AI-DRIVEN SHIP REPAIR TIME ESTIMATION FOR A SUSTAINABLE BLUE ECONOMY

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Abstract

Efficient ship repair time estimation is vital for optimising dockyard operations, reducing delays, and supporting the Blue Economy by minimising resource wastage and environmental impact. Inaccurate predictions lead to higher operational costs, excessive fuel consumption, and increased carbon emissions, undermining sustainable development in the maritime sector. Traditional estimation methods struggle with uncertainties in repair scope, resource availability, and unforeseen socio-technical complexities. This study applies Artificial Intelligence (AI), namely Machine Learning (ML) and Deep Learning (DL) techniques, including Linear Regression (LR), Random Forest (RF) Regression, XGBoost Regression, and Deep Neural Networks (DNNs), to predict ship repair durations with improved accuracy. These models are trained using historical data on ship specifications, repair scope, and past maintenance durations. By enhancing efficiency and sustainability, this research contributes to a data-driven, eco-friendly maritime industry, aligning with global efforts toward a resilient Blue Economy. Future research will explore real-time data integration and hybrid modelling approaches to refine predictive capabilities further.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Ship Repair, and Scheduling.

1. Introduction

The maritime industry lies at the heart of the Blue Economy, playing a pivotal role in facilitating global trade, creating employment, and driving sustainable development, especially for coastal nations like Bangladesh. With the country's strategic location along the Bay of Bengal, the efficiency and reliability of its maritime infrastructure, particularly ship repair facilities, are critical to unlocking its full economic potential.

Ship repair is a time-sensitive and resource-intensive complex activity. Delays or inaccuracies in estimating repair durations can lead to operational bottlenecks, inflated costs, and inefficient resource allocation. These challenges affect individual ship operators and ripple across the wider maritime logistics chain, impacting port schedules, cargo movement, and carbon emissions (Lam and Notteboom, 2014). Bangladesh's ship repair sector is under increasing pressure to modernise and deliver high-value services while aligning with international safety, environmental, and sustainability standards.

Despite these demands, traditional estimation methods for ship repair time remain largely empirical and heavily dependent on expert judgment (Butler, 2000). While valuable, these approaches often lack precision and scalability, especially in complex or multi-phase repairs. Integrating Artificial Intelligence (AI) and Machine Learning (ML) offers a transformative pathway in this context. By learning patterns from historical data and capturing nonlinear relationships among repair variables, AI-driven models can deliver faster, more accurate, and explainable predictions.

This research proposes a machine learning-based framework to estimate ship repair time using real-world datasets from a Bangladeshi repair yard. The study compares the performance of multiple ML and Deep Learning models - Linear Regression (LR), Random Forest (RF) Regression, XGBoost Regression, and Deep Neural Networks (DNN). The proposed approach contributes to operational efficiency and environmental stewardship by streamlining repair scheduling and improving predictability - two key pillars of a sustainable Blue Economy (Visbeck, 2018). The findings of this work aim to support more thoughtful decision-making in ship maintenance planning and help maritime stakeholders in Bangladesh transition toward data-driven practices for long-term competitiveness. The following sections elaborate on the problem definition and solution techniques.

2. The Ship Repair-Time Estimation Problem

Estimating ship repair time is a complex but essential task in maritime operations, especially for shipyards, operators, and project managers who aim to reduce downtime and control costs. At the core of this estimation lies the Scope of Work (SOW), which must be defined with precision. The repair type - mechanical, structural, or electrical - significantly influences the timeline. Tasks such as repainting, minor welding, or replacing mechanical components vary drastically in terms of time requirements. The location of the repair (in dry dock or afloat) also affects the accessibility and, thus, the repair duration (Surjandari and Novita, 2013; Abdullah, 2021). Figure 1 shows a flowchart of a typical ship repair procedure, which incorporates various time-critical phases and indicates the complexities in estimating ship repair time.

2.1 General Aspects of Ship Repair Time Estimation

A thorough damage assessment is a foundational element for repair time estimation. For scheduled maintenance, this is straightforward, but inspecting the damage - often using non-destructive testing (NDT) techniques - is vital for unexpected failures or post-accident repairs. The inability to assess the damage frequently leads to underestimated workloads and timeline overruns. From here, detailed man-hour estimation becomes critical. Calculating the required time based on standard man-hours for each task and adjusting those figures for worker availability, skill level, and whether functions can be performed concurrently is essential. Historical data and task breakdowns are often used to enhance this accuracy.

Material and part availability is another key aspect that directly impacts repair schedules. Delays in sourcing essential components - especially if they are custom-made or imported - can lead to project stagnation. Similarly, equipment and dock availability must be synchronised with the repair timeline. For example, delays in dry dock slot allocation or crane usage can force rescheduling, which creates ripple effects across other planned activities.

In addition, the workforce plays a crucial role. Even with all materials and tools in place, a shortage of skilled labour or low productivity due to fatigue or environmental conditions (like monsoons or extreme weather) can slow things down. Regulatory and inspection requirements further affect the timeline. Surveyors from classification societies or port authorities often need to verify the work, and their availability or additional repair requests can add significant time.

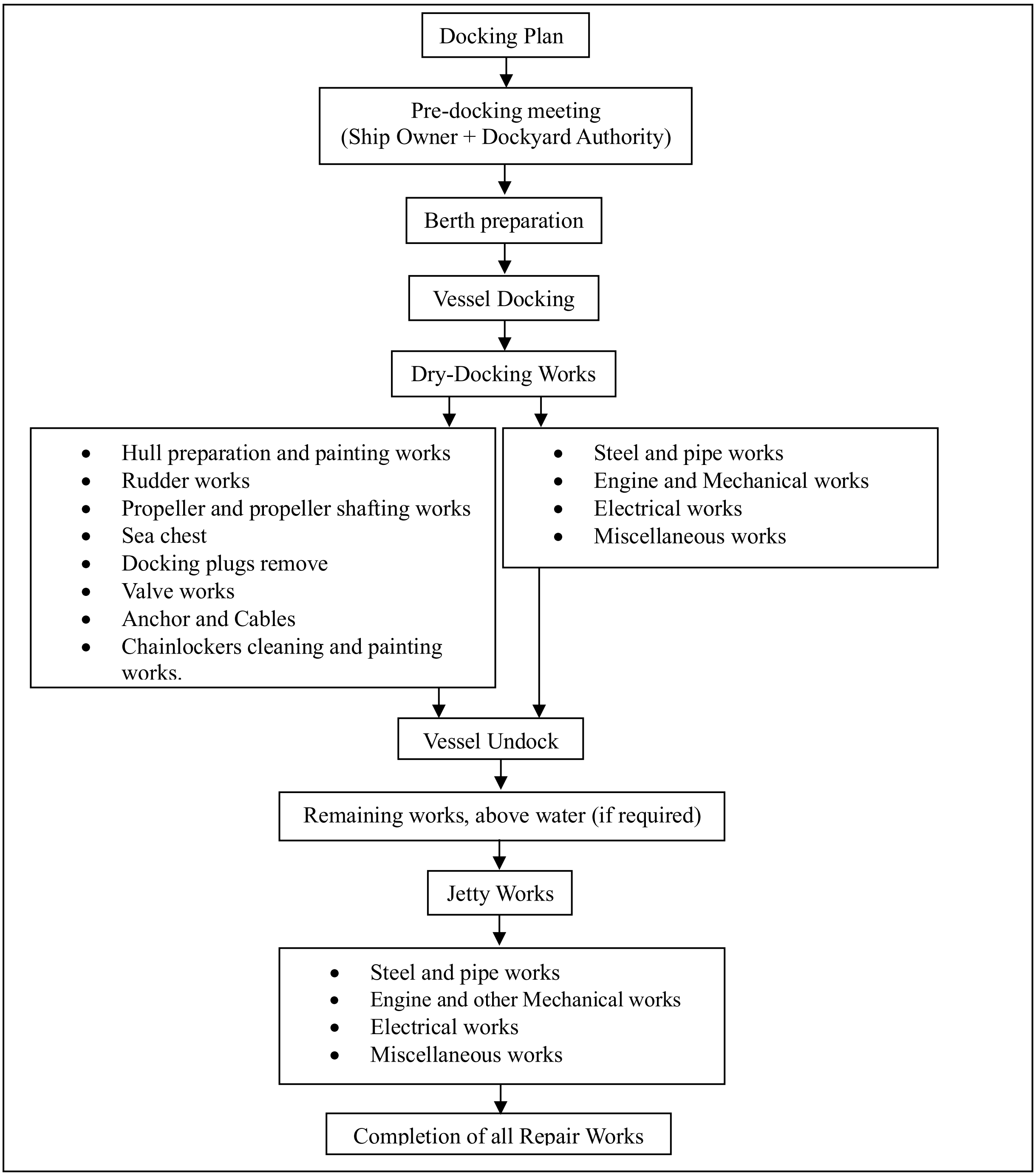


Figure 1: The ship repair flowchart showing the complexity of estimating repair time (Abdullah 2021).

Project planners increasingly rely on scheduling tools like Gantt charts, the Critical Path Method (CPM), regression models, and even simulation models (Awal and Abdullah, 2020). These help visualise dependencies, sequence repairs logically, and identify the longest delay-prone paths. Additionally, smart yards incorporate risk buffers - a percentage of extra time added to cover unexpected events like rework or supply chain failures. These contingencies ensure that the project stays on track despite hiccups (Apostolidis et al., 2012). Learning from the past is one of the most underused yet powerful practices. Reviewing previous projects, analysing what caused delays, and updating estimation models ensure continuous improvement (Cristóbal, 2009; Dev and Saha, 2015; Dev and Saha, 2016).

2.2 Specific Aspects of Ship Repair Time Estimation

This research identifies several aspects that may contribute directly to estimating ship repair time. These are as follows:

i. The amount of plate work required in tons
ii. The amount of sandblasting area in square meters
iii. The amount of painting area required in square meters
iv. The amount of hull cleaning required in cubic meters
v. The amount of tank cleaning required in cubic meters and
vi. The amount of needed valve work in quantity

The following subsections elaborate on these aspects in detail, presenting the complexity of these types of works. Also, Figure 2 illustrates some of the labour-intensive tasks generally performed during ship repair.

Figure 2: Labour-intensive and complex tasks. Upper left: Staging for; Upper right: Sandblasting; Lower left: welding works; Lower right: Painting works. (Abdullah, 2021)

2.2.1 Plate Work (Ton)

Plate work involves repairing, renewing, or reinforcing steel plates that form the ship's hull and structural components. Over time, hull and steel structures deteriorate due to corrosion, mechanical stress, and environmental exposure. The plate renewal process consists of the following:

i. Inspection and Marking: Identifying corroded or weakened areas requiring replacement.
ii. Cutting and Removal: Deteriorated sections are cut out using oxy-fuel or plasma cutting.
iii. Preparation and Welding: New steel plates are cut, shaped, and welded using MIG, TIG, or arc welding.
iv. Surface Treatment: The repaired area is ground, primed, and painted for corrosion protection.

Plate work is labour-intensive, and its extent directly influences the total repair time, particularly in larger vessels requiring significant steel work.

2.2.2 Sandblasting (sq. m)

Sandblasting, also called abrasive blasting, is a surface preparation technique that removes rust, old paint, and contaminants from metal surfaces. It ensures proper adhesion of protective coatings and involves:

i. Selection of Abrasive Material: Materials like silica sand, steel grit, or aluminium oxide are used based on the substrate.
ii. Blasting Process: High-pressure air or water propels the abrasive onto the surface.
iii. Cleaning and Inspection: The surface and roughness are checked for optimal coating adhesion.

Sandblasting is a time-consuming process that significantly impacts repair scheduling, especially when dealing with large surface areas and thick coatings.

2.2.3 Painting Work (sq. m)

Painting protects ships from corrosion, fouling, and environmental degradation. The process includes:

i. Surface Preparation: Ensuring the surface is free from rust, old coatings, and contami¬nants.
ii. Primer Application: A corrosion-resistant primer is applied to bond with the metal.
iii. Coating Layers: This involves applying multiple layers of marine coatings, such as anti-corrosion, anti-fouling, and topcoat finishes.
iv. Curing and Drying: Allowing the coatings to dry under controlled conditions.

The extent of painting work influences the overall repair schedule, particularly due to drying times and environmental conditions.

2.2.4 Hull Cleaning (cubic m)

Hull cleaning removes marine growth, rust, and sediments from underwater surfaces, improving hydrodynamic efficiency and reducing fuel consumption. The process consists of:

i. Underwater Inspection: Divers or remotely operated vehicles (ROVs) inspect hull conditions.
ii. Cleaning Techniques: High-pressure water jets, mechanical brushing, or chemical treatments are used.

iii. Final Inspection: Ensuring the cleaned hull meets operational standards.

Heavily fouled hulls require longer cleaning durations, affecting the ship's docking schedule and repair timeline.

2.2.5 Tank Cleaning (cubic m)

Tank cleaning is crucial for maintaining cargo, ballast, and fuel tanks. It prevents contamination, ensures safety, and meets environmental regulations. The process includes:

i. Draining and Ventilation: Remove residual fluids and gases and ventilate the tank.
ii. Manual or Automated Cleaning: High-pressure washing, chemical cleaning, and sludge removal.
iii. Inspection and Coating: Inspect the cleaned tank for corrosion and apply protective coatings.

Tank cleaning duration depends on tank size and complexity, affecting the overall repair schedule, particularly when handling hazardous materials.

2.2.6 Valve Work (Qty)

Valves control fluid flow in a ship's piping systems, including fuel, ballast, cooling water, and hydraulics. Valve work in ship repair involves:

i. Inspection and Testing: Checking for leaks, corrosion, and operational efficiency.
ii. Repair or Replacement: Cleaning, lapping, and reassembling or replacing damaged valves.
iii. Pressure Testing: Ensuring functionality by testing repaired or new valves under pressure.

Since valves are distributed throughout the ship, their maintenance significantly affects repair time estimation, especially when dealing with difficult-to-access systems.

Each of these activities involves complex procedures that require skilled labour, specialised equipment, and considerable time to complete. Plate work, for instance, is highly labour-intensive as it involves cutting, welding, and surface treatment, which can extend the repair duration depending on the extent of steel renewal required. Sandblasting and painting work are equally crucial as they prepare and protect the ship's surface from corrosion and environmental damage. The time needed for these processes depends on the ship's size, coating thickness, and environmental conditions, making them critical components of repair time estimation. Similarly, hull and tank cleaning are essential for maintaining operational efficiency and compliance with regulations, but their duration varies based on the extent of fouling and contamination. Valve work involving inspection, repair, or replacement can further impact repair schedules, particularly when dealing with hard-to-reach areas or complex piping systems. Since these parameters are interrelated, delays in one aspect can cascade into other areas of the repair process, emphasising the need for precise estimation. Accurate repair time estimation is essential for optimising docking schedules, minimising downtime, and ensuring cost-effective maintenance planning. By understanding these factors and their impact, shipowners and repair teams can better manage resources, improve workflow efficiency, and enhance operational readiness.

3. Linking the Blue Economy with Ship Repair Time Estimation

The Blue Economy advocates for the sustainable exploitation of ocean resources to drive economic growth, ensure social inclusion, and protect marine ecosystems (Silver et al., 2015). Among its many sectors - fisheries, coastal tourism, offshore renewable energy, and marine biotechnology - shipbuilding and repair play a pivotal role in maintaining the operational integrity of global maritime transport and infrastructure.

Within this framework, ship repair time estimation emerges as a critical enabler of sustainability. It goes beyond logistics or cost-saving - it directly influences the environmental footprint of maritime operations. Inaccurate estimations lead to unnecessary downtime, excessive emissions from support systems, poor workforce planning, and material waste. Overestimated schedules reduce throughput and inflate costs, while underestimated ones may force unsafe, rushed repairs, increasing the risk of pollution incidents at sea.

Modernising ship repair planning through data-driven techniques, such as machine learning and simulation modelling, can significantly enhance scheduling accuracy. This approach reduces inefficiencies, minimises idle vessel time, and aligns with carbon reduction goals. It transforms ship repair from a reactive necessity into a strategic asset for maritime sustainability.

By embedding accurate time estimation into shipyard operations, nations can reinforce their Blue Economy initiatives, linking environmental stewardship with industrial performance. In an era where climate resilience and economic viability go hand-in-hand, optimising ship repair is no longer optional—it is foundational.

4. Model Development

4.1 Data Collection and Parameter Analysis

The dataset used for this research was collected from Abdullah (2021). It shows the ship repair time of various ships with different characteristics and maintenance tasks. This includes parameters such as the Length and Gross Tonnage for multiple vessels and the required activities for repair, such as Plate Work, Sand Blasting, Painting, Hull Cleaning, Tank Cleaning, and Valve Work, which influenced the total repair time of those ships. Larger vessels and extensive repair requirements generally lead to longer repair durations. The dataset helps analyse how repair activities impact maintenance scheduling and cost estimation. The repair activities that affect the ships' total repair time are described in detail in the following sections. Figure 3 shows the histogram and correlation of various parameters of the dataset.

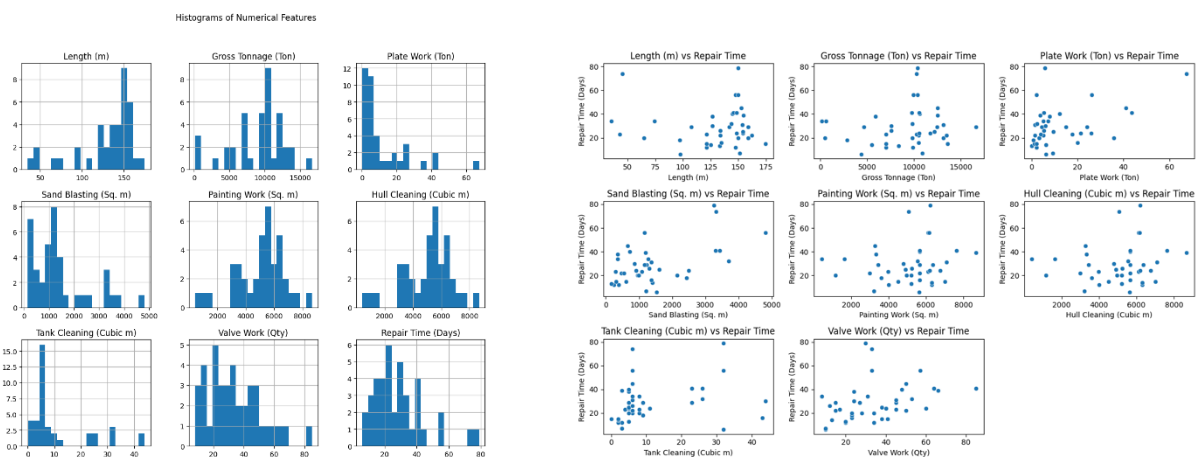


Figure 3: Histogram (left) and correlation (right) of various data set parameters.

4.2 Machine Learning Methods for Ship Repair Time Estimation

For the estimation of ship repair duration based on the vessel and specific parameters, four regression-based machine learning techniques have been employed: Linear Regression (LR), Random Forest Regression (RF), XGBoost Regression, and Deep Neural Networks (DNNs). Each method provides unique advantages in capturing underlying relationships between input variables and target outcomes (Hastie et al., 2009; Goodfellow et al., 2016).

4.2.1 Linear Regression (LR)

Linear Regression models the repair time as a linear combination of input features. Mathematically, the model assumes:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \epsilon$$

Where,

y is the estimated repair time
X_i are the predictor variables (e.g., gross tonnage, hull work, age of ship)
β_i are the regression coefficients
ϵ is the error term.

While easy to interpret and computationally efficient, LR cannot model nonlinear interactions often present in real-world ship repair scenarios.

4.2.2 Random Forest Regression (RF)

Random Forest is an ensemble technique that constructs multiple decision trees and averages their predictions. Formally:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(X)$$

Where,

T is the total number of trees
$h_t(X)$ is the prediction of the$t$-th tree for the input

RF can capture nonlinear and complex interactions, offers robustness to overfitting, and provides variable importance scores.

4.2.3 XGBoost Regression

XGBoost is a gradient-boosting technique that builds decision trees sequentially to minimise a loss function. The model output is given by:

$$\hat{y} = \sum_{k=1}^{K} f_k(X);\ f_k \epsilon\ F$$

Where,

f_k are individual regression trees
F is the functional space of trees
K is the number of boosting rounds

4.2.4 Deep Neural Networks (DNNs)

DNNs consist of multiple hidden layers of neurons capable of learning high-level abstractions. A fundamental layer transformation can be written as:

$$a^{(l)} = f\left(W^{(l)}a^{(l-1)} + b^{(l)}\right)$$

Where,

$a^{(l)}$ is the activation of layer
$W^{(l)}$, $b^{(l)}$ are the weights and biases
f is a nonlinear activation function (e.g., ReLU).

DNNs are particularly powerful in learning from high-dimensional and nonlinear data spaces, making them suitable for complex ship repair datasets.

5. Results and Discussions

The results were evaluated using two metrics: R-squared Score and MSE (Mean squared error). R-squared score (R^2) indicates how well the model explains the variability of the target variable. A value closer to 1 means the model fits the data well, while a value near 0 suggests poor explanatory power. While, Mean Squared Error (MSE) measures the average of the squared differences between predicted and actual values. Lower MSE values indicate better predictive accuracy and less error in the model's estimations. The results for all the algorithms are shown in Table 1.

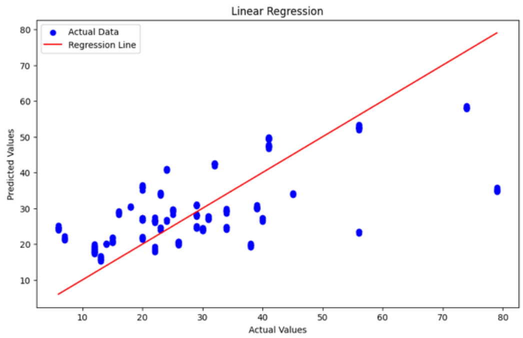
Table 1: Comparison of results of different algorithms.

Algorithms	R^2 Values	MSE
Linear Regression	0.4856	142.66
Random Forest Regressor	0.9997	0.0838
XGBoost	0.9755	6.791
DNN	0.9994	0.1572

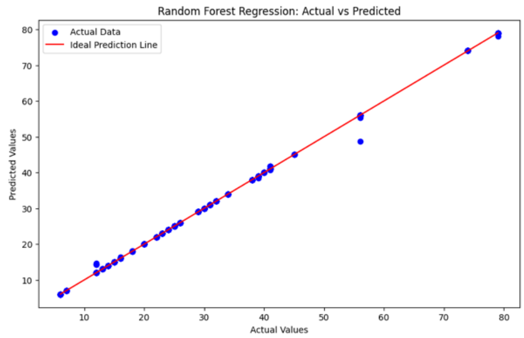
Based on the evaluation metrics, Random Forest and Deep Neural Networks emerge as the top-performing models, achieving near-perfect R^2 scores. However, between the two, DNN is preferred due to the following:

i. Generalisation Ability: Unlike Random Forest, which may overfit small datasets, DNN can generalise well when trained on sufficient data.
ii. Scalability: DNNs can be further fine-tuned and expanded to accommodate larger datasets, making them suitable for future enhancements.
iii. Feature Representation: Neural networks extract hierarchical features, allowing a better understanding of the underlying patterns in ship repair data.

Figure 4 shows the regression lines fitted into the data points by Linear Regression, Random Forest regression, XGBoost Regression and Deep Neural Network (DNN). Linear Regression, being the simplest of the models, assumes a strict linear relationship between the independent variables and the target variable. While this approach provides a fundamental baseline, results show it does not effectively capture the complex interactions between ship repair features. The model demonstrated a high Mean Squared Error (MSE) and a relatively low R^2 score, confirming that it struggles with the intricate dependencies in real-world repair time estimation. The residual plots further illustrate the model's shortcomings, revealing significant variance and systematic patterns that indicate poor fit. Consequently, Linear Regression is not viable for this task, especially when dealing with a dataset containing nonlinear relationships.



(a)



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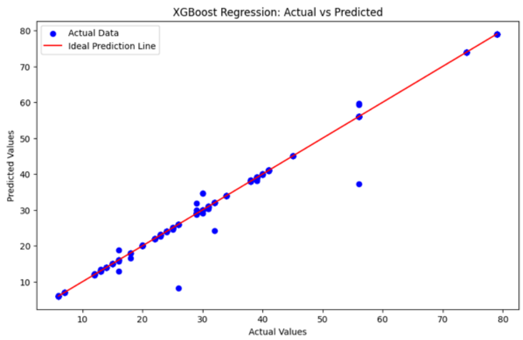

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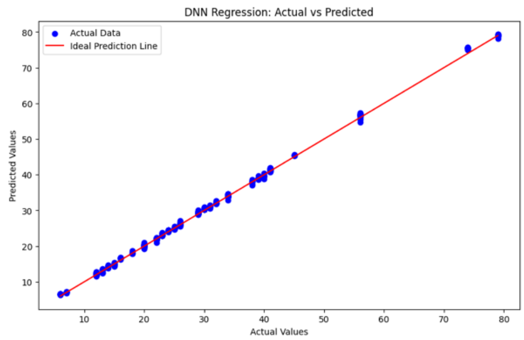

(d)

Figure 4: Model prediction results against actual data (a) Linear Regression, (b) Random Forest Regression, (c) XGBoost Regression and (d) Deep Neural Network (DNN)

In contrast, ensemble-based methods such as Random Forest and XGBoost significantly enhance predictive accuracy. Random Forest Regression, which operates by constructing multiple decision trees and aggregating their outputs, provides a robust and highly accurate prediction model. The scatter plot of actual versus predicted values illustrates a close alignment with the regression line, demonstrating strong predictive capability. Additionally, the residual plot indicates a well-distributed error pattern, signifying that the model captures most of the variance present in the data. One of the key advantages of Random Forest is its ability to handle non-linearity effectively while remaining relatively resistant to overfitting.

XGBoost, another tree-based algorithm that builds upon the principles of gradient boosting, also performs well but exhibits slightly lower performance than Random Forest in the experiments. Despite being an advanced boosting algorithm that refines weak learners into a strong predictor, XGBoost's predictive power is marginally outperformed by Random Forest, likely due to hyperparameter sensitivity and the dataset's specific characteristics. Nonetheless, it remains a highly competitive model and an excellent alternative for regression tasks in ship repair estimation.

Deep Neural Networks (DNNs) emerged as the best-performing model in the study. Unlike traditional machine learning models, DNNs leverage multiple layers of artificial neurons to learn intricate representations of the input data. By capturing deep feature interactions, these models provide unparalleled predictive accuracy. Results demonstrate that DNNs yield the lowest MSE and highest R^2 score among all tested models. The scatter plot confirms the strong correlation between predicted and actual values, while the residual plot showcases minimal variance. This indicates that DNNs successfully model the complex, nonlinear dependencies inherent in ship repair time estimation, making them the most suitable approach for this problem.

6. Recommendations

This study highlights several limitations and recommendations that can guide future research using artificial intelligence in estimating ship repair time. Future studies may incorporate richer and more diverse datasets, including sensor data, maintenance logs, and environmental conditions, which can help models uncover deeper contextual patterns. Advanced architectures like transformers, known for their effectiveness in structured data and time series modelling, could better capture nonlinear dependencies. Additionally, exploring multimodal learning approaches - integrating structured inputs with visual data or textual repair logs using CNNs or hybrid models - can enhance model robustness and predictive power. Real-time data integration through IoT devices may enable dynamic and adaptive prediction systems, making maintenance strategies more proactive. Further improvements can be achieved through automated hyperparameter tuning techniques like Bayesian optimisation, and translating these refined models into user-friendly decision support tools will be essential for practical adoption in the maritime industry, helping stakeholders make informed, data-driven repair decisions and reduce operational downtime.

7. Conclusion

This study demonstrates that machine learning techniques provide powerful and practical solutions for estimating ship repair time, a complex yet essential component of maritime operations. Among the models evaluated, Deep Neural Networks (DNNs) achieved the highest predictive accuracy by effectively modelling nonlinear relationships, while Random Forest Regression offered a robust and interpretable alternative, and XGBoost performed competitively despite its sensitivity to hyperparameters. In contrast, Linear Regression served only as a basic benchmark, falling short in capturing the intricacies of real-world repair scenarios. These findings highlight the importance of selecting models aligned with data complexity and accuracy needs. As the maritime industry embraces digitalisation and sustainability, adopting advanced AI techniques like DNNs can significantly improve maintenance planning, reduce operational delays, and contribute meaningfully to the goals of the Blue Economy.

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