. The digital twin allows to generate additional scenarios for training, familiarization and decision-making. This is useful not only for operational decisions aimed at avoiding short-term failures, but also because digital twins can help observe how machinery responds over time with satisfactory precision. Instead of training only isolated procedures, the trainee can see how operating decisions affect temperature, pressure, vibration, wear or efficiency.

This is important because actual engine-room failures are rarely isolated events. They usually develop through interactions between operating conditions, degradation and system behaviour. Also, the processes can be presented to the trainees at a much timely sequence (and higher pace) than the real occurrence on board, to question the trainees' efficacy at reacting to the facts, to accelerate the training.

A set of systems, or even a vessel-specific training twin could be developed from the actual configuration of a ship or ship class for a specific company. In this case, the trainee would interact with systems, alarms, operating limits, responses and failure modes similar to those found on board. This approach can support familiarisation before joining a vessel, preparation for maintenance operations, emergency-response training and engine-room resource management.

With the proper use of this tool, the training can be used to improve the diagnostic reasoning of the trainees and system level understanding.

– Predictive maintenance onboard with Digital twins.

A maintenance-oriented digital twin uses actual operational data to detect degradation well before a failure might occur, this is one of the expected more relevant applications of maritime digital twins. For example, it can analyse vibration, temper-

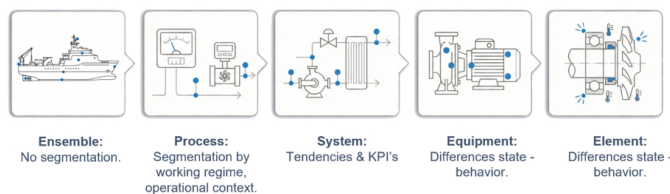
ature, power, pressure, flow rate, oil condition, emissions and operating hours. If the system detects abnormal patterns or unexpected tendencies, it can generate warnings and help the crew or maintenance team understand what is happening. [Kalafatis, (2025)]

The usefulness of predictive maintenance digital twins depends strongly on the level of analysis. At fleet or vessel level, the digital twin can compare the overall condition, performance and availability of different ships operated by the same company. This is useful for benchmarking, maintenance planning and identifying vessels that show abnormal operating trends. Offshore diagnostic twins, also show that measurements are limited by temporal resolution and space. So some models are needed to interpolate and augment data, even with this synthetic data, useful warnings can still be generated hours before failure [Stadtmann, F. et al, (2024)].

This family of digital twins is quite demanding on number and selection of data to be treated, data acquisition frequency, and communications (to transfer the data to analyse them). This is consistent with the equipment health assessment approach described previously, where shipboard machinery and electrical equipment are statistically analysed and evaluated through a real-time health-scoring mechanism developed with input from equipment manufacturers and experienced chief engineers [Abughaida, M., 2024; Cai, (2026)].

According to the segmentation level or class, the maritime digital twins can be classified as we can see in the Fig. 3:

Figure 3: Segmentation and level of detail.



Source: Authors.

C0: Whole-vessel / fleet-level monitoring with no segmentation, a ship is viewed as a whole, with no separation of elements, we can see the operational situation on the ship. A digital twin at this level may focus its operation on position, speed, route, fuel consumption, cargo and mission profile. This level of segmentation is especially useful on logistics, it is relatively similar to the digital twins that are used for logistics, as trucks voyage planning, fleet coordination and high-level operational monitoring this level is usually not suitable for predictive maintenance.

C1: Process level: At process level, the digital twin could analyse full operational processes on the vessel. This level is especially useful for studying optimisation of energy consumption, operating conditions and interactions between systems. Also, it is very condition-drive. This is an improvement on actual direct systems that activate alarms only because the system is not on optimal operation, or not operating at all.

C2: System level: At system level, the digital twin can help identify which part of a technical system may be responsible

for a failure. For example, in a cooling system, abnormal temperatures may be related to pump performance, heat exchanger fouling, valve position or insufficient seawater flow, besides operation outside usual ranges.

C3: Device level: At device level, the analysis focuses on individual equipment, such as pumps, centrifugal compressors, turbochargers, filters or heat exchangers. This allows the detection of progressive degradation before the equipment reaches a critical condition. Data from equipment itself is needed to support reliable monitoring and diagnosis. [Afanaseva et al., (2026)].

C4: Component level: Finally, at component level, the digital twin could focus on specific mechanical elements such as bearings, seals, impellers, injectors or valves. In order to properly work, this level of segmentation needs very detailed data provided in real time with sensors, and as a consequence it can help anticipate the failure of the mechanism itself and support condition-based maintenance. But it can encounter serious bottlenecks obtaining and transferring the data needed to work with.

In this way, predictive maintenance can be approached - through different levels of segmentation, from fleet-level monitoring to component-level diagnosis. The appropriate level depends on the available data, the criticality of the asset, the required diagnostic resolution and the maintenance decision that the digital twin is expected to support. [Tsitsilonis, K. et al, (2023)]

However, as the system increases in complexity and on liable real data to make precise predictions, the digital twin will increase its requirements, because these digital twins may require high-resolution sensor data, continuous synchronization, accurate calibration, reliable communication links, and more complex diagnostic models and computing power. With the usual restrictions and boundaries, the resulting model will be less reliable if some data is corrupted or missing. On the other hand, a robust model, needing less data, might give sufficiently approached useful results in some cases [Lee et al, (2024)].

Failures in data acquisition and/or communications could lead to bad predictions on the digital twin. This, could be a frontier to overcome if someday digital twins could not only predict degradation on the conditions of the ship and its systems, but further take decisions (for instance, use or load other auxiliaries or backup systems), or help the crew to make critical decisions about maintenance and operation. These would require secure data to avoid costly erroneous decisions.

For this reason, the most detailed digital twin is not always the most appropriate one for any ship and any operation condition. The selected level of segmentation should be justified by the criticality of the asset, the expected maintenance decision, the available instrumentation and the operational constraints and situation of the vessel. In many maritime applications, a robust system-level or device-level twin may be more useful than an excessively complex component-level model that cannot be reliably fed, validated or maintained during normal operation.

3. Results.

Based on the research conducted, the proposed functional classification for maritime digital twins is structured as shown on following subsections.

3.1. Rationale for the classification.

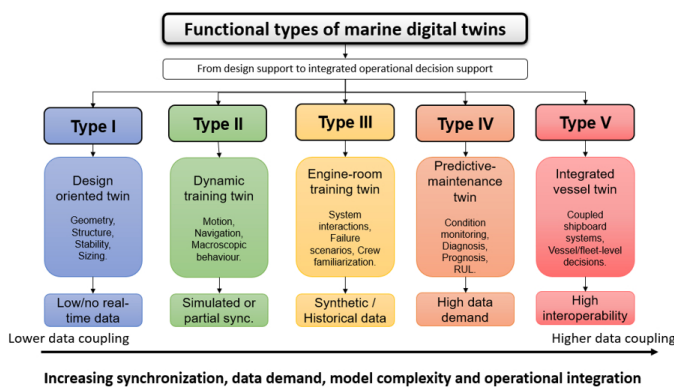
The previous sections show that marine digital twins cannot be defined only by the physical asset they represent or by the number of points where data are collected. Their practical implementation depends on the intended purpose, the required fidelity, the level of synchronization needed to obtain useful information from the data, and the extent to which these data can be reliably acquired, processed and maintained.

Since clarity on the implementation of marine digital twins is still limited, a purpose-oriented classification can help distinguish between different levels of functionality, synchronization and integration [Zocco, F., Wang, H.-C., & Van, M., (2023); Sadeghi et al., (2024)]. Based on the previous observations and segmentation levels discussed above, we propose a general classification of digital twins, primarily intended for the maritime sector, but not limited to ships, which can be developed into the following types:

3.2. Functional types of marine digital twins.

As summarized in figure 4, this section introduces the results of the research related to the established classification of the functional types of marine digital twins depending on their application.

Figure 4: Proposed functional types of marine digital twins.



Source: Authors.

-Type I: Design-oriented digital twin. It is more useful in the design process, with macroscopic aspects and low or no time dependence. These models deal, for instance, with the structural soundness and stability of the ship. This first category of digital twin is mainly used during the conceptual or detailed design stage. They usually have low or no real-time dependency because the physical vessel may not yet exist, may not be operating, or may be in stand-by condition. The principal use is to compare design alternatives and reduce uncertainty.

-Type II: Dynamic training digital twin. It deals mostly with macroscopic motion, time-dependent effects and macroscopic interactions, such as vessel motion and manoeuvring, as most navigation bridge simulators used for training do. These models can introduce behaviour and macroscopic interactions that may require some level of synchronization. They may include partial synchronization or scenario-based data, but they do not usually require continuous real-time synchronization with an operating vessel. Therefore, they can also be useful for low-resolution analyses or for studying systems in which full synchronization is not required.

-Type III: Engine-room training digital twin. It is useful for training in working operations and maintenance, as it includes sophisticated time- and parameter-dependent interactions among systems. These digital twins are expected to be more relevant for engine-room training, operational familiarization and maintenance procedures. The main objective of this type of digital twin is to reproduce the behaviour of specific systems in the engine room. Unlike basic procedural simulators, they can represent how operating decisions affect system variables and how these variables affect engine-room operation and preventive maintenance. In order to work properly, they may use synthetic data, historical data or instructor-defined scenarios, and real-time synchronization with an operating vessel is not always required, although it could be a feature of these digital twins.

-Type IV: Predictive-maintenance digital twin. It deals with systems connected to real-time data in order to support predictive maintenance of operating systems. These digital twins are expected to be connected to operating systems and real operational and condition-monitoring data, in order to track the changes that occur in the system, detect degradation of system elements, identify abnormal behaviour and support maintenance and operational decisions. The types of data that may need to be monitored are complex and have to be selected and processed, from temperature in system elements, fatigue history, energy produced and used, to operating hours and alarm history [Mohammadi Moghadam et al., (2021); Sun et al., (2025)].

-Type V: Integrated vessel digital twin. Type V digital twins extend the predictive-maintenance approach to the full vessel or to highly integrated shipboard systems with full real-time synchronization. They deal with connected operating systems, rather than nearly independent systems, and represent the most complex level of digital twins that can be implemented on a ship. They connect several shipboard systems, which may be created by multiple stakeholders such as component suppliers, shipyards and ship operators, and create a full image of the vessel as an integrated operational asset. The objective of this integration is to detect and assess interactions between the different systems of the vessel. This category is technically demanding because it requires interoperability between systems, including systems that may be shut down, redundant data, fully synchronized systems, consistent data models and clear boundaries between local system behaviour and vessel-level decision-making [Fonseca, Í. A., & Gaspar, H. M. (2021); Wang & Ab-doli, (2026)]. See Figure 4.

4. Discussion.

Data demand, synchronization and temporal resolution are important aspects that have to be considered within the proposed classification. The required temporal resolution on a digital twin cannot be taken as a universal element, as it emerges from the previous classification, it will depend on the characteristic time scale of the physical process being represented, and the need for the operator or digital twin to know the real data, also, previous works on multi-timescale digital twins shows that a single twin may need to track distinct operational time scales in parallel, in addition to the system's intrinsic dynamics, rather than relying on one uniform refresh rate. [Chakraborty S. et al, (2020)].

As an example, slow thermal degradation in cooling or lubrication systems may be assessed using lower-frequency trends, whereas vibration analysis in rotating machinery requires higher-frequency acquisition, in the first case, we can predict with a very high resolution the output, with little data and using heat-transfer equations, in the second case, high-frequency signals may be needed to detect transient or frequency-domain indicators related to mechanical degradation; the output of the degradation will be less accurate with low frequency data.

Also, in some cases, synthesized, averaged, interpolated or extrapolated data may be used, when we cannot process or receive all data at the frequency that the Digital twins need. These data should not be understood as a fully functional substitute for the original data, also not be used to maintain the instrumental data validation, should be marked as synthetic data in the digital twin model, with the purpose to be a practical mechanism to maintain continuity of the data in the model calculations under operational or communication constraints.

In terms of pre-processing and communication constraints, vessels might not need a full high frequency data synchronization, for every system, because load processes, thermal variations, degradation trends are relatively slow and have lots of inertia, but some component-level diagnostics, such as vibration analysis, rotating machinery or electricity generation could need higher frequencies.

For this reason, we could use the ship to locate a first processing unit aboard, reducing the need to transfer this data continuously in raw form, this could be made when the conditions are better, like when communications are easier, or even when the ship is near land or inside a harbour. This behaviour, create the necessity to operate at different cadences of sending this data; therefore, predictive capability does not necessarily imply transmitting all raw data at high frequency, but rather selecting and processing the relevant information needed for diagnosis, prognosis or RUL (Remaining useful life) estimation [Stadtman et al., 2023].

Some data may be processed on board and transformed into diagnostic features such as RMS values, spectral components, frequency bands, trend indicators or health scores. This reduces communication requirements while preserving useful diagnostic information.

In respect of robustness, maintainability and adoption barriers, selecting the appropriate configuration of digital twin will

be essential for each intended use or task. If the level of detail, data acquisition frequency of synchronization are not aligned with the necessities of the system and the operation, results could be misleading the system or making unnecessarily expensive or difficult to operate. The proposed classification with the five types from I to V are intended to support the practical selection for every digital twin according to their purpose and their state on their life cycle, operating constraints and required fidelity of the results:

For design purposes, especially in the early stages of the vessel development, design and construction, non - time - dependent models, and models with low time dependency, should be preferred to obtain fast responses and characteristics. At this stage, preliminary geometry, material properties and main consumption estimates allow relevant data to be obtained to refine the design. As the process advances, additional aspects such as fatigue, expected maintenance needs, life-cycle cost and operational constraints may be integrated into the model. Type I digital twins are particularly appropriate because they can provide fast and cost-effective responses without requiring a high data profile and continuous data synchronization with operating vessels.

For training purposes, digital twins may rely on rule-based models, instructor-defined scenarios and simulated responses instead of continuous real-time data. This could be important and relevant because the development of failures in real operating conditions could take long periods of time, whereas in training simulators these processes must usually be compressed into shorter sequences, which can make use of predefined scenarios to train long-term failures, despite the limitations of this method. Simulated events, predefined fault progression or even randomized scenarios can help trainees develop operating knowledge, anticipation capacity and improved operating practices based on reducing long-term faults in the vessel. Depending on the scope, training-oriented twins may correspond to Type II or Type III level digital twins, using the more complex models for engine-room training.

For regular maintenance, crew response to unexpected conditions, and training to optimise working points, more detailed models, taking into account the possible interactions between different systems and devices, are needed. In this case, Type III DT and Type IV can be used depending on the level of complexity. Type III would be more suitable for procedure-based maintenance, while Type IV models can be introduced when real operational data are needed to monitor degradation or estimate RUL.

Finally, predictive maintenance requires models capable of interpreting time-dependent data acquired from the vessel or from other shipboard systems with a consistent frequency. Type IV digital twins could be an option when the objective is to detect degradation and anticipate faults that could generate failures in the range of hours or days. When the analysis is extended to the whole engine room and the whole vessel, analysing external operational conditions and all the data that the digital twin could need, the digital twin would approach Type V. This level may be especially relevant for Maritime automated or autonomous ships (MASS), also to support crew decision-making

for predictive maintenance. But this level will require more data availability, stronger interoperability, higher computational capacity, more robust validation, reliable communication and a better-trained crew in order to correctly analyse data and detect failures in data acquisition elements. This means that increasing the complexity and precision of a digital twin also increases its operational demands. Higher-fidelity twins would require more sensors, higher acquisition frequency, redundant data, better data quality and greater computational capacity, even more robust communication. This could make that the high frequency digital twins are not necessarily the most appropriate one for vessels. The selected type of twin should be justified by the decision it is expected to support.

Increasing the complexity and precision of a digital twin also increases its operational demands. Higher fidelity twins would require better sensors, data transmission and will have more redundant data. These requirements may limit the practical applicability of highly detailed twins when instrumentation, communication, validation or crew capability are insufficient.

5. Conclusions.

In this work it has been proposed a functional classification of marine digital twins for maritime systems, with particular attention to training and predictive maintenance on the engine room applications. The proposed Type I to type V helps to distinguish between the different uses on this digital twins.

A central conclusion of this work is that the most detailed or highest-frequency digital twin is not necessarily the most appropriate option for every vessel or operational context. The selected type of twin should always be justified by the decision it is expected to support, the available data, the criticality of the asset and the operational constraints of the vessel.

The analysis shown, that the amount of data that it produces and have to be sent and consider to function properly is related to the level of detail of the digital twin. This strongly increases with complexity, and also, the quantity of data is proportional to the frequency of the generation of the data that is being used. This dimension problem can translate as a problem to manipulate and communicate all this data properly. It seems desirable that the raw data would not be sent before a pre-process the more data-rich segments aboard the ship, in order to reduce the data to the most relevant one. Another option that can be considered is to select a more lightweight Digital twin instead [Montana, F. et al, (2023); Hyun et al, (2025)].

Increasing the detail level on a digital twin will not be always the most appropriate for every vessel and every operating condition. The selected segmentation level must be justified by the critically of the asset, the planned maintenance decision, the available instrumentation, operational constraints, appropriate use of available resources, reducing the environmental impact of the technology, economic aspects, and the vessel's situation, this will mean that the frequency and detail will also have to endure modifications on the volume of data received overtime. The modification of an asset or element aboard the ship for a different one, could and must modify the simulation results, this could become a problem, as it may make it difficult to replace a

vessel's components with newer ones if they cause the existing digital twin to not work properly or generate wrong results with the replaced elements, this generate an urge to implement standardization on the data generation of the components that are suitable to be implemented in ships with operating digital twins [Fonseca, Í. A., & Gaspar, H. M. (2021); Hasan, A., Asfihani, T., Osen, O., & Bye, R. T. (2024)].

In many maritime applications, a robust, efficient, low emission, economic system, or device-level twin can be more useful in the ordinary working situation than an overly detailed complex component-level model that cannot be reliably fed, validated, or maintained during normal operation, mostly because of communication difficulties. More complex systems can also be more difficult to understand and operate by the crew, leading to errors, bad working conditions and maintenance of the systems, and even malfunctions, also increasing the difficulty to motivate the shipowners to integrate this new technology in their ships.

In conclusion, maritime digital twins have significant potential to support design, training, and support on the operation of the engine room, the vessel and the fleet, and improve predictive maintenance. The future of this technology will not only depend on creating more detailed efficient, faster and higher frequency models, but selecting the appropriate level of fidelity segmentation and synchronization, avoiding excessive data, problems on synchronization, communication limitations and unnecessary complexity that could undermine the purpose of the digital twin.

A useful maritime digital twin should therefore be robust, interpretable, maintainable and operationally viable. Smart data retrieval, onboard pre-processing and purpose-oriented model design will be essential to transform digital twins from advanced conceptual tools into practical systems for real vessel operation. This could open the gates to new innovations in maritime transport.

While preparing this manuscript, the authors consulted ChatGPT to improve the English language. After utilizing this tool, the content was reviewed and edited as necessary and after revision, the authors assume full responsibility for the final text.

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