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Analysis of Operational Drivers of Unscheduled Downtime in a Container Fleet

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Abstract

Unplanned downtime in liner shipping undermines voyage reliability and increases costs. This study systematically compiles 397 unplanned downtime events in a container ship fleet between 2017 and 2021, standardizing them according to system/subsystem and time/location attributes. A risk score consisting of frequency × duration × impact components was defined to quantify the severity of downtime on the operation. Pareto analysis was applied to identify a small number of critical causes. Variables driving downtime were extracted using a Classification and Regression Tree (CART) model and supported by Ward's linked hierarchical clustering. The findings show that 89% (352/397) of downtimes were propulsion/propulsion system-related, representing approximately 1,460 hours of the total 1,767 hours; main engine events predominated in this group with 256 incidents and ~730 hours. Despite their rarity, shaft/propeller/stern-tube failures lead to very long delays per event (≈96 hours on average). CART outputs reveal that the longest downtimes are associated with fuel pump and injection failures (median ≈153.6 hours), while exhaust and lubrication-related failures are also high-impact. Pareto analysis showed that oil mist detector (OMD) related events accounted for 63.1% of the total risk, fuel injection 14.8%, and exhaust 7.9%; these three factors accounted for 85.8% of the risk. The findings suggest prioritizing fleet wide condition-based maintenance packages, targeted spare parts management, exhaust gas trend monitoring, rigorous OMD calibration/validation flows, and role-based training programs across the fuel, exhaust, and lubrication triad. Key indicators should be defined to track annual downtime reductions of ≥10-15% in critical clusters and improvements in diagnostic speed.

Keywords: Unscheduled downtime, Marine propulsion failures, CART decision tree, Pareto analysis

1. Introduction

Maritime transport, which constitutes a large part of global trade, is a strategic sector in a race against time. Ships engaged in container transport in the maritime industry are operated with the goals of on-time delivery, high operational efficiency, and low downtime. However, due to the nature of maritime operations, unplanned downtime is sometimes unavoidable. These stoppages can occur for a wide variety of reasons, such as technical failures, environmental conditions, operational errors, or maintenance negligence, and consequently lead to significant time losses and damage costs.

While there is a significant body of literature on ship malfunctions across diverse areas, such as predictive maintenance, statistical analysis of accident data, and human and organizational factors, these studies often focus on single systems or the single-ship scale, and limited fleet-scale downtime assessment based on event records remains limited. While recent studies have demonstrated the technical potential of data-driven/hybrid approaches for main engine

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and auxiliary systems (e.g., risk prioritization, maintenance scheduling, contextual effects), the integration of these methods with real-world field incidents in container ship fleets and the direct translation of findings into maintenance prioritization and role-based training planning have not yet been sufficiently demonstrated. In the Turkish context, empirical evidence that quantitatively maps downtime causes at the fleet scale and translates the results into fleet management decisions is lacking. This study aims to fill this gap with a workable framework that organizes field-sourced incident data at the fleet level, introduces risk concentration (Pareto) and waiting time determinants [Classification and Regression Tree (CART)], and links the resulting patterns to condition-based maintenance and role-based training priorities.

The existing literature covers a wide range of topics, focusing on technical system failures and maintenance strategies that cause unplanned downtime. In academic studies on similar topics, predictive maintenance models for ship systems play a critical role in anticipating potential field failures and ensuring uninterrupted ship operations. Kalafatelis et al. [1] noted that artificial intelligence (AI)-supported predictive maintenance systems in the maritime sector have great potential, particularly in terms of preventing failures in main engines and auxiliary equipment. Budimir et al. [2] developed models for optimizing maintenance scheduling using Weibull and Markov-based analyses. A comparative study by Tinga et al. [3] demonstrates how data-driven and physics-based prognostic models can be used in fleet management. Shen et al. [4] aimed to automatically extract information from written text in maintenance/failure records for the rapid identification of malfunction causes and symptoms on ships. They used the graph transformer networks to capture important fragments of the text (e.g., “failure cause”, “symptom”, “equipment name”).

Operationally, Karmelić et al. [5] examine disruptions that reduce voyage reliability in container liner shipping, using both literature and internal operational reports, classifying delay causes into four tiers: land transport, anchorage, port, and cruise. Nguyen [6] has demonstrated with mathematical models that optimal maintenance planning under limited resources and time can directly reduce unplanned downtime. In studies focusing on the human factor, Islam et al. [7] emphasized the triggering effect of environmental influences and organizational deficiencies on human error in maintenance processes. Specifically for Türkiye, Ünlügençoğlu [8] analyzed maritime accidents and statistically evaluated the relationship between human error and equipment failure.

Unplanned stoppages can occur not only during navigation but also during port operations and under the influence of environmental factors. Romano-Moreno et al. [9] linked stoppages at ports to meteorological data, demonstrating that operational planning must include these factors. Millefiori et al. [10] analyzed the effects of coronavirus disease-2019 on global maritime transport, illustrating the pressure of extraordinary conditions on operational continuity.

The system-level literature offers greater technical depth. Simion et al. [11] argued that AI-based predictive maintenance solutions for ship machinery provide efficiency in terms of reliability. Soltani Motlagh et al. [12] and Jimenez et al. [13] reported that the integration of physics-based models with machine learning in propulsion systems provides high accuracy in fault detection. BahooToroody et al. [14] used Gaussian Process Latent Variable Model and Bayesian inference to non-parametrically model the prediction of ship machinery failure risk. The model provides strong evidence for Pareto-based diagnosis and adaptive maintenance planning under uncertainty. Onwuegbuchunam et al. [15] developed models related to the temporal distribution of shaft and gearbox failures. Crankcase explosion risk and oil mist detectors (OMD). Numerical/computational studies of crankcase explosions and experimental research examining the morphological characteristics of oil mist particles provide direct evidence for determining OMD thresholds and reducing false alarms [16,17]. These findings provide a framework for why unplanned downtime originating from the main engine are critical in terms of both safety and operational time. At the critical subsystem level, thermal behavior and wear in stern tube bearings, risk prioritization in boiler systems [18,19], and duty cycle effects in deck equipment [20] have been identified as factors directly contributing to unplanned downtime.

In studies related to hull damage and structural reliability, reliability studies on critical load conditions such as strength comparisons between damaged/intact states and asymmetric bending in container ships confirm from a structural perspective that a limited number of events can produce very high downtime durations [21]. Network and dynamic impact analyses link to maintenance and operational planning by showing how reliability limits change in operational scenarios [22]. Modeling accident data using Bayesian approaches also enables learning cause-effect relationships and prioritizing “high impact–low frequency” risks [23,24].

Taken together, these strands offer robust methods and mechanisms, yet there is limited empirical, fleet-scale synthesis of forced stoppages grounded in incident records—particularly for Turkish container-ship fleets. Our study addresses this gap by organizing field data at fleet level, quantifying risk concentration (Pareto) and waiting-time drivers (CART), and mapping the results to actionable levers for maintenance planning and role-specific training.

This study aims to reveal which systems and subsystems experience the highest concentration of unscheduled downtime events based on five years of records from 50 container ships, and which factors explain the duration of these stops. The research question can be summarized as follows: "Which technical clusters drive the most unplanned stoppages at the fleet level, and which variables are more influential in determining the level of downtime?" To this end, recorded technical stoppages were examined. The 397 incidents identified over the five-year period were coded in a standardized manner according to systems and subsystems. Subsequently, a Pareto analysis was performed using risk scores derived from the frequency-duration-impact components of the events to identify the critical minority, and CART regression was used to extract the variables and threshold distinctions explaining the waiting time. The findings were interpreted through the decision tree structure and importance scores. The objective is to reveal frequently recurring failure patterns, evaluate the impact of these outages on operational performance, and develop recommendations that will contribute to maintenance, training, and fleet management processes based on the results.

This study examines in detail the forced downtime events that occurred on the ships of a shipping company with a container ship fleet between 2017 and 2021. Unplanned downtime during navigation and port operations over a five-year period involving a fleet of 50 ships was analyzed in terms of both technical causes and operational and training impacts. The aim is to identify recurring failure patterns, assess the impact of these stoppages on operational performance, and develop recommendations to contribute to maintenance, training, and fleet management processes based on the findings.

2. Materials and Methods

2.1. Study Area and Data Set

Unplanned downtime events of a private maritime company with a large container ship fleet based in Türkiye were examined over a 5-year period. The company operates 50 vessels and manages Türkiye's largest fleet in this field. The vessels are actively engaged in various trade routes worldwide.

The dataset was created by compiling and digitizing unplanned downtime reports prepared by ship personnel by the company's technical department. The dataset records variables such as ship name, date, duration and location of the stoppage, system/component name, and reason for the stoppage for each event. A total of 397 unplanned downtime events were recorded.

The data was compiled from technical maintenance and incident report forms obtained from the company's operational reporting system. The incidents were digitally entered into the system by engineers on board and ship technical superintendents, who are marine engineers and fleet managers. Standardized analysis tables were created from this raw data. Each incident was classified according to technical category. Within the three main operational categories (propulsion system, cargo operations, and mooring operations), the propulsion system-related issues with the highest number of incidents were divided into subcategories and analyzed in detail.

This study uses incident records from a single Turkish container-ship fleet operating predominantly on liner trades. While this yields high internal consistency (common procedures, documentation standards, and engine families), it constrains external validity in several ways. First, risk concentrations and waiting-time drivers may differ in fleets with distinct operating profiles, vessel types (tanker, bulk carrier, ro-ro), class/age distributions, or propulsion configurations. Second, the dataset intentionally excludes non-technical delays (e.g., weather, port/terminal operations); this design choice isolates technical stoppages but can inflate their relative share of total downtime and limits comparisons with studies using all-cause delays. Third, organization-specific maintenance practices (spares policies, OMD calibration routines, training cadence) may alter shipboard crew competency skills.

Only recorded technical downtimes were included in the analysis. Unreported minor interruptions were excluded from the study; unexpected technical failures that caused operational disruptions were considered. Planned maintenance, adverse weather conditions, port operational delays, or externally caused downtimes were excluded from the analysis; the focus was on technical downtimes. Data processing included data cleaning and categorization. Incomplete, inaccurate, or duplicate records were eliminated.

2.2. Analysis Method

The analytical framework adopted in this study is designed to balance methodological rigor with operational interpretability. Rather than maximizing predictive accuracy through black-box models, the focus is placed on transparent, rule-based methods that allow failure mechanisms and downtime drivers to be directly interpreted by fleet managers and marine engineers. Pareto analysis is employed to identify risk concentration and critical subsystems at the fleet level, while the CART algorithm is used to uncover threshold-based relationships and nonlinear patterns governing downtime duration. This combined approach enables both prioritization of dominant failure modes and actionable insights for maintenance planning and role-based training, grounded in real operational data.

2.2.1. Risk assessment and pareto analysis

Risk scores were calculated for each type of failure to determine the impact of failures on the operational efficiency of ships. Risk scores were determined using a weighted scoring method based on the frequency of occurrence, duration of the failure, and its operational impact. The Pareto chart created using these scores visually demonstrated the dominant effect of main engine failures on waiting time. Pareto analysis was applied to confirm the finding that approximately 80% of the total downtime is concentrated in approximately 20% of the failures.

2.2.2. CART algorithm

The CART algorithm was used to analyze the effects of ship main engine failures on ship waiting times. CART is a powerful and flexible machine learning approach widely used in classification and regression problems [25]. In the regression context, CART creates a binary decision tree structure that iteratively partitions the dataset into two subsets to identify the relationship between variables.

The modeling process begins by treating the entire dataset as a single node (root node). The algorithm then partitions the dataset into two subsets by determining the most appropriate independent variable and threshold value that minimizes the variance or mean square error (MSE) of the target variable. This process continues iteratively until one of the predefined stopping criteria is met (e.g., maximum tree depth, minimum terminal node size). In the final stage, the mean value of the target variable at each terminal node (leaf node) is assigned as the predicted value for all observations belonging to that node.

The CART model, being a nonparametric method, is highly effective in capturing nonlinear relationships between variables. Furthermore, the model's visualizability and interpretability facilitates easy understanding for both technical and operational stakeholders in decision-making processes. In this study, model performance was evaluated using R^2 (coefficient of determination), root MSE (RMSE), MSE, mean absolute deviation (MAD), and mean absolute percentage error (MAPE) statistics.

In addition, a dendrogram analysis was performed using Ward's linkage method and the Euclidean distance metric to support the findings obtained from the CART model. This approach measures the similarity between failure types to form hierarchical clusters, thereby enabling a visual classification of the relationships among different categories of engine failures.

3. Findings

3.1. General Situation: Summary of the Number of Downtime

During the five-year evaluation period, a total of 397 unscheduled downtime events were recorded in the container ship fleet under review. These stoppages were grouped under three main operational categories: Propulsion System, Cargo Operation, and Mooring Operation activities.

When examining the distribution of stoppages by system, as shown in Figure 1, 89% of downtimes (352 incidents) were due to propulsion systems. Stoppages during cargo operations accounted for 10% of unplanned stoppages, with 39 incidents. The remaining 1% (6 incidents) occurred during mooring operations.

Table 1 shows the total number of stoppages and durations by category. The total unplanned stoppage duration was calculated to be approximately 1,767 hours over the five-year period. The duration distribution is also parallel to the number of incidents.

Based on these data, the average duration of a downtime is calculated to be approximately 4.5 hours. Across the fleet, the annual average number of unplanned downtimes per vessel is approximately 1.6. When the average main engine

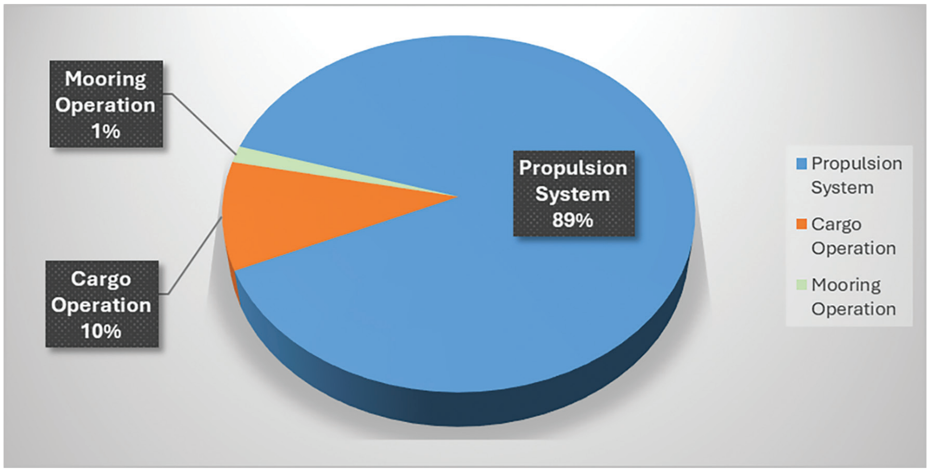

Figure 1. Distribution of stoppages by system.

operating time is assumed to be 4,200 hours per year, the ratio of time spent on downtime to total sailing time is approximately 0.15%. While this low ratio indicates that fleet operations are generally planned and controlled, it also points to the need for priority intervention in terms of propulsion system failure density, maintenance planning, and technical training.

3.2. Distribution by Cause of Downtime

Of the 397 unplanned downtimes that occurred during the five-year period under review, 89% (352 incidents) were directly attributable to propulsion systems. This high percentage highlights how critical main propulsion systems are to operational continuity on container ships.

Based on this criticality, stoppages related to propulsion systems were detailed in terms of their technical components. The propulsion system data, shown in Table 2 with a total of 352 incidents and 1,460 hours of downtime, was broken down into subsystems and analyzed.

Due to the combined reporting of some incidents, mandatory downtime caused by main propulsion systems has been divided into nine main technical categories. This analysis aims to contribute to fleet management, maintenance planning, and technical training content by identifying the subsystems where downtime is concentrated.

In this distribution, main engine failures are clearly ahead not only in terms of the number of incidents but also in total downtime duration. The entire propulsion system alone accounted for approximately 50% of the downtime, with a total of 730 hours of downtime across 256 incidents. The most frequently recurring issues include fuel injection problems, fuel pump (FP) failures, and problems caused by the exhaust system.

In contrast, although only 4 incidents occurred in the propeller, drive shaft, stern tube, and bow thruster group, the total downtime was quite high at 384 hours. This group, with an average downtime of 96 hours per incident, shows that these system failures are rare but cause very long operational interruptions. In such cases, the complete operational downtime of the ship brings with it commercial losses as well as safety risks. These types of failures usually require the ship to wait in port for weeks for repairs. Emergency intervention is not possible; dry docking is usually required. Therefore, these components are considered critical priority. Preventive vibration analysis, oil analysis programs, and proactive maintenance scheduling are vital for this type of system failure.

Some systems with relatively few incidents stand out due to their singular impact. Specifically, in the "Hull/Fire/Maneuvering" category, despite only 8 incidents, the total downtime was 116 hours, with an average interruption of 14.5 hours per incident. This finding demonstrates that some infrequent failures have a high operational impact.

Boiler systems stand out with a total of 151 hours of downtime across 33 incidents. The average downtime of 4.6 hours highlights the need for continuous maintenance and monitoring of this system. Especially, boiler tube perforations lead to prolonged port delays and deviations from estimated arrival times.

Twelve incidents occurred in the Piping, Valves, Pumps, Coolers, and Heaters group, resulting in a total of 36 hours

Table 1. Number of downtimes and durations by category.

	Propulsion system	Cargo operation	Mooring operation	Total
Total downtime (number)	352	39	6	397
Total downtime duration (hours)	1460	272	35	1767

Table 2. Summary of downtime in propulsion systems by subcategory.

Propulsion system	Number of incidents	Duration (hour)	Average duration
Automation & Alarm systems	7	4	0.6
Boiler system	33	151	4.6
Generator load sharing & Black out	25	19	0.8
Hull & Fire & Maneuvering	8	116	14.5
Main engine	256	730	2.9
Piping, valves, P/P, cooler/heater	12	36	3.0
Propeller & Shaft & Stern tube & Thruster	4	384	96.0
Others	7	20	2.9
Total	352	**1460**	**4.1**

of downtime. With an average downtime of 3 hours, these components are classified as medium priority. Diesel generator load sharing, automation and alarm systems, and other groups have a limited impact on propulsion system downtime, with both low frequency and low duration. Most failures in these systems were resolved in less than 1 hour per incident. Incidents under the "Other" category include delays due to GPS display errors, pitch control failures, rudder & pitch-controlled propeller system failures, and items recorded during flag state inspections in port.

As a result, not only the frequency of propulsion system stoppages but also their individual impacts and system-based temporal intensity should be considered in fleet management. In addition to the main engine, boiler systems, maneuvering control systems, and propeller structures are also highlighted as priority areas in terms of preventive maintenance, spare parts inventory management, and training.

3.3. Critical System Analysis: An in-Depth Look

Detailed analysis of fleet data shows that some technical systems fail more frequently than others and have a much greater operational impact. In this section, critical subsystems causing the most downtime or leading to long durations in individual incidents are analyzed separately. The aim is to provide targeted insights for optimizing fleet management and technical maintenance strategies. Table 3 presents the number of main engine failure incidents and their downtimes by subcategory.

In the critical system analysis, main engine-related failures were divided into subcategories and examined. CART regression analysis and hierarchical clustering (Ward-Linkage, Euclidean Distance) methods were evaluated together to determine the impact of main engine failures on ship downtime. The overall goal was to reveal the distribution of downtime events by main engine subcategories and to identify which systems most significantly impact operational continuity.

In the CART regression analysis, waiting time (in hours) was considered the dependent variable and failure types were considered the independent (explanatory) variables. The entire data set consisted of 11 different failure types, and the total number of events and average durations for each failure type were evaluated. The model was evaluated using the median and median absolute deviation (MAD) metrics, taking into account the distribution structure of the data and the sample size. This approach mitigated the impact of outliers in the data set, providing a more robust statistical representation.

Statistical performance metrics for the model generated using the CART method demonstrate that the analysis results have a strong predictive capacity. A total of four predictor variables were used in the resulting model, all of which were found to be statistically significant. The model's coefficient of determination (R^2=99.78%) indicates that almost all of the variance in the dependent variable can be explained. Furthermore, the error measures (RMSE=1.6601, MSE=2.7561, MAD=0.7304, MAPE=0.0377) were quite low. These results demonstrate that the model successfully predicts ship waiting times with high accuracy and low error (Table 4).

Figure 2 demonstrates the variation in model error, measured by Relative MAD, with respect to the number of terminal nodes. While increasing the number of nodes typically lowers the error rate, an excessive number of nodes can

Table 3. Number and duration of main engine incidents by subcategory.

Main engine failures	Number of incidents	Duration (hour)	Duration (day)
Oil mist detector	27	53.8	2.2
Fuel pump & Inj VV/Inj pipe	52	153.6	6.4
Fuel line & Fuel filter	24	60.3	2.5
Exhaust	44	96.1	4.0
Automation & Sensor failure	17	23.6	1.0
Lubrication system & Water in oil & LO filter	16	76.0	3.2
Cooling system & Cover	14	54.0	2.2
Piston & Rings	7	49.5	2.1
Start & Maneuvering & Governor system	24	76.1	3.2
Alpha lubricator	10	15.9	0.7
Other	21	71.3	2.9
Total	**256**	**730.2**	**30.4**

lead to model complexity and overfitting, thereby reducing the model's ability to generalize. Therefore, identifying the optimal trade-off is crucial. The analysis determined the optimal structure to be 8 terminal nodes, where the Relative MAD was minimized to 0.0291. At this optimal configuration, the correlation coefficient of the training set was calculated as 87.33%.

The regression tree generated as a result of the analysis is shown in Figure 3. At the root node of the tree (Node 1), the median waiting time for all faults was determined to be 60.25 hours. This value serves as a general indicator of performance across all fault types examined. The high median absolute deviation (MAD=25.13) indicates significant differences in waiting times across fault types.

The model categorizes failure types into two main groups. The main difference between these two groups is the median values in the waiting time distributions. The first group (Node 2) consists of failures with shorter waiting times on average, while the second group (Node 5) includes failure types characterized by longer waiting times. The first separation of the model was based on the "main engine event type" variable, which revealed two main groups. The first group represents events in the categories of alpha lubricator, automation & sensor, cooling system, fuel line & filter, OMD, piston & rings (Alp_Lub, Au_Sen, Cool, FL, OMD, Pist), while the second group includes events in the categories of exhaust, FP & injection valve (inj vv), lubrication system, other, and start & manuevring (Exh, FP, Lub, Other, Star). The median value for the first group on the left branch was calculated as 51.63, and for the second group on the right branch as 76.05. This shows that waiting times due to engine failures in the second group have a higher impact.

In particular, the median value for FP and valve failures was determined to be 153.64, standing out as the factor with the highest impact on the system. This clearly demonstrates that fuel injection system malfunctions are a key parameter significantly affecting downtime. Fuel injection line malfunctions (pump barrel and plunger wear, control rack/governor lockup, fuel valve nozzle clogging, common-rail pressure leaks, timing deviations) directly reduce cylinder combustion pressure and ignition quality. The resulting effects include power loss, unsteady combustion, exhaust temperature deviations, vibration, and the necessity of slowdowns/stoppages for safety reasons. Many interventions on the fuel injection system at sea can extend downtime due to the need for equipment cooling, fine-tolerance component replacement, calibration, testing procedures, or limited equipment and spare parts availability.

Similarly, faults related to the "Exhaust (Exh)" and "Lubrication (Lub)" systems were observed to have high median values. Because these are critical parameters that directly affect engine performance, they stand out as the most

Table 4. Performance metrics for the CART regression model.

Total predictors	4
Important predictors	4
Number of terminal nodes	8
Minimum terminal node size	1
R-squared	99.78%
Root mean squared error (RMSE)	1.6601
Mean squared error (MSE)	2.7561
Mean absolute deviation (MAD)	0.7304
Mean absolute percent error (MAPE)	0.0377

CART: Classification and Regression Tree

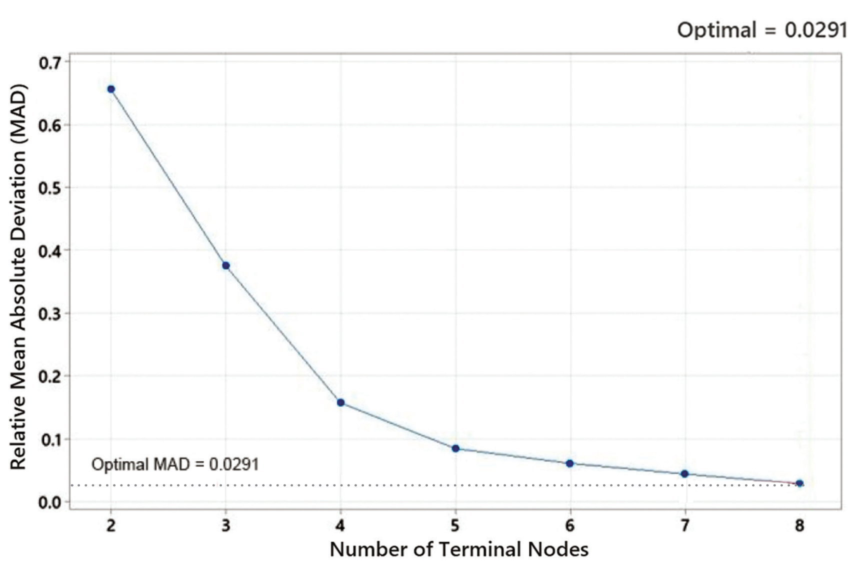

Figure 2. Optimization of the node.

significant contributors to downtime and require careful attention. It is technically expected that exhaust (Exh) and lubrication (Lub) faults produce high median downtime. Soot/oil carryover in the exhaust line, turbocharger fouling, or manifold and seal leaks increase back pressure, disrupting combustion. Safety measures such as power reduction/stop, cooling, cleaning, and rebalancing (turbo, sensor, insulation) prolong downtime. On the lubrication side, pressure drop/pump failure, filter blockage, viscosity and temperature deviations, or increased metal particles lead to critical scenarios such as bearing damage and the risk of crankcase explosion. This necessitates time-consuming interventions such as oil sample analysis, circuit checks, filter and cooler maintenance, and bearing inspections. In conclusion, Exh and Lub faults are critical parameters that directly affect engine performance.

In contrast, failures occurring in the "sub-components (Alp_Lub)", "cooling (Cool)", and "sensor (Au_Sen)" systems have lower median values. This result can lead to shorter downtimes due to the early detection of these failures and rapid intervention during maintenance processes. Failures in these three groups are generally localized and are quickly managed onboard using redundant/twin equipment (stand-by pumps, parallel heat exchangers), isolation valves, and modular component replacement. In cooling circuits, flow is maintained with a pump/heat exchanger switch-over; system safety is maintained by calibration/restart or rapid replacement on the sensor side; and in lubrication sub-components, filter replacement, leak repair, and bypass options shorten downtimes. Furthermore, since these failures are often detected with early warning (alarm), they can be deferred until port under power-limited operation rather than

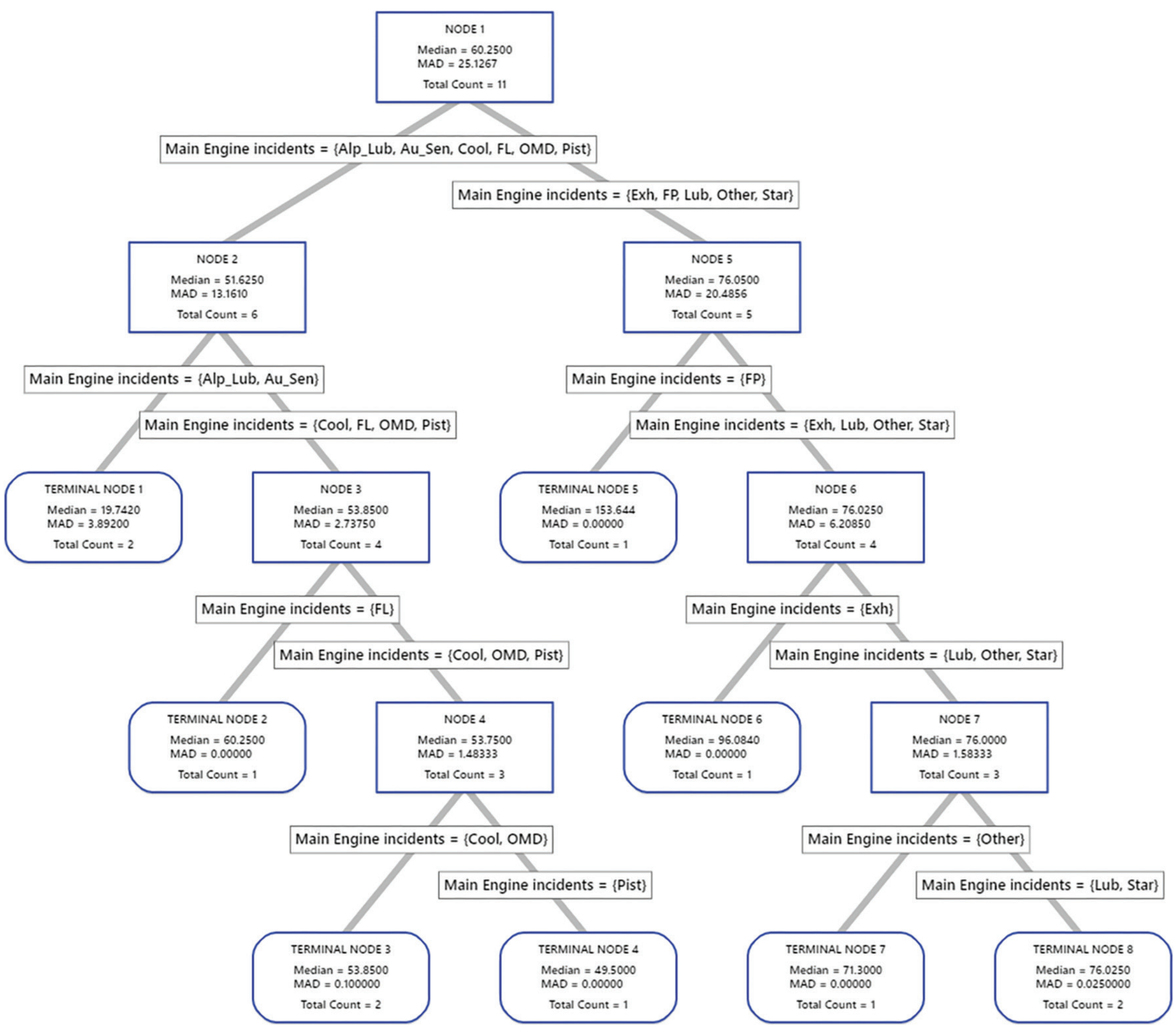

Figure 3. CART regression analysis results showing the effect of main engine failures on downtime.

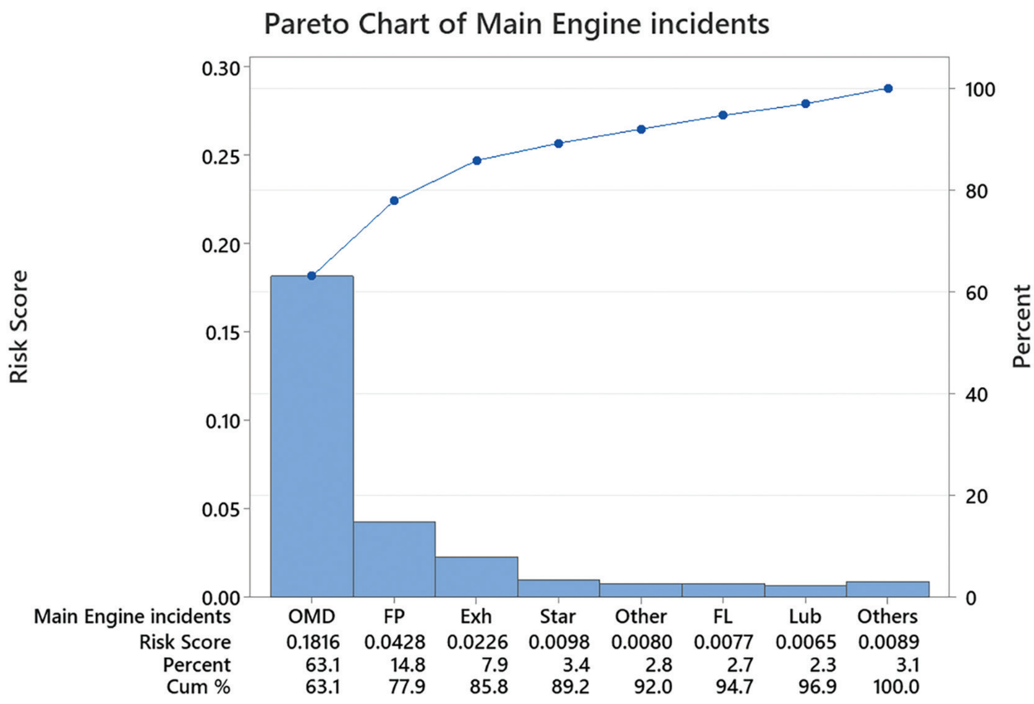

Figure 4. Pareto chart showing the severity of main engine failures according to risk scores.

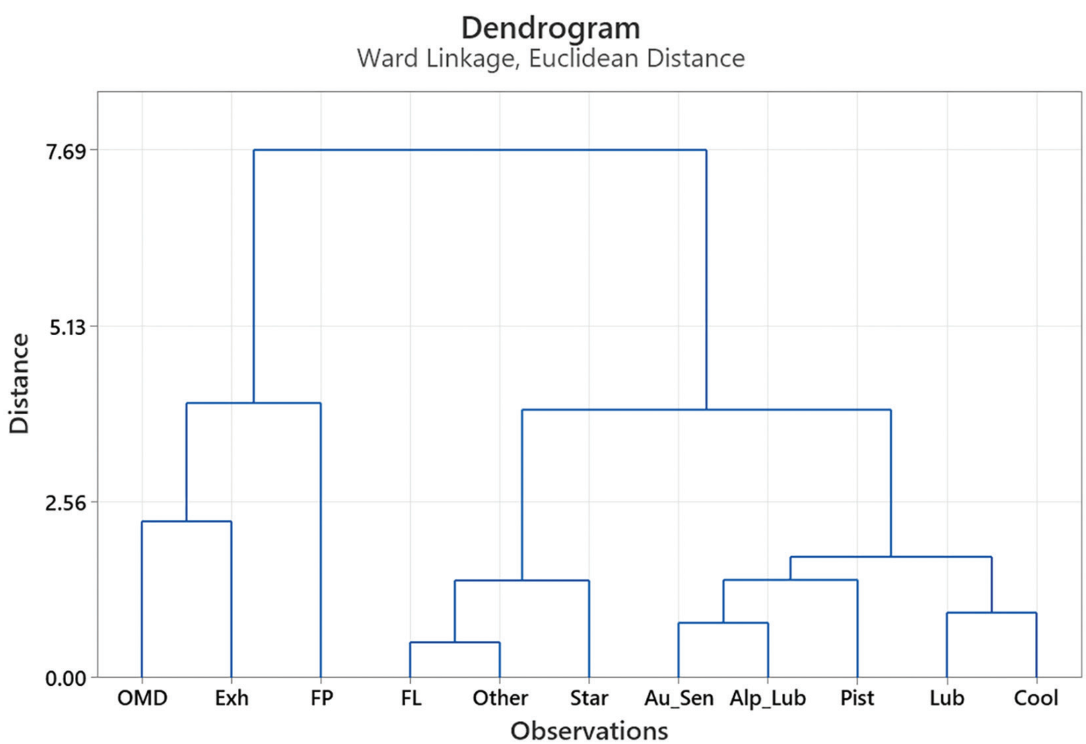

Figure 5. Dendrogram showing the similarity levels of fault types.

a full shutdown for safety reasons; consequently, downtimes are typically short.

Figure 4 shows a Pareto analysis of main engine failures. The graph shows the severity of failure types based on the risk score in ship operations. According to the analysis results, failures caused by OMD were identified as the most critical failure type, accounting for 63.1% of the total risk. This result demonstrates the crucial importance of regular maintenance and monitoring of OMD systems for main engine safety and operational continuity. OMD alarms are generally based on two factors: actual oil mist detection (crankcase fire risk, high density) or false alarms due to sensor sensitivity and air pressure adjustment. In these events, the operational impact is significant because the engine automatically shuts down or reduces speed. Often, the ship must be shut down until the alarm is verified. While some failures in these systems do not pose a real risk, each one triggers a maximum operational response due to safety protocols. Even if there is a sensor error, the engine must be shut down and the necessary checks performed seriously, just like the actual oil mist risk. A high-priority, critical alarm is due to the potential for major damage to the engine or a crankcase explosion. This demonstrates that factors such as calibration frequency of OMD systems, sensor quality, and crew diagnostic ability are critical for operational continuity.

OMD failures are followed by FP and valve failures (14.8%) and exhaust system (Exh) failures (7.9%). When these three failure types are considered together, they account for 85.8% of the total risk, indicating that operational disruptions in the majority of the system are caused by these components. Other failures (starting system, fuel leakage, lubrication system, etc.) constitute only less than 15% of the total risk.

This finding is consistent with the "80/20 Pareto principle" and demonstrates that preventive maintenance of critical components, particularly OMD, fuel, and exhaust systems, should be prioritized to improve system performance and reduce ship downtime.

Comparing the findings with those obtained through hierarchical cluster analysis (Figure 5), significant parallelism was observed between the two methods. The clustering of "OMD", "Exh", and "FP" failures within the same cluster in the dendrogram is consistent with the high median values of these parameters in the CART analysis. Similarly, the close clustering of "Cool", "Lub", and "Run" failures confirms the high correlation between these components due to common operating conditions (e.g., heat transfer and lubrication processes). Another cluster includes the auxiliary sensor (Au_Sen), alpha lubricator (Alp), and starting system (Star) failures, indicating that these failures are related to electronic control and monitoring systems.

4. Discussion

In this section, the findings obtained in the study are compared with similar studies in the literature and their operational implications are evaluated. The fact that 89% of the unplanned stoppages identified in the study were caused by propulsion systems reveals that ship operations are largely dependent on these systems. This finding coincides with the assessment in Vizentin et al.'s [26] study. Vizentin et al. [26] states that propulsion systems are the main source of failures in container ships, particularly concentrated in the main engine and shaft lines. The high failure rate poses a risk not only technically but also in terms of operational reliability. Numerical and experimental studies on the risk of crankcase explosions and the reliability of OMD provide concrete scientific evidence for optimizing detector threshold values and reducing false alarms by analyzing the morphological characteristics of oil mist particles in the crankcase [16,17].

Failures occurring in systems such as stern tube and propellers cause quite long downtimes despite being observed at low frequencies. This creates a special risk profile in terms of fleet management. A technical report prepared by Kuroiwa et al. [27] states that stern tube bearing failures are mostly caused by deterioration in lubrication systems, leaks in gaskets, and inadequate temperature control. Similarly, an experimental study by Chang et al. [28] showed that water-lubricated shaft sleeve bearings are sensitive to parameters such as temperature, load, and speed, and even a small tolerance deviation can cause long-term operational downtime. In this context, shaft sleeve and propeller systems should be considered strategic critical systems due to their high downtime, despite the low number of incidents.

The source of some unplanned stoppages of ships is not technical failure but rather faulty or overly sensitive alarm notifications from automation systems. In particular, "false positive" alarm events originating from OMD systems create uncertainty in the crew's decision-making mechanism and sometimes lead to unnecessary stoppages. Thorpe and Pabby's [29] comprehensive analysis indicates that the high sensitivity of OMD systems does not always provide a safety advantage; on the contrary, false alarms lead to a loss of confidence and psychological stress among the ship's crew. In this context, it is evident that topics such as alarm management and crew decision-making competence should be an integral part of technical training.

5. Evaluation and Results

This study systematically evaluated 397 unplanned downtimes recorded on container ships during the 2017-2021 period. The center of gravity of downtimes was the propulsion system (352 incidents; 89%), while cargo operations (39 incidents; 10%) and mooring downtimes (6 incidents; 1%) were among the remaining downtimes. Total unplanned downtime was calculated as 1,767 hours, with an average duration per incident across the fleet of approximately 4.5 hours. Downtimes related to the main engine alone, within the propulsion system, accounted for approximately half of the total duration, with 256 incidents and 730 hours.

A detailed examination of the main engine subtypes revealed that FP-injector, exhaust (Exh), and lubrication (Lub) failures were characterized by high median wait times, while cooling (Cool), sensor (Au_Sen), and subcomponent (Alp_Lub) failures were managed in relatively short times. In the CART regression tree, the root node began with a median wait time of 60.25 hours; after the decomposition, one branch corresponded to a median wait time of 51.63 hours, and the other to 76.05 hours. In this structure, the median for FP failures reached the highest value of ~153.64 hours, indicating that fuel injection failures significantly prolonged wait times. Hierarchical clustering results supported this picture; the close clustering of OMD-Exh-FP indicated a tendency toward long waits, while the association of Cool-Lub-Pist indicated a common behavior related to heat transfer and lubrication conditions. Pareto analysis showed that OMD-related events accounted for 63.1% of the total risk, FP for 14.8%, and Exh for 7.9%; these three items together reached 85.8%. This overall picture indicates that a small number of critical items at the fleet level drive a large portion of the total waiting time.

A condition-based maintenance package is recommended for the fuel-exhaust-lubrication triad, where risks are most pronounced. As a technical maintenance strategy, cyclical component replacement programs should be established fleet-wide for injectors, FPs, and exhaust components. To reduce both fuel and exhaust system problems, main engine performance values, especially maximum combustion pressure values, should be checked more frequently, and maintenance should be planned to anticipate potential problems.

On the fuel side, test bench calibration records for injection pumps/injectors should be regularly maintained. To save time in the event of malfunctions in these systems, especially based on competency, third- or fourth-level engineers should be trained and made aware of maintaining spare parts for replaceable fuel system components.

Exhaust gas temperature trend monitoring should be implemented in the exhaust; deviations above ±30 °C between cylinders can be detected before they reach alarm levels, enabling early intervention. To achieve this, implementing a checklist for systems under the control and monitoring of watchkeeping engineers can prevent forced shutdowns related to the exhaust system, particularly through regular monitoring of exhaust temperatures.

Monthly oil analysis (particulate matter/viscosity/BN) results in the lubrication system should be visualized using a "traffic light" approach. Laboratory results should be closely monitored by the office and the ship. Onboard oil analyses should be increased in frequency, and all engineers should be trained on this subject.

To support these systems, which frequently cause shutdowns, the minimum critical onboard inventory (fuel valve nozzles, plunger/barrel, exhaust valve spares, pressure/temperature sensors, filters) should be recalculated according to route and lead time; low-threshold warnings should be entered into the planned maintenance system. The goal is to reduce the number of stoppages caused by these three by ≥15% per year and to shorten the wait per event by ≥30 min.

Delays in OMD-related shutdowns often arise from the inability to quickly distinguish between true and false alarms. A three-tiered approach is recommended for every ship: (i) Hardware: Sensor calibration intervals should be shortened; a 2-minute quick checklist for aspiration lines, filters, and sampling should be standardized. (ii) Workflow: A one-page "procedure/verification protocol" (reserve sensor, local heat/vibration, oil mist monitoring) to be followed when an alarm occurs should be visible in the engine control room. (iii) Recording: The "alarm time-verification steps-result" fields should be mandatory in the engine room logbook. The goal is to reduce unnecessary OMD-related delays by 30% and reduce verification time in real-world situations to <5 minutes.

The utility of the CART decision tree depends on up-to-date and consistent data. Mandatory, coded fields (system/subsystem, start and end, steps implemented, verification period, result) should be added to incident forms; free text should be kept to a minimum. The model should be retrained at least annually with new data; tree depth, number of terminal nodes, R^2, and RMSE should be reported. The risk thresholds used in Pareto should be updated with annual reviews based on fleet age, fuel quality, or line changes. A "top three root causes - top three actions" table should be communicated to the fleet through ship-to-office feedback meetings. Average waiting per stop, incident frequency, and duration in critical clusters should be monitored as indicators of success.

To translate technical measures into lasting results, a structured fleet-wide competency development program is recommended. A role-based competency matrix (3rd, 2nd, chief engineer, electrician, etc.) should be established. OMD alarm management, critical subsystem diagnostics derived from CART, fuel-exhaust-lubrication package procedures, and shaft line early warning signals should be core modules within this matrix.

Two channels for training delivery: (i) Microlearning (10-12-minute videos/notes), (ii) scenario-based exercises (monthly online + quarterly live demonstration). Standardized checklists and time objectives should be used for each scenario. An onboarding package, familiarization training (first 30 days) should be mandatory for newly appointed personnel, and competency should be verified with an annual refresher exam (≥80% success). To track the impact of training, KPIs (Key Performance Indicators) (training participation rate, drill success score, and fault response time after training) should be monitored, and ships with low performance should be inspected and trained. The goal is to reduce downtime in critical clusters by 10-15% and diagnosis times by 20% in the first 12 months after training.

6. Conclusion

This study presents a fleet-scale analysis of unscheduled downtime in container ship operations based on five years of operational records from 50 vessels. By combining risk-based Pareto analysis with an interpretable CART regression framework, the research identifies a limited number of technical subsystems that dominate both downtime frequency and duration. The results demonstrate that propulsion-related failures particularly those associated with the main engine fuel, exhaust, lubrication, and oil mist detection systems account for a disproportionate share of operational disruption, despite the presence of numerous lower-impact failure modes.

Beyond identifying critical failure clusters, the study contributes a practical, data-driven framework that links empirical downtime patterns to maintenance prioritization and role-based training strategies. The emphasis on interpretability enables direct translation of analytical outcomes into actionable decisions for fleet managers and marine engineers. While the findings are specific to container ship operations within a homogeneous fleet, the proposed analytical approach is transferable to other vessel types and operational contexts. Future studies may extend this framework by incorporating additional fleets, integrating exposure-normalized indicators, and evaluating long-term performance improvements resulting from targeted maintenance and training interventions.

Footnote

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