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ARITIME

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Application of AI and ML for Ship's Environmental Monitoring and **Compliance**

AI in Shipping; a Boon or a Bane *35*

Leveraging AI To Build ESG Roadmap for the Maritime Industry *40*

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EDITORIAL

There is no Planet B. - aeon.co Poster on Climate Change (Anonymous)

Another Conference of Parties (COP29) came to a close but with bitterness and fewer billions. With the geopolitical equations shifting, an ending on a positive note was imperative for the optics. The biggest takeaway of the meet: carbon markets (UN approved). The earlier COPs could not see convergence on this. The C-markets move will help increase the pace of the efforts by countries and the coming years will see more of the market measures which could translate into lesser emissions. Yet, keeping the rise below 1.5° C is improbable.

The biggest disappointment of the meet was that it failed to work out a good roadmap on the 'New Collective Quantified Goal' on financing the measures to mitigate. Several countries including India have expressed open disappointment on developed countries' reluctance to contribute to the Fund. Consolation lay in the agreement with an 'aim to mobilise' US\$1.3 trillion (every year) and developed countries assenting to help in efforts to bring in US\$300 billion per year, which falls very short of the target. From the tone and tenor of the concluded conference, it appears that the kitty might not fill by any projections. While the 1.5 will be breached in the temperature, the funding will fall short of 1.3. This is significant because the pool is to assist the transition/ GHG mitigation measures of the developing countries. This will have an impact on achieving the Nationally Declared Contributions. Countries need to work on their alternate plans (or ongoing plans) to meet the emission targets. Be it Plan A or Plan B, the net damage will be for the Planet E.

In this issue…

Artificial Intelligence (AI) and Machine Learning (ML) will remain topical in times to come. While the scope and reach of AI and ML could keep expanding and amplify, the energy requirements for such expansive progresses are humungous. The elasticity of marine sector to accommodate applications will be part of the discourses. This thematic collection is an ostensive effort.

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For this thematic run, we have cherry picked a few manuscripts from the GLOMARS Conference held in March 2024. We start with an article from the IRS team. Zia Ur Rahman et al., delve into marine design spaces where AI & ML are being applied. The article not only dwells on the current applications but also on approaches. The hull optimisation is one which could interest many of us. Though this is a technical read, it is digestible for a marine engineer with more than casual interest in AI & ML.

The next article talks about AI & ML application to environment monitoring. Anil Sharma connects well with the marine engineering aspects and explains how the application may help. The best takeaway is the brief discussion on digital twins. This is an easy read.

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This is followed by a discussion on pros and cons of AI & ML in marine sector. Angadjeet Singh and Dr. Rao presents the case with many advantages and with a simplistic appeal that AI-human interface is essential and cannot be excluded entirely. Of course.

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The last of this collection is on Environmental, Social, and Governance (ESG). Arpit Raj and Malini Mohan Das from DNV explains the importance of ESG and then go on to juxtapose Regulatory compliances, issues with the reference tending more towards emissions. The important takeaway is the Science Based Targets Initiative (SBTi). This is an easily comprehensible read.

And we wish to share that we have more good articles on AI&ML. We will feature them in the coming issues. As I had shared earlier, another Thematic Issue on Polar Dialogues is in the making. We have a good clutch of quality papers from the WMTC 2024 and we shall bring them also in the coming year.

Meanwhile here is the December issue with the Season's Greetings for the New Year!

> **Dr Rajoo Balaji** Honorary Editor editormer@imare.in

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Review of Application of Artificial Intelligence (AI) and Machine Learning (ML) in Marine Sector

Zia Ur Rahman Anil Kumar Korupoju Arun Shankar Vilwathilakam Asokendu Samanta

Abstract/Summary:

Advancements in capabilities of Artificial Intelligence (AI) and Machine Learning (ML) have resulted in its increased application across various industries and Marine Industry is also in the pursuit of reaping benefits of this technology. Adoption of this technology has become pivotal in transforming shipping to be safer, efficient and sustainable. Data from various sources like remote sensing, numerical simulations and testbeds is used to train Machine Learning and Artificial Neural Network (ANN) models. These models are being used in areas like design optimisation, Structural Health Monitoring (SHM), fault diagnosis, hull resistance evaluation and wave modelling. It is also employed in aspects such as ship operational performance, predictive maintenance, estimation of emissions, collision avoidance and fuel consumption. Recent developments in AI & ML demonstrate promising trend in obtaining desired results in these areas along with increased efficiency. This study explores recent trends and developments in the application of AI & ML in Marine Industry and investigates various processes involved in model development such as data collection, data pre-processing, learning algorithms, performance metrics, and model validation. The paper also reviews various challenges in application of these technologies along with methods to address these challenges.

Keywords: *Artificial Intelligence; Generative Models; Machine Learning; Marine Structures; Ship Design Optimization*

Introduction

The design and optimisation of ships and marine structures is a complex and often iterative task involving various aspects of structural and fluid engineering. The process of ship design is evolving with the developments in data science and machine learning. The design abstractions are being handled using data driven expert systems like statistical learners and deep learning models. These systems are trained using data from various sources like remote sensing, numerical simulations and data from testbeds. Recent developments in generative AI demonstrate promising results in obtaining optimised geometries with little computational effort and time. As we progress towards adopting unconventional and novel approaches to solve design related problem statements, we encounter an ever growing corpus of academic literature providing innovative solutions.

Machine learning algorithms come in various forms, from supervised learning, where models are trained on labelled data to make predictions, to unsupervised learning, where algorithms uncover hidden patterns in unlabelled data. Additionally, reinforcement learning enables machines to learn through trial and error, receiving feedback based on their actions.

The applications of machine learning span across industries, from personalised recommendations in e-commerce and targeted advertisements in digital marketing to predictive maintenance in manufacturing and autonomous vehicles in transportation. By harnessing the power of big data and advanced algorithms, machine learning is driving innovation and unlocking new possibilities across sectors.

However, the journey towards fully realising the potential of machine learning is not without challenges.

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Ethical considerations, such as bias in algorithms and data privacy concerns, must be carefully addressed. Additionally, the complexity of machine learning models and the need for skilled professionals pose hurdles to widespread adoption.

As we delve deeper into the realm of machine learning, it is crucial to foster collaboration between experts across disciplines, promote transparency and accountability in algorithmic decision-making, and ensure that the benefits of this transformative technology are accessible to all. One of the foundational aspects of deep learning constitutes Neural networks (**Figure. 1)**, a class of machine learning models inspired by the structure and function of the human brain. They consist of interconnected nodes, called neurons, organised into layers. Each neuron receives input signals, performs a computation, and generates an output signal that is passed on to other neurons.

Physics-informed neural networks (PINNs) and scientific machine learning represent a cutting-edge intersection between traditional physics-based modelling and modern machine learning techniques

Figure 1 One hidden layer MLP[1]

Physics-informed neural networks (PINNs) and scientific machine learning represent a cutting-edge intersection between traditional physics-based modelling and modern machine learning techniques. These approaches leverage the power of neural networks to incorporate physical laws and constraints directly into the learning process, enabling accurate predictions and insights while reducing the need for extensive empirical data.

In physics-informed neural networks, the architecture of the neural network is designed to embed known physical principles and equations as constraints. By integrating these constraints into the loss function during training, PINNs can learn to approximate solutions to complex physical systems while ensuring consistency with underlying laws of nature. This enables more efficient and accurate modelling of complex phenomena, such as fluid dynamics, solid mechanics, and quantum physics.

Scientific machine learning, on the other hand, encompasses a broader range of methodologies that aim to leverage data-driven techniques to enhance scientific understanding and discovery. This includes not only physics-informed neural networks but also other approaches such as Gaussian processes, Bayesian optimisation, and graph neural networks. By combining domain knowledge with data-driven methods, scientific machine learning enables researchers to extract insights from data, accelerate simulations and optimise experiments.

The integration of physics-informed neural networks and scientific machine learning holds tremendous promise across various scientific disciplines. These approaches enable researchers to tackle complex problems with limited data, simulate physical systems with high fidelity, and discover new insights from experimental observations. Moreover, they provide a powerful framework for interdisciplinary collaboration, bridging the gap between traditional physics-based modelling and modern data-driven approaches.

However, challenges remain in the development and deployment of physics-informed neural networks and scientific machine learning techniques. These include the need for interpretable models, robust uncertainty quantification, and scalable algorithms for highdimensional and nonlinear systems. Addressing these challenges will be crucial for unlocking the full potential of these approaches and accelerating scientific discovery and innovation.

This study aims to systematically review the developments in the field of ship design using machine learning and artificial intelligence. A ship is a complex system consisting of numerous sub systems which makes the design of vessel and further optimisation an onerous and challenging task. With the advent of artificial intelligence and machine learning, the possibility of application of these capabilities are being explored across the maritime sector. The application includes ship response prediction, sea state prediction, voyage optimisation, hull optimisation, operational performance, predictive maintenance, estimation of emissions, collision avoidance

etc. the investigation is directed at understanding the recent trends and developments in application of AI & ML design and optimisation of ship structures. The study delves into the state-of-the-art methods within artificial intelligence and machine learning, addressing various facets of machine learning, such as data collection, data pre-processing, learning algorithms, performance metrics, and model validation. By scrutinising these elements, the research aims to contribute to the evolving landscape of AI and ML applications in the maritime domain, offering insights into the current methodologies and highlighting potential avenues for further advancements in the field.

Application in Marine Sector

Structural Optimisation by Q-learning

Structural optimisation forms a significant part of ship deign optimisations. It requires the designer to determine optimum shape and scantlings of the structural elements to achieve the required strength as prescribed by the rules of classification societies, while keeping the light weight of the ship as low as possible. Cui et al., 2012 [2] puts forward a novel ship design optimisation approach based on Q- learning. Of the two available approaches for building expert systems, obtaining the complied knowledge of the expert or modelling the raw memory of the expert, the authors choose the latter. This hybrid optimisation algorithm uses Reinforcement learning with traditional optimisation algorithms like multi-objective particle swarm optimisation method, Non-dominated sorting genetic algorithm-II, multi-agent system, and CAE software are employed to achieve optimised design of mid-ship section in a demonstrative case study. The process of reinforcement learning as shown in **Figure. 2** consists of four primary components agent 'B', environment 'T', input signal 'I', and reinforcement signal 'R'. the agent 'B' receives an input 'i', based on the input signal it initiates an action 'a' which alters the environment 'T', that change of state in environment is communicated back to the agent through the reinforcement signal 'r'.

Figure 2 Classic reinforcement learning model[2]

A case study is carried to demonstrate the optimisation potential of the approach wherein a 50,000 DWT Handymax bulk carrier mid ship section is optimised for weight and fatigue life. CSR rules are used as the guiding criteria to decide the minimum scantling requirements and fatigue life of the design. ABAQUS with FORTRAN was used for Finite element simulations and the calculations are implemented in JAVA. The scantlings of mid-ship section were divided into 34 variables, with each variable having the minimum and maximum value range along with the step increment values, forming a multidimensional grid of various design alternatives. The objective was to optimise the design for weight and fatigue life. The proposed hybrid optimisation algorithm was able to successfully reduce the weight by 8.15% as compared to the original design.

Hull resistance estimation

Determination of hull resistance accurately and quickly is essential during the design stage and for optimising the hull form in per se of resistance. Ao et al., 2023 [3] developed a neural network model to estimate ship resistance in design stage. Data of various ship hull forms and their resistances was synthesised to train the neural network model. KCS container ship hull was used as the base model and free form deformation method was used to parametrise and morph the base hull form cad files and generate different hull forms from it. PyGem [4] framework was used to implement the free form deformation approach to carry out parametric transformations. Potential flow method was used to calculate the resistances of these newly generated hull forms. This was also used as ground truth to validate and test the predictive model performance. The parameter set for deforming the hull forms is generated using truncated normal distribution space, which controls the shape and deformation of new hull forms. This distribution based approach to guide the shape morphing helps in avoiding outliers in the data set. The Fully Connected Neural Network (FCNN) model as represented in **Figure. 3** is trained to map geometry modification parameters with the performance metrics, thus the trained model will be capable of predicting the vessel performance parameters like resistance given the geometry modification parameters as inputs avoiding the hull form modelling and analysis process.

Figure 3 Simplified schematic of the FCNN model[3].

The model performs relatively better when the resistance estimation is carried out on modification parameters lying within the domain of the training dataset,

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the performance drop is observed when predicting for parameters outside the domain.

Ship hull form generation

As availability of good quality data is a common challenge faced by machine learning researchers. Specifically in the marine field the availability of ship designs and the associated performance data is highly unlikely. Bagazinski and Ahmed, 2023 [5] proposes a novel approach to parametrise the ship hull with the help of 45 different parameters. This is very essential for computationally generating ship hulls based on parameter matrix. This method to generate the hulls covers a large variety of typical hull forms used in the industry. It has been validated with its ability to re-generate standard hull forms. This effort is directed towards providing an effective methodology for generating engineering data (hull geometry) to aid research and development of machine learning based ship design. A large dataset of 30000 ships was successfully generated and provided open access. As it is required to have the hydrodynamic performance of the hull along with the geometry to successfully carry out the training of machine learning models, this paper uses potential theory based Mitchell integral approach to calculate the total resistance of the generated hulls. Further a surrogate model **(Figure. 4)** is developed using this data of different hulls and resistances to generate hulls while optimising for least resistance.

Figure 4 residual neural network[5]

This surrogate model was able to successfully generate designs that had 60% lower resistance as compared to the based design. Even though the generated design was practically infeasible, the approach open new frontiers for

research in machine learning augmented computational ship design optimisation.

The research work by Khan et al., 2023 [6] is one the first of its kind effort to use generative networks in ship design. The authors propose to train a deep convolutional generative adversarial network (DCGAN) to automatically generate practical and feasible hull designs for a variety of ship types. To obtain a valid dataset of ship hulls, many different series and parent hulls like FORMDATA, KCS, KVLCC etc. were considered. The shape parameters of these hull forms were varied to obtain a large dataset of 52,591 different hulls. The researchers developed and used a body-plane based, hull geometry vectorisation approach to discretise the hull forms. This method consists of 56 planes each defined n=by 25 points, which comes to 1400 points to define a hull. All the hull geometries were deconstructed using body plane-based approach, where each ship was represented by [25*56] matrices. Shape awareness is induced by incorporating geometric moments into the data. This changes the input matrix shape to [25*57]. A generator and a discriminator model are trained simultaneously. The generator **(Figure. 5)** learns to create novel designs based on the data mappings in training data, while optimising for the parameters in objective function.

The discriminator differentiates between the generated model and the designs in training dataset, it penalises the generator based on the similarity of the generated models with the original design, incentivising the generator to create novel designs. The trained generator is then used as a parametric modeller to obtain optimised ship hull forms based on input design parameter matrix.

Engine brake power prediction using ANFIS

The main parameter affecting the fuel consumption of the ship is the brake power as it indicates the efficiency of the engine operation. Karatuğ et al. [7] has carried out detailed literature survey on modelling and simulating marine engines and identification of its characteristics which are validated by the experimental data or from the data provided in the manufacturer in the guidebook. They also studied Machine Learning (ML) application in marine industry for improving energy efficiency of ships and observed that output parameters such as engine power and fuel consumption are estimated by correlating

Figure 5 Convolutional architecture of the generator used in ShipHullGAN[6]

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them with some input parameters such as exhaust gas outlet temperature, engine rpm, and ship speed.

They believe that among the advanced smart methods, the application of the Adaptive Neuro-Fuzzy Inference System (ANFIS), which combines Artificial Neural Network (ANN) and fuzzy logic approaches, is rare in the maritime field although it is an effective way for modelling the systems. ANFIS model is developed with Membership Functions (MF) and fuzzy rules formulated by incorporating existing data into the model and the relationship between given input and output parameters is determined based on the created IF-THEN rules. The ANFIS structure **(Figure. 6)** has five layers which are the fuzzification layer, the rules layer, the normalisation layer, the defuzzification layer, and the output layer, respectively.

Figure 6 Structure of ANFIS model [7]

Accordingly, they proposed a novel strategy to control and improve the operational efficiency of a container ship by hybridising simulation and smart methods which focuses on either developing an engine simulation model or analysing real-time data collected from a ship.

In the study, a container ship is selected which has 118.18 m length, 19.50 m breadth, and 7.24m draft and is operated using a four-stroke marine diesel engine coupled to a single propeller through a gearbox. A simulation model of a large four-stroke marine diesel engine complying with the IMO Tier 2 is developed in Ricardo Wave software to compute its performance in various conditions.

The 1D engine simulation software is coupled with an optimisation model with a nonlinearly constrained optimiser in MATLAB/Simulink to find the key configuration of the engine at each operating point inside the engine load diagram and validated by the actual data obtained from the ship.

The noon report collected from a container ship with data such as fuel rate and engine rpm for more than 1 year of operation is used in engine simulation model to generate additional significant parameters such as volumetric efficiency and Brake Mean Effective Pressure (BMEP). These additional parameters according to engine operations are included in the original noon report such that an enlarged noon report is created.

Figure 7 Methodology of the analysis [7]

Some engine-related parameters, such as brake power, engine rpm, fuel rate, scavenging ratio, exhaust gas temperature, and volumetric efficiency along with the derived and measured parameters are merged into a dataset and analysed by a data-driven model to control and improve the efficiency of engine operations. Further this dataset is randomly divided by 70% for training and 30% for testing.

Four different ANFIS models were developed considering this methodology **(Figure. 7),** which have 2, 3, 4, and 5 MF. The models were examined by error metrics such as Coefficient of Determination (R^2) , Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) and ANFIS model with 3 MF is determined as the most successful model for the analysis with the smallest MAE score.

Thus, brake power is predicted through the ANFIS model combining these parameters with data collected from the ship, such as fuel rate and engine speed.

Structural health monitoring (SHM)

Marine structures are subjected to environment loads such as wind, waves, and current throughout its life and Structural Health Monitoring (SHM) will be crucial in damage detection for identifying corrective measures. Leng et al.(2023) [8] has utilised artificial intelligence (AI) technology for structural health monitoring (SHM) of offshore jackets. It was noted by the authors that Vibration-based SHM approaches based on recording and analysing the vibration response are effective for SHM of the structure. They identified that Parameter method is widely used for SHM using vibration. As structural damages will change physical parameters such as mass, stiffness and damping of the structure, the function of damage detection can be established by analysing the change in these parameters before and after the damage along with modal parameters, response characteristics of the structure.

Accordingly, authors have explored damage location of offshore jacket structures using three deep learning methods based on Kernel Extreme Learning Machine

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Figure 8 The flow chart of WOA-HKELM [8]

(KELM). They are Poly-KELM, RBF-KELM and WOA-HKELM **(Figure. 8).** These three methods eliminate the process of labelling the signals in the training set compared with the traditional supervised learning, improve the calculation efficiency, and reach accuracy of more than 97%.

Based on these aspects, authors have developed a physics-enhanced AI method based on parametric damage identification and used Hybrid Kernel Extreme Learning Machine (HKELM) for constructing AI structure to enhance the SHM detection capacity on the structural modal parameters. Whale Optimization Algorithm (WAO) was applied to identify proper parameters for HKELM and optimise the values of regularisation coefficient and kernel parameter array.

Experimental results show that the WOA-HKELM Model has strong learning ability, generalisation ability, fast computing speed and greater accuracy to detect damage location.

Further, damage detection ability of the AI method using WOA-HKELM is improved by applying wave denoising (WD) which pre-processes the acceleration signal caused by impulse force **(Figure. 9).** It is demonstrated through numerical simulation and model experiment that WOA-HKELM has excellent ability of damage location.

Finally, they conclude that the study made progress with some limitations. Study achieves damage detection under offline conditions and real-time damage detection is not explored. Also, it only considers damage scenarios

involving broken elements in the structure without considering small cracks and early defects in the structure. Environmental factors such as temperature and wind loads are also not addressed in the study. As such, the authors believe that these aforementioned issues can be effectively addressed in the future with continued in-depth research and the rapid development of artificial intelligence technology and noted that SHM of other offshore structures may benefit by applying this method in various aspects.

Fault diagnosis using ANN

Karatuğ et al.(2022) [9] has noted that the reliability and sustainability of the machinery systems of ships can be increased by optimising the maintenance strategy on marine vessels which historically evolved to be as reactive maintenance (RM), time-based maintenance (TBM), and predictive maintenance (PM), respectively. A conditionbased maintenance (CBM) **(Figure. 10)** strategy, under predictive maintenance (PM), is an up-to-date approach for maintenance where decisions could be made based on past information of the related systems.

Accordingly, authors carried out a study by collecting data from different sensors mounted in the engine room of a big container ship with length of 328 m for 489 days (approx. 2 years) for determining the main diesel engine power. Main engine is a two-stroke compact engine with ten cylinders and manufactured as a super-long stroke engine with 3260 mm length of the stroke and 900 mm diameter of each piston.

A dataset is created using this data and with the data obtained from engine logbook and is pre-processed by filtering the data such that incorrect values are removed. Normalisation of useful data is carried out in order to realise a better analysis process.

Figure 9 Flow of numerical simulation and model experiment [8]

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Figure 10 Proposed CBM methodology [9]

Correlation of various parameters **(Figure. 11)** is carried out and visualised as below:

Figure 11 Correlation of the variables [9]

The following are observed:

- **i.** All collected parameters are highly related to the ME outlet power.
- **ii.** FO inlet low pressure has a negative correlation with almost every variable.
- **iii.** Correlation values of ME power and exhaust gas outlet temperature of each cylinder differ due to the different combustion processes occurring in each cylinder.

It is noted that these data could directly affect the in-cylinder combustion and will be helpful in identifying a combustion-related fault with a decision-making system.

The performance model of the engine **(Figure. 12)** is developed using ANN based on feed-forward backpropagation in MATLAB software considering 1 input layer with 16 input variables, 1 hidden layer with the 10 number of neurons, and 1 output layer with 1 output variable. The number of layers and variables are obtained by using the trial-and-error method.

Then the dataset is randomly divided into 3 subsets; training (70% of the dataset), test (15% of the dataset), and validation (15% of the dataset) and the model is trained using Levenberg-Marquardt optimisation with activation function as hyperbolic-tangent. Also, the network has been trained with 1000 epochs.

Fault diagnosis scenarios are created applying constraints with recommendations of the engineers and the engine manufacturer as given in Table 1.

Constraints	
Deviation of exhaust gas out temperature	40 $°C$
Maximum exhaust gas outlet temperature	380 °C
Acceptable fuel oil viscosity	$10-15$ cSt
FO inlet low pressure	$7-8$ bar
Threshold between ANN model and real value	±5%

Table 1 Applied constraints to scenarios

Figure 12 The ANN model structure [9]

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The hull girder of the ship can be damaged due to a variety of reason such as explosion, grounding, collision and fatigue cracks. Identification of hull girder damage in time is very crucial for employing the corrective measures

The output parameter predicted by the performance model is compared with measured real data in the user interface and the developed ANN model is evaluated with metrics such as R2, MSE and MAE values as 0.9968, 0.024 and 0.019, respectively.

FMEA analysis was carried for in-depth diagnosis of the detected differences between estimated and measured real data regarding the issues that could affect the combustion process and a decision support system is developed which is illustrated with three different scenarios and the detection of some faults such as early injection timing, piston ring failure, clogged injection nozzle are presented. Further, authors plan to focus on developing a tool suitable for the developed methodology in the future.

Damage Identification of hull girder based on PNN

The hull girder of the ship can be damaged due to a variety of reason such as explosion, grounding, collision and fatigue cracks. Identification of hull girder damage in time is very crucial for employing the corrective measures. Zhang et al.(2021) [10]this paper proposes an indirect damage identification method based on Probabilistic Neural Network (PNN proposes a damage identification method based on the vibration characteristics of the hull girder. The damage in hull girder is manifested as deformation and fracture. However, the damage impacts the stiffness of hull girder and changes its vibration response such as natural frequency and mode shape. Probabilistic Neural Network (PNN) is utilised to develop model for prediction of damage. PNN is a neural network model introduced by Specht (1990)[11] and is used in classification and pattern identification task.

A hull girder damage database is developed for model training. A test ship is identified and is divided into 20 units. 700 damage conditions are assumed wherein the damage extends from 0 to 50%. The hull girder damage alters its natural frequency and mode shape. The hull girder natural frequencies are calculated for these damage cases using transfer matrix method. The damage database is based on five modes of natural frequencies. The damage data is normalised with respect to index natural frequency change which is computed as the ratio of difference of natural frequencies of various orders.

The structure of PNN is divided into four layers - input layer, sample layer, summation layer and output layer as shown in **Figure. 13.** The PNN Structure is optimised using Particle Swarm Optimization (PSO) and Generic

Algorithm (GA). The PSO is an optimisation algorithm based on swarm intelligent techniques inspired by bird flocking behaviour. The efficiency and accuracy of algorithm depends on learning factor, maximum velocity, number of particles and inertia weight. The GA is an optimisation method based on natural selection and genetic mechanism of biological evolution. The GA method was found to be more efficient as it iterated optimal value of smoothing factor in fewer steps.

The test data consisted of cases of damage of 13% and 23% which are also used in training set. This was to test if optimised neural network can retain the accuracy of the original data. The results showed an identification accuracy of 0 indicating that the network can retain the accuracy of original database. However, testing with test data corresponding to damage case of 28.5%, 33.5% and 48.5% produced results with an average error of 1.38% and maximum error of 23.6% which was present only in one case.

Figure 13 Layers of PNN Structure [10]this paper proposes an indirect damage identification method based on Probabilistic Neural Network (PNN

There are important applications of such tools including identification of damage below waterline of military vessels due to underwater explosion. And Structural Health Monitoring (SHM) of vessels.

Challenges in application of AI/ML

As discussed in the previous sections, there are lot of areas in the field of marine design which is seeing increased application of ANN and ML. However, there are many challenges or barriers at present on application of ANN or ML to marine design. Fan (Fan et al.2021) [12] observes that lack of interpretability as one of the barriers of application of deep leaning methods. Juan et al. [13] observed that ANN is a 'black box' model

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without any physical explanation about the results. The development of explainable AI (Arrieta et al., *Adadi and Berrada, 2018*) [14], [15] is looked forward to overcome such weakness of AI models.

Mahadi Imran et al. (2024) [2] documents various challenges in application of ANN and RF in corrosion studies in marine industry. The challenges related to data included availability of data, collection, and integration of data from various sources, quality and reliability of data, bias in data and privacy and data security. Model training related challenges included diversity of data, efficiency of the sample, and difficulty of model to perform during deployment in domain different than trained

domain and simulated environment to real environment transfer of the model. Real time implementation challenges included integration with existing control systems, Decision making based on real time environment, scalability and computation efficiency and memory.

Abdar et al. (2021) [16] discusses various methods of uncertainty quantification and notes that Bayesian

Alestoric component Input V^o of inputs uncertainty Epistemic component Quantity of data Algorithm Parameter Weights uncertainties Data Model partitioning uncertainty Transfer functions Structure V^o of layers uncertainties N° of nodes per layer

Figure 14 Uncertainties in application of ANN in marine design [17]

technique and ensembling are two wisely used methods to deal with uncertainties in deep learning.

Juan et al. (2023) [17] discusses various uncertainties about application of ANN in marine design. The paper identifies two uncertainties related to ANN, Input and model uncertainty **(Figure. 14)**. Input uncertainty is related to input variable and associated noise. Model uncertainty

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related to ANN model and its forecasting capacity. Model uncertainty can be further divided into parameter and structure uncertainty. Parameter uncertainty is related to the parameters used in developing the model such as algorithm selection, initial weights and division of data. Structure uncertainties are related to model architecture such as number of layers of network, transfer function between each layers and number of nodes in each layer. The paper further explains various methods to handle the ANN input uncertainties and provides insights on extent of usage of these methods in various studies to handle different uncertainties **(Figure. 15).** Trial and error is a valid techniques used in traditional models, but it is computationally expensive in case of ANN. The author notes that in studies involving wave height and tides trial and error followed by statistical analysis were most commonly employed. For studies involving maritime structures statistical analysis along with Kfold cross validation method was used. Ensembling is another technique where best performing models are combined with appropriate weightage. Sensitivity analysis is also used to account uncertainty where effect of small perturbations of each input variable on output is studied. Other advanced methods include Bayesian techniques, fuzzy methodologies, bootstrapping, Monte Carlo simulations and optimisation methods. With regards to parameter uncertainty- selection of algorithm, trial and error was extensively used and only 10% of the studies used more advanced techniques such as optimisation methods or Monte Carlo simulations. The paper notes that uncertainty related to initial weights and data division are not considered in most of the studies, which can have a significant impact on ANN. Similarly, structure uncertainty was also dealt using trial and error approach in most of the studies. The paper summarises that majority of the studies only addressed input related uncertainties meanwhile only a small number of studies dealt with model related uncertainties.

Figure 15 Methodologies used in various studies to deal with ANN uncertainties[17]

Conclusion

The study attempts to investigate specific applications of Artificial Intelligence (AI) and Machine Learning (ML) in marine industry. The paper explores different types of ML and ANN models that are used in various marine design studies.

Cui et al. (2012)[2] used reinforcement learning for ship design optimisation, achieving significant weight reduction in mid-ship scantling of a Handymax bulk carrier. These approaches offer innovative ways to enhance ship design, efficiency and performance. Ao et al. (2023) [3] developed a neural network model to estimate ship resistance during design, using a base model and free form deformation method. Bagazinski and Ahmed (2023) [5] proposed a parametrisation method for ship hulls, generating a large dataset of 30,000 hulls for machine learning-based design. Khan et al. (2023)[6] employed generative adversarial networks to automatically generate optimised ship hull designs.

Leng et al. developed a physics-enhanced AI method for offshore jacket structural health monitoring (SHM), using Hybrid Kernel Extreme Learning Machine (HKELM) and wave denoising (WD) to enhance damage detection. Their model, validated against experimental results, showed strong learning ability, generalisation and accuracy in detecting damage location. They foresee AI advancements addressing real-time damage detection and environmental factors in SHM. Karatug et al(2023) [7]. developed an ANFIS model to predict ship brake power, crucial for fuel consumption. Using a year's worth of operational data, they integrated significant parameters from an engine simulation model. The ANFIS model with 3 membership functions yielded the most accurate predictions. Additionally, Karatug et al.(2022) [9] built an ANN-based performance model for ship engines using MATLAB. Leveraging engine room sensor data and logbooks, they identified combustion-related faults and developed a decision-making system for fault diagnosis. Evaluation metrics included R^2 , MSE, and MAE, with further analysis via FMEA for enhanced fault diagnosis and decision support. Zhang et al.(2021) [10] this paper proposes an indirect damage identification method based on Probabilistic Neural Network (PNN proposed a damage identification method based on the vibration characteristics of the hull girder using PNN and optimised using Particle Swarm Optimization (PSO) and Generic Algorithm (GA).

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It can be seen that these technologies can also play a significant role in design and optimisation of marine structures through developing designs with improved performance and cost effectiveness. The application of AI/ML algorithms to marine design is also expected to facilitate advancements in decision-making processes, enhance efficiency, accuracy, and safety in maritime operations and help in developing sustainable solutions.

Despite rapid development of AI/ ML technologies, there are several challenges for application of these technologies to marine domain. These include lack of explainability, availability of quality data and identification of appropriate algorithms. Various uncertainties related to ANN such as input and model uncertainty are also explored and it is noted that advance methods such as Bayesian methods, Monte Carlo Simulations and Optimization methods can be applied to deal with uncertainties rather than adopting a trial-and-error approach which is computationally expensive.

It can be concluded that with more technological advancements, a rapid increase in use of AI/ML tools in the field of marine design is expected with extended applications.

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Application of AI and ML for Ship's Environmental Monitoring and Compliance

Abstract:

This paper introduces mandatory environmental-related regulations applicable to ship owners and explores the possibility of the application of Artificial Intelligence (AI) & and Machine Learning (ML) for shipboard machinery and hull optimisation using the concept of Digital Twins and Condition Monitoring, helping shipowners to meet environment-related regulatory norms and improve safety in engine rooms. Several advanced sensors that are used to generate data from machines for condition monitoring are also listed with explanations in the paper for more clarity.

Keywords: CII, IMODCS, SEEMP, virtual twins, predictive twins, IOT, edge computing

Introduction:

Artificial Intelligence (AI) and Machine Learning (ML) are revolutionising every industry across the world and shipping is no exception. Though AI found its inclusion in shipping in the last few years, however, its penetration is increasing day by day. The world's first autonomous, crewless, and zero-emission container vessel Yara Birkeland has already done its first maiden voyage on 05 April 2022 and is presently under a two-year trial. This was made possible using AI.

The use of AI in the shipping industry is wide and useful in many aspects such as autonomous ships, e automated

equipment, improved safety and security, voyage route optimisation, Trim optimisation, conditioning monitoring and performance forecasting of shipboard machinery, supply chain logistics, port management reducing downtime and saving cost.

A major element for the functioning of AI is the transfer of large amounts of data with high speed to and from the ships. Until recently, digital data information flow was limited due to the difficulty in transmitting data from ships. However, due to the rapid digitisation of the shipping industry and advancement in maritime communication technology, the speed of data transmission has increased manifold.

One of the key focus areas at present for the Shipping Industry is the move towards sustainability and environmental protection by reducing Greenhouse gases (GHG) from ship operations, which is in line with the United Nations (UN) Sustainable Development Goals (SDGs). AI can help monitor ships' fuel consumption and assess whether greenhouse gas emissions are declining, or ships are using more resources than necessary.

To achieve GHG emission reduction goals, the International Maritime Organisation (IMO) brought in an initial strategy in April 2018 to reduce CO2 emission to 50% by the year 2050 compared to the year 2008 and also contemplated complete decarbonisation of shipping in the second half of this century. The strategy was further strengthened in the year 2023 and the overall ambition is now to reach net-zero GHG emissions by or around, i.e. close to, 2050. To achieve these targets, MARPOL ANNEX VI was revised to introduce GHG regulations. Ships are now required to calculate two ratings: their attained Energy Efficiency Existing Ship Index (EEXI) to determine their energy efficiency at the design stage,

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and their annual operational Carbon Intensity Indicator (CII) and associated CII rating. Both EEXI and CII link the GHG emissions to the amount of cargo carried over the distance travelled.

The Broad Equation of CII can be presented below:

CII= CO2 Emission/Capacity X Distance

CII= Annual fuel consumption x CO2 factor of fuel used/ Annual distance x Capacity (in dwt)

IMO has also made it mandatory for shipping companies to report GHG emission data on an annual basis. Using these data, companies can calculate their ship's attained operational Carbon Intensity Index (CII) and ensure these index values are below the limit values specified by regulatory requirements. The first year of the attained annual operational CII verification will be 2024 for the operation in calendar year 2023. Vessels, based on their performance, will receive an environmental rating of A (major superior), B (minor superior), C (moderate), D (minor inferior), or E (inferior performance level). The rating thresholds will become increasingly stringent towards 2030.

The CII values are not just the regulatory requirement but also involve financial implications. Maintaining good CII scores will bring a competitive edge to the business since large ship charterers and shippers are adopting sustainability in the shipping business.

CII limit values are being reduced by regulation year after year to be in line with initial ambition. In other words, ships need to keep monitoring their fuel consumption and take suitable action to reduce the fuel consumption if required, to meet environmental compliance. This means a large amount of ship data is required to be generated, and analysed in real-time, and critical decisions are to be taken to avoid non-compliance.

As ship owners strive to achieve good CII ratings, they need to optimise their machinery design and operation to reduce their GHG emissions. AI & ML can be applied in various fields for shipboard machinery designing ensuring that the machinery selected for the vessel is of optimum specifications. The concept of using Digital

Maintaining good CII scores will bring a competitive edge to the business since large ship charterers and shippers are adopting sustainability in the shipping business

Twins is one such possibility, which not only helps during the designing stage but also can monitor ship hull fouling during operation. AI & ML can also help to optimise shipboard Machinery operation, condition-based maintenance, and troubleshooting by taking proactive decisions. Consequently, this will reduce fuel consumption during ship operations and help meet environmentalrelated obligations for ship owners.

Conceptual understanding of terms: AI & ML

Artificial Intelligence can be broadly defined as the capacity to acquire knowledge and apply it to achieve an outcome. Artificial intelligence is the simulation of human intelligence processes by machines, especially computer systems.

It is now well recognised that AI has the potential to change the way humans work, especially when there are repetitive or when there are large amounts of data to be analysed. In several areas, AI can perform tasks much better than humans. AI platforms can gather data on lifelike exchanges with people, or an image recognition tool can learn to identify objects in images by reviewing millions of examples. One simple example of an AI application is connecting riders to taxis, without using AI, it seems very difficult to imagine. However, using AI computer software, Uber has become a Fortune 500 company.

AI is a vast field and can be compared with a river. Machine learning and Deep learning can be compared with streams of this river. AI programming focuses on cognitive skills that include learning- self correction-Creativity. Out of these three skills, learning can be defined as acquiring data and creating rules for how to turn it into actionable information. The rules, which are called algorithms, provide computing devices with step-

Figure 1: Connection between the CII, IMO DCS[1], and SEEMP[2]

WORLD MARITIME TECHNOLOGY CONFERENCE Chennai, India 2024

GLOBAL SHIPPING - A BATTLE FOR SURVIVAL OR A TORCH BEARER OF HOPE?

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"It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us, ...'

Charles Dickens comes to our minds as we reflect upon the state of shipping today. Juxtaposed between Trade Wars, Galloping Technology, Regulatory Challenges and Climate Change issues, we could be looking like a deer caught in the headlights, unable to comprehend where our future lies.

The Lehman Brothers crisis of September 15, 2008, now close to 15 years ago; yet we have not been able to overcome its impact, just as we have never been able to avoid the odd bout of flu every winter, and of course the Covid-19. There has been a continuous stream of regulations, in the wake of galloping technology, escalating political gamesmanship across nations, and also with safety management continuing to be an issue, duty of care towards crew remains questionable.

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What Factors contribute to lower fuel costs?

Figure 2: Factors contributing to lowering fuel consumption

by-step instructions for how to complete a specific task. Machine learning means using software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. Machine learning algorithms use historical data as input to predict new output values.

An algorithm can be described as a procedure for solving a problem or performing a computation. Algorithms act as an exact list of instructions that conduct specified actions step by step in either hardware- or software-based routines. In simple words, it refers to a small procedure that solves a recurrent problem. There are several types of algorithms, all designed to accomplish different tasks.

Use of AI & ML for ship's environmental monitoring

Companies must monitor fuel consumption from their ships and the performance of various fleets so that they can benchmark and improve on poorly performing vessels. Leading ship owners or managers therefore resorted to hiring/ jointly working with third-party fleet optimisation companies. These companies are capable of handling large amounts of data from a pool of ships and carrying out real-time fuel consumption monitoring.

These companies integrate systems and communication between ships, shore offices, and ports.

It provides a shared digital platform for all industry stakeholders to exchange data and combines cloudbased analytics, and AI together with intelligent automation to monitor, manage, and optimise everyday processes onboard and onshore.

Fuel consumption optimisation systems not only provide the amount of fuel used during the trip but also

Artificial Intelligence can be broadly defined as the capacity to acquire knowledge and apply it to achieve an outcome. Artificial intelligence is the simulation of human intelligence processes by machines, especially computer systems

provide additional data related to fuel usage. Information on statistical information on various parameters, such as the amount of fuel used by a particular engine or generator while moving at sea or in port. To analyse fuel consumption, it is possible to gather and use data not only about the engine but also many other external parameters affecting fuel consumption. The external parameters can be broadly divided into Hull condition, Engine condition, Trim and draft, weather condition, and vessel speed.

Earlier it was possible to analyse data on consumption only after arrival at the port. For example, the speed of the vessel during the voyage if not appropriate will incur additional costs and GHG emissions but will be realised only after reaching to port. Now it is possible to see this data in real time and fleet optimisation companies can suggest during voyages to plan for optimal routes.

fleet optimisation companies use AI and ML to monitor the amount of fuel that vessels use and provide ways to cut back on fuel consumption for better resource and expense management. Machine learning helps to submit analytical and forecast data for approval to the management of the ship's company and the master for a reduction in fuel consumption.

Research and development activities are undergoing to use of alternative fuels in place of conventional fossil

> fuels. In the future when alternative fuels replace fossil fuels, AI and ML will help to enhance sustainability and meet environmental compliance.

Use of AI and ML in Condition monitoring of machinery

Regular maintenance and inspection of machinery components is vital for keeping machinery in optimised condition, which will not only help in reducing breakdown but also help in optimising fuel consumption.

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A preventive maintenance system or PMS is used on the present generation of ships, where the maintenance is carried out as per the running hours of the machinery or by calendar intervals. For example, the Main engine unit overhaul is carried out after 8000-16000 running hours, bearing clearances are checked once a year, etc. The drawbacks of this system are as below:

- **a)** Maintenance required to be carried out irrespective of the condition of the machinery. The parts must be replaced if it is written in the schedule, even if they can still be used.
- **b)** The number of crew is being reduced on board and most of the ships carry 3-4 engineers and support staff in the ship's engine room. The port stay of the ships is reduced and the machinery is increased. This will result in finding time and manpower for heavy maintenance work.

Ships have been using sensors on board for a long time. These sensors are basic sensors used for basic operational information such as speed, pressure, and temperature in the fuel systems, cooling water systems, exhaust systems, motor current sensors, and differential pressure sensors for filters, coolers, etc. Much of this data (about 90%) generated onboard ship, remains in the ship, which means operators lose invaluable insight and analytics that can improve performance and efficiency every day. This data analysis can be the key to unlocking optimal efficiency and sustainability.

Condition monitoring of machinery helps ship operators to switch from preventive maintenance system to predictive maintenance system or condition monitoring system. With the development of instrumentation technology, a lot of advanced sensors are developed. In the condition monitoring system, these advanced sensors are being provided in engine internal components to check the health of the engine continuously and if deviation is noted, then only the maintenance is planned. However, the drawback of this system remains to be the analysis and interpretation by ship operators. Machinery condition must be accurate otherwise it may lead to damage to the machinery and costly repairs. With the advent of AI & and ML, the analysis and interpretation by

A leading ship classification and certification body made the prediction, that in the near future, mechanical machinery onboard vessels will benefit from thermal imaging to identify and target equipment and systems that need maintenance as well as to eliminate necessary work

using sensor data can easily be done using the machine itself, and dependence on human expertise is reduced. Sensors monitor for abnormalities in the system and based on past data they can correlate and estimate the current health of the system. The potential problems can be identified. It can notify operators that the machine requires inspection and repairs when it notices unusual variations in fuel consumption and heat production. Thus, AI helps in improving visibility and awareness for the crew members.

The list of various advanced sensors used for condition monitoring is large, consequently, the data generated is large and due to advancements in digital technology and satellite communication, this data can reach in real time to vessel managers and technical experts for their evaluation and monitoring.

Some of the advanced sensors are listed below for condition monitoring:

- **1)** Vibration sensors are used to detect roller bearing wear, gearbox wear, shaft misalignment, unbalance, and mechanical looseness. Speed sensors work with vibration sensors to correlate vibrations to rotating speed and shaft angular position. Similarly, Temperature sensors can accompany vibration sensors to collaborate on assessing vibration-detected degradation.
- **2)** A thermal imaging camera can detect hundreds of temperatures within the camera's field of view. An image produced by an infrared (IR) camera is called a thermogram. Infrared thermography is a technique for producing an image of the invisible to the eyes. A thermography camera produces a live video picture of

Figure 3:Photograph in visible light of the engine with the generator (a) and thermographic image (b)

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Figure 4: photo of injection pump (a) and temperature field recorded with the thermal imaging camera (b)

Figure 5: Photograph in the visible light of the internal combustion engine head without cover a) and the temperature field from the infrared camera b)

heat radiation intensities. More sophisticated cameras can measure the temperature values of any object or surface in the field of view and produce colour images that interpret thermal patterns more easily.

A leading ship classification and certification body made the prediction, that in the near future, mechanical machinery onboard vessels will benefit from thermal imaging to identify and target equipment and systems that need maintenance as well as to eliminate necessary work.

Contactless and non-invasive IR cameras can be fitted near selected components of machinery such as crank gears, which can be used to detect faults in the bearings and fuel oil supply systems to assess the performance of fuel pumps, fuel injectors, etc.

3) Main bearing temperature sensors: These sensors are mounted on the main bearing girder with the tip of the sensor in direct contact with the bearing shell. The sensor measures the combined temperatures of the bearing shell and of the lubrication oil that flows from the bearing.

- **4)** Cylinder liner temperature sensors: These temperature sensors are installed very close to the sliding face of the piston and connected to the existing engine junction boxes. Abnormal piston behaviour increases cylinder liner temperatures, which may cause piston scuffing.or breakdown in case of piston seizure – ultimately leading to an unexpected engine stop.
- **5)** Ultrasonic sensors can detect electrical problems including corona [3], arcing, and tracking [4]. They can also be used to detect early signs of roller bearing wear.
- **6)** Oil sensors [5] can detect wear debris from bearings and gears. They also can detect contaminants in the oil that reduce the lubrication ability of the oil. The magnetic type of debris sensor can detect abnormal metallic wear in machinery components well within time to prevent extensive damage to the machinery and save on costly and time-consuming repairs.
- **7)** Torsion meter for marine shaft power calculation directly by measurement of torsion. Ship operators were earlier relying on a theoretical baseline propulsion

efficiency curve developed by the manufacturer giving the relationship between various factors such as scavenge air pressure, exhaust gas receiver pressure, and RPM with respect to engine load. The baseline curve is prepared during sea trial/shop trial stages and does not count the drop in performance over time. Shaft power thus provides more accurate and realtime data.

The data provided by these sophisticated sensors can be analysed and important decisions can be made about machinery overhaul/repairs using Machine learning.

Use of digital twins along with AI and ML for the Maritime industry

The Maritime Industry like other Industries is becoming largely focused on software-driven automation and control systems because of the digital revolution. This advancement is pushing this industry towards autonomous functions for example unmanned ships in the maritime business. There will be complex integration of computation, networking, and physical processes, key features such as safety, reliability, and availability. Such a complex process cannot be verified solely on paper, or by analysing individual components and subsystems and then aggregating data. The requirement would be to combine a system in a simulated environment, which can be achieved by digital twins.

Digital twin can be defined as the digital proxy of a physical asset or device. It is device virtualisation and can be implemented in different ways. A combination of the virtual and physical worlds in simulations can make it feasible for to data be analysed and systems may be monitored to prevent unnecessary outcomes, reduce downtime, discover new opportunities, and even prepare for the future. While many digital twins have a 2D or 3D computer-aided design (CAD) image associated with them, visual representation is not a prerequisite. The digital representation, or digital model, could consist of a database, a set of equations, or a spreadsheet.

A digital twin can help to successfully deploy and use an IoT application [6] on an IoT platform [7]. It digitally represents the data, processes, operation states, and lifecycle of the asset. The use of the digital twin model provides:

- **a)** better visibility machinery and its interconnected systems can be seen continuously.
- **b)** accurate prediction -of the future state of the machine
- **c)** What-if analysis -can predict how a machine can react in a specific situation, by simulating that unique condition in the digital twin
- **d)** Scaled-up cyber security: Digital Twin allows the system to replicate the behaviour of security systems in the face of potential attacks, which is very useful in detecting breaches or weaknesses so that they can be handled in time. Machine Learning-based programmes with pattern recognition trained on standard operating data were used to distinguish malicious attacks from routine anomalies.
- **e)** Optimizing Fleet with Virtual Transition of Ship Control System: A digital twin can understand trade patterns from the past, present, and future and can make operational and strategic decisions. Virtual vessels with integrated software can go through atypical situations for example weather reports and simulate the condition of a virtual vessel in real-life conditions and modification that may be required for its physical counterpart. The digital twin's copy of the control system can be tested in simulated conditions identical to those encountered in reality. Apart from control system software, vessel components, machinery systems, and ship hulls can be identified as areas where digital twins could make a valuable contribution. For example, Hull sensors sending data to a digital twin would allow the operator to correlate stress on the hull to weather conditions, in which a ship has sailed.

Figure 6: Illustration of digital twin

Machine Learning-based programmes with pattern recognition trained on standard operating data were used to distinguish malicious attacks from routine anomalies

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Figure 7: Advantages of Digital twin in the Maritime field

f) Improving the port operations: A port handles various cargo and passengers from all over the world. It required strategic planning to control the continuous output and input of assets. A digital twin of the port terminal will address problems like berth allocation, complete cargo handling on time, cargo space management, and unnecessary waiting of vessels waiting for berthing will be minimised.

Thus, port optimisation will indirectly help to optimise the ship's resources optimisation.

g) End-to-end supply chain Management: Digital twins can help resolve issues related to End-to-end supply chain management, specifically for the movement of containers, which transit through various shipping ports managed by different entities. Adopting smart containers [5-1] is resolving many information-related issues of container movement. A large amount of flowing data is generated by these smart containers and the use of digital twins using ML can further optimise the supply chain and provide opportunities for the stakeholders to select the vessel's ideal route for

serving customers and coordinating transport buyers.

h) Awareness of the situation about operational parameters: by linking digital twins, all stakeholders can have transparency over cargo movements and can mitigate repercussions in case of variations. A portal for collaborative decision-making can be made to address common goals like emission reductions, estimate risk level, structural reliability, or

Figure 8: illustration of digital twins

improvement to the structure or machines to be more productive.

Data used for digital assets can be in the form of graphical 3D models, dynamic simulation models, virtualised control systems and communication networks, analytical models, data models, sensor data, relationship data, process data, as well as digital information such as documentation and reports.

The digital twin combines all available information and models of the object throughout its lifecycle. A digital twin provided with sensor data allows decision-makers to react, within a time frame to enable actions that still have value. Also, as more and more operation data accumulate, the model becomes more predictive, which enables greater proactivity to avoid risks and maximise profitability.

The digital twin model can be implemented in two types:

- **1)** *Virtual twin* It is a virtual representation of a physical device or an asset in the cloud. A virtual twin uses a JSON [9]-based model that contains observed and desired attribute values and uses a semantic [10] model. An example of a virtual twin can be taken as a fleet of connected ships, an IoT application monitors a collection of operating parameters. The semanticsbased model enables the edge [11] to decide whether the operating parameters are in the normal range and if notice deviation, identify using Machine Learning, whether each deviation is urgent, important, or routine. The edge can intelligently detect that a lubricating oil failure notification is an urgent message, and that oil viscosity is high is a routine message.
- **2) Predictive twin:** Also called probabilistic twin. while the virtual twin is a digital copy of the physical asset, the probabilistic twin is a forecasting tool to support effective risk management in operations, coupling the digital twin to risk models which are continuously updated based on actual conditions and new knowledge.

Both digital twins mentioned above are in the research stage to be utilised in the Maritime field.

Conclusion:

The use of AI and ML is revolutionising every aspect of the maritime industry. Though it is in the beginning stage,

its use is increasing day by. Digitisation is the backbone of AI and ML, where machines can fetch necessary data from the system, learn, and make critical decisions based on the analysis of data, which is difficult for human analysis. Some of the marine useful applications are fuel consumption monitoring and calculating data for environmental regulatory compliance, machinery condition monitoring using advanced sensors, and digital twins for designing and operation.

Annex -1: Definitions:

- **1)** IMODCS is an IMO data collection system consisting of requirements for ships to record and report their fuel oil consumption.
- **2)** SEEMP is a ship energy efficiency plan, that was introduced in the year 2013 and further enhanced in 2023. It consists of IMODCS and the ship's operational carbon intensity plan.
- **3)** Corona Effect: Due to High Voltage Transmission and high current flow in cables (Transmission Cables Overhead), they IONIZE the air around it. This ionisation causes a faint purplish glow around the

Tracking refers to the flow of current over the surface of the insulation

cable. This glow is called CORONA Effect & is visible only at nighttime against a dark background.

- **4)** Tracking is a phenomenon in Electrical Insulation. Tracking refers to the flow of current over the surface of the insulation. Tracking causes heating which results in damage to the insulation. As the current gets a path to the ground or another energised conductor, tracking can lead to a flashover. Tracking is caused by many factors. One principal reason is dust. Dust forms a layer over the insulation, this when combined with moisture in the atmosphere provides a conductive layer for the current to flow. Other factors that can cause tracking are humidity which can cause condensation, temperature, air pressure, etc. Tracking can be prevented by ensuring proper creepage distance. Equipment should be kept at the right temperature and humidity.
- **5)** Oil sensors are inductive debris sensors based on a high-gradient magnetic field. The excitation coil of the sensor is driven by a constant current to generate a high-gradient magnetic field, and the induction coil is wound around the flow path. When wear debris cuts the magnetic line through the flow path, a corresponding induced voltage is generated.
- **6)** IOT The Internet of Things (IoT) describes the network of physical objects or "things"—that are embedded

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with sensors, software, and other technologies to connect and exchange data with other devices and systems over the internet.

- **7)** An IoT platform is an application or service that provides built-in tools and capabilities to connect every "thing" in an IoT ecosystem. By providing functions including device lifecycle management, device communication, data analytics, integration, and application enablement.
- **8)** Smart containers are normal containers fitted with internet-connected devices and interconnected sensors that collect, collate, and transmit container data. These sensors and devices act like traditional data loggers. But you can view all the information (near) real-time anywhere across the globe at any time.
- **9)** JSON stands for JavaScript Object Notation. It is a lightweight format for storing and transporting data. It is often used when data is sent from a server to a web page. JSON is "self-describing" and easy to understand.
- **10)**Semantics assigns computational meaning to valid strings in a programming language syntax. It is closely related to and often crosses over with, the semantics of mathematical proofs. Semantics describes the

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processes a computer follows when executing a program in that specific language.

11) Edge computing or just "Edge" is a distributed information technology (IT) architecture in which client data is processed at the periphery of the network, as close to the originating source as possible. Rather than transmitting raw data to a central data centre for processing and analysis, that work is instead performed where the data is generated whether that's a retail store or a ship's data centre.

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AI in Shipping; a Boon or a Bane

Angadjeet Singh B.V.R.L Rao

ABSTRACT

This article is about the integration of big data, artificial intelligence (AI), and autonomous systems in the maritime industry. The shipping industry is crucial for the global economy. Businesses in this sector should invest in AI to automate processes and enhance decision-making. AI has advantages such as predictive analytics for vessel scheduling, but there are drawbacks, including data quality issues. Digitalisation requires investment, but it can lead to simpler and more effective processes. Job displacement is a concern with the advancement of AI.

1. INTRODUCTION

Big data and artificial intelligence (AI) are important for making data-driven decisions in many industries, including the maritime sector. While this sector has traditionally relied on intuition, big data, and AI have gained significant attention in recent years. The term "big data" refers to large volumes of data, and ongoing research aims to develop advanced methods for analysing it, which has become an integral part of AI. AI research has evolved from mimicking human decision-making to the development of autonomous ships that operate without human intervention, resulting in lower error rates compared to human-operated vessels. This shift is revolutionising the traditional operational framework of the maritime industry and creating new opportunities to enhance productivity, efficiency, and sustainability. However, there is a lack of comprehensive studies focusing on the use of big data in the maritime sector, creating a noticeable gap in the academic literature. The maritime industry stands to gain significant economic and environmental benefits from integrating big data

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and AI into its operations. As maritime trade accounts for approximately 80% of global trade and faces challenges due to its vast expanse and evolving regulatory mandates, big data and AI offer viable solutions to these challenges. These solutions include monitoring vessel performance and improving operational efficiency. The industry generates large amounts of data, which, when effectively used in decision-making, can lead to improvements in maritime safety, a reduction in environmental impact, and lower operational costs. Leveraging this data can empower the maritime sector to make meaningful contributions to the economic and environmental aspects of its operations.

2. INTERNET OF VESSELS

2.1 Architecture

The Internet of Things (IoT) plays a vital role in today's global information era. The concept of the Internet of Vessels (IoV) is built upon IoT technology, ship characteristics, and different application environments. In 1998, the USA developed the Intelligent Website System (IWS), which incorporated an AIS, data exchange, navigation, and information network system. In the early 21st century, the European Union introduced River Information Services (RIS) as a prototype of the IoV for inland waterways. The IoV is described as a network of interconnected smart vessels and shore facilities with various digital entities [2]. Its structure encompasses vessels, island base stations, climatic observation systems, communication satellites, buoys, wireless devices, and command systems.

2.2Applications and Benefits of the IoV

The Internet of Vehicles (IoV) system enhances ship navigation by providing functions such as navigation, collision avoidance, information display, monitoring, alarms, satellite communication, and ship management. These features improve crew and onshore commander

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efficiency and optimise data from various equipment for better ship safety.

GPS navigation systems use stored maps to identify the best routes and automatically reroute vessels if issues arise. Vessels must remain vigilant and use radar for early warnings according to the International Regulations for Preventing Collisions at Sea (COLREGS). The current regulatory framework includes tools such as human sight, echo sounders, radar, AIS, ECDIS, and GNSS, but does not guarantee safety for remotely controlled or autonomous vessels. The International Maritime Organization (IMO) is working on new

GPS navigation systems use stored maps to identify

the best routes and automatically reroute vessels if issues arise

regulations to facilitate the safe operation of Mobile Autonomous Systems (MASS). Sensor systems monitor the maritime environment from three viewpoints: above the water's surface, below sea level and from space, providing crucial data for the safe navigation of MASS across low-traffic, deep ocean areas.

2.3Drawbacks

Adopting autonomous navigation systems is difficult for maritime companies due to their high cost—up to \$500,000 per vessel. Avikus and other providers need to innovate to reduce sensor and hardware costs, and government subsidies and grants can help manage upfront costs [3]. Shipping companies and vessel owners with narrow profit margins find it difficult to justify this expense. The high costs also put smaller operators at a disadvantage, impeding the market penetration of autonomous technology. Reductions in insurance costs, increased fuel economy, reduced crew size, and increased safety should eventually offset the original

Figure. 1. Structure of the IoV [1]

outlay. For navigation, autonomous marine systems mainly rely on camera and sensor data. However, the harsh sea environment and elements like erosion and corrosion make it difficult to maintain high-quality data.

Algorithms for navigation may become inconsistent and erroneous when data from several sensors is integrated. As autonomous systems develop, they must incorporate reference data such as sea charts and vessel tracking information along with real-time sensor data. Errors or compromises in the quality of sensor data can impact decision-making and situation awareness.

3. Autonomous Ships a.k.a AI Powered Vessels

3.1 Risk Assessment of Autonomous Ships

Autonomous ships have two aspects, namely, equipment (i.e., the ship itself and its machinery) and ship operation using that equipment. Autonomous ship systems integrate equipment design and risk assessment, with the former being closely related to the latter. In 1997, the International Maritime Organization (IMO) approved the Interim Guidelines for the Application of Formal Safety Assessment (FSA) for use in the IMO Rule-Making Process [4], which introduced risk assessment in rulemaking. This practice has continued to be used in the IMO Rule-Making Process. The title of the Guidelines includes the language "for use in the IMO Rule-Making Process," but because risk assessment techniques used there are basics and the content is comparatively substantial, it is often used outside the context of "rule-making," as a guideline for general risk assessment techniques

> when assessing the safety of ships and their equipment. Since the 2000s, there has been a growing discussion on risk-based design approval, leading to the introduction of various guidelines, such as those for fire safety and alternative design arrangements for engines, electrical equipment, and lifesaving equipment in the SOLAS Convention Annex. Autonomous ships integrate operations and equipment, with an automated navigation system replacing human operators across multiple components. For this reason, the guidelines of ship classification societies point out the importance of verifying the concept of the operation and equipment use methods [5] but do not go so far as to recommend

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concrete assessment methods. On the other hand, because actual ship experiments with autonomous ships will be conducted in ocean waters. the IMO approved Interim Guidelines for MASS Trials (MASS: maritime autonomous surface ships) [6].

According to these guidelines, it is essential to address safety, security, and environmental risks when conducting actual ship experiments. Identification of risks, implementation of countermeasures, and preparation of an emergency plan for foreseeable incidents are necessary. When carrying out an experimental actual-ship operation, it is acceptable to identify hazards through a risk assessment using the automated navigation system and prepare for foreseeable events in advance.

3.2Will AI replace humans onboard?

Artificial Intelligence (AI) stands on the cusp of transforming the shipping industry, a longstanding pillar of global trade and transportation. Given the escalating interconnectivity of the global landscape, the pivotal roles of global trade and passenger transport in driving economic growth and facilitating cultural exchange cannot be overstated. Approximately 90% of global trade is reliant on maritime transportation, rendering AI a potential disruptor to the employment landscape of seafarers. Nevertheless, it is more conceivable that AI will assume the mantle of routine operational and analytical tasks, rather than entirely supplanting human crew members.

In 1997, the International Maritime Organization (IMO) approved the Interim Guidelines for the Application of Formal Safety Assessment (FSA) for use in the IMO Rule-Making Process [4], which introduced risk assessment in rulemaking

Persisting regulatory and technological barriers thwart the realisation of fully unmanned ships, encompassing considerations such as situational handling, liability concerns, and the accommodation of autonomous vessels by ports

Critical human proficiencies such as leadership, teamwork, problemsolving, and situational judgment are poised to remain challenging for AI to emulate at a level commensurate with humans. While it is plausible that certain crew roles, such as navigation officers, may undergo reduction with the escalation of bridge automation, a fundamental team comprising engineers, technicians, captains, and officers will continue to constitute a necessity aboard vessels, even those endowed with high levels of automation. Roles within shore-based fleet management may be subject to greater impacts stemming from AI and automation encroaching upon tasks in data analytics and optimisation previously executed by humans. Nonetheless, the imperative of human oversight, governance, and decisionmaking remains undiminished.

Persisting regulatory and technological barriers thwart the realisation of fully unmanned ships, encompassing considerations such as situational handling, liability concerns, and the accommodation of autonomous vessels by ports. While AI promises to engender substantial efficiencies and transformations in onboard tasks, the inimitable human capacity to respond in high-pressure situations and tackle open-ended challenges substantiates suggestions that human role replacement in the shipping domain remains a distant prospect.

The industry is poised to witness partial automation in conjunction with

Figure. 2. Risk assessment of AI-powered vessel [7] Figure. 3. Vessel operated by AI [8]

joint operations featuring humans and AI across various roles in the foreseeable future. This trajectory is expected to reshape specific tasks and potentially diminish certain roles over time.

The growing discourse surrounding AI's potential to supplant human roles across various industries, including shipping, has drawn considerable attention and debate. Despite AI's rapid technological advancement and its increasing capacity to automate tasks customarily undertaken by humans, it is underscored that complete replacement remains improbable in the short term. In the realm of shipping, AI is positioned to streamline operations, optimise routes, enhance efficiency, and bolster safety through predictive analytics and automation. Nonetheless, human involvement remains indispensable for effective decision-making, problemsolving, and adaptation to unforeseen circumstances. Humans are uniquely equipped with creativity, intuition, and ethical discernment – qualities challenging for AI to fully replicate. Moreover, certain responsibilities and roles within shipping necessitate human expertise and interaction, such as customer service, intricate problemsolving, and regulatory adherence. While AI can amplify human competencies and automate repetitive tasks, its capacity to utterly supplant the requisite for human involvement within the shipping industry is dubious. Instead, a mutually beneficial alliance between humans and AI, capitalising on the strengths of both, is often deemed the most efficacious approach to yield optimal outcomes.

CONCLUSION

The integration of artificial intelligence (AI) in the shipping industry offers benefits such as predictive analytics, predictive maintenance, faster regulatory compliance checks, intelligent navigation, and overall efficiency gains. However, concerns include high upfront costs, data quality issues, legal uncertainties, cybersecurity risks, job impacts, over-reliance on automation, and ethical implications.

It is unrealistic to replace human roles with AI completely. A more likely scenario involves a collaborative human-AI partnership, with humans contributing critical thinking, leadership, adaptability, and sound judgment, while AI excels in optimisation, analytics, monitoring, and routine tasks. Responsible implementation of AI requires managing costs, ensuring data quality, updating policies, securing systems, mitigating job impacts, maintaining human oversight, and securing public confidence through transparency.

Prudent investments and sensible governance can provide a competitive advantage to the shipping industry and its workforce while elevating safety, sustainability, and customer service. Successful integration relies on collaborative human-machine operation.

I acknowledge receipt of the detailed academic paper titled "AI in Shipping; a Boon or a Bane" by Angadjeet Singh and Dr. B.V.RL Rao from the Indian Maritime University, Cochin, Kerala.

The paper includes several figures illustrating concepts such as the structure of IoV, maritime environment sensor systems, and data quality integration challenges. The document concludes by weighing the opportunities and challenges presented by AI in shipping, emphasising the need for responsible implementation and human-AI collaboration. The paper is well-referenced, citing 13 sources including IMO guidelines, research projects, and industry reports. This comprehensive document provides valuable insights into the current state and prospects of AI applications in the maritime industry.

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Leveraging AI To Build ESG Roadmap for the Maritime Industry

*Abstract***— The application of environmental, social, and governance (ESG) factors is growing in prominence as a means of assessing** h**ow a company is performing, informing investment decisions, and influencing consumer purchasing. Increasing regulatory requirements and frameworks that establish stringent standards for the maritime industry are presenting maritime-related businesses with a challenge regarding ESG disclosure. Artificial intelligence (AI) is an emerging field of study that utilises numerical techniques to address a wide range of challenges, including classification, segmentation, and prediction and has proven to be very useful in tackling ESG challenges. While many publications discuss the potential of AI, few focus on the pain points of the maritime industry and even fewer highlight the potential of AI to devise a strategic roadmap for the maritime industry towards achieving ESG goals. This paper fills the gap by reviewing the practical AI applications and use cases which can help the industry become more transparent in terms of ESG disclosure.**

Keywords—ESG, Artificial Intelligence (AI), Maritime Industry, roadmap, AI applications.

I. introduction

Major corporations, regulatory bodies, and investors are now focusing on integrating ESG into supply chain management as they have understood that a major chunk of the ESG risks lie in the supply chain which may be beyond the organisation's operational boundaries. Scope-3 emissions are an important example which often represent the majority (more than 70%**¹**) of an significant challenges in achieving net zero emissions and complying with stringent environmental regulations. With 34 regulatory bodies across 12 markets, inconsistencies in ESG reporting complicate efforts. The maritime sector's diverse global shipping, manual reporting, heavy debt, and low margins hinder reliable ESG data collection. Initiatives like the IMO's GHG strategy, Poseidon Principles, and SBTi drive ambitious goals, while new regulations like the CSRD and German Supply Chain Due Diligence Act enforce stricter compliance. Machine Learning (ML) and Artificial Intelligence (AI) can bridge the technology gap, enhancing ESG data accuracy and supporting decarbonisation strategies. Continuously acquiring knowledge from users' behaviours and improving the outcomes is an essential process for creating adaptable ESG reports**²** . AI has the capability to analyse various data repositories such as supply chain, procurement, and accounts to detect irregularities, fraudulent activities, and patterns in processes. It can also generate notifications for possible system malfunctions, allowing for proactive reporting. Artificial intelligence can provide users with the most pertinent ESG metrics for a specific industry sector. On ships, the well-being and safety of employees are significant issues, particularly in relation to accidents such as fires and machinery failures**³** . This technical paper addresses the ESG (Environmental, Social, and Governance) challenges in the maritime industry, focusing on regulations, frameworks, and reporting difficulties. It highlights how AI can analyse industryspecific factors and local regulations to enhance ESG disclosure's informativeness, relevance, and transparency. The paper provides examples of AI's role in helping maritime companies address ESG issues and improve disclosure practices. Additionally, it reviews DNV's (Det Norske Veritas) progress in using AI to streamline maritime processes and support stakeholders in building sustainable businesses, ultimately aiming to prevent biodiversity loss at a corporate level.

organisation's total emissions. Maritime logistics face

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II. ESG and its impact on the maritime industry

The pillars of ESG frameworks, which are Environmental, Social, and Governance, are crucial elements that companies must report on. The goal of ESG is to encompass all the non-financial risks and opportunities that are inherent to a company's daily operations. The ESG framework was first introduced in the United Nations (UN) Principles for Responsible Investment in 2006**4**. Since the release of the 2019 business roundtable (BRT) statement, there has been an increasing emphasis on ESG as a benchmark for global companies to improve their corporate competitiveness**⁵** . In

today's interconnected economy, shipping companies are enhancing competitiveness through fleet expansion, larger ships, strategic partnerships, M&A, and integrated logistics systems. Success now depends not only on service quality, rates, and digital platforms but also on using eco-friendly fuels like LNG, methanol, ammonia, and hydrogen. Additionally, protecting seafarers' rights and promoting diversity among foreign seafarers are crucial. Additionally, it's important to ethically manage tax evasion issues related to the flag of convenience and establish an anti-corruption ethical management system**6**. The section below discusses E, S and G in the context of the maritime industry.

A. 'E' – in the maritime industry context

Shipping accounts for 2.16% of global greenhouse gas (GHG) emissions⁷ and this figure is projected to increase in the future. Nevertheless, the impact of shipping on the environment extends beyond air emissions. Our ecosystems can also suffer from noise pollution, vessel discharges, and various other factors.

B. 'S' – in the maritime industry context

The maritime industry faces significant social issues, particularly regarding seafarers' well-being, including long work hours, poor living conditions, and low pay. The International Labour Organization's Maritime Labour Convention sets minimum standards for seafarers' working and living conditions. Additionally, the International

Figure. 1

The ESG framework was first introduced in the United Nations (UN) Principles for Responsible Investment in 2006

Safety Management (ISM) Code by the IMO establishes global safety standards for ship management and operation. Adherence to these standards is crucial for shipping companies to prioritise employee well-being.

C. 'G' – in the maritime industry context

The shipping sector functions inside a framework of stringent rules, necessitating all participants to comply with rigorous governance protocols. Due to the worldwide scope of the sector and the changing geopolitical situation, maritime players must carefully address substantial issues. Thorough due diligence is crucial, as

emphasised by regulatory organisations including the Office of Foreign Assets Control (OFAC), the UK Bribery Act, and the Foreign Corrupt Practices Act (FCPA). The initiatives undertaken by the Maritime Anti-Corruption Network (MACN) are a substantial step towards addressing corruption in more prominent locations.

III.net zero targets for the maritime industry

Looking across frameworks and regulations, the overall aim for all agrees on the 'Net Zero by 2050' target, however, the pathways and trajectories towards achieving this can vary. In the following section, three trajectories are compared.

International Maritime Organisation (IMO) 2023 Revised Strategy trajectory: The IMO's Revised Strategy on the reduction of GHG (Greenhouse Gas) emissions from ships sets out a vision of a pathway to reach net-zero GHG emission by or around 2050, as seen in **Figure 1**, and to achieve indicative checkpoints that aim to reduce total GHG emissions by 20% and strive for 30% by 2030, 70% and strive for 80% by 2040, both relative to 2008**⁸** . Figure 1 below shows the revised IMO strategy for GHG reductions.

Figure. 2 Strengthened IMO strategy on GHG reductions (Source: DNV).

Poseidon principles (PP)**:** The current carbon reduction trajectory (version 4.2**9**) , employed by PP establishes

Figure. 2 GHG Intensity trajectories for IMO, SBTi, PP *(Source: DNV).*

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the necessary rate of decrease in carbon intensity to be in line with the IMO's Initial Strategy objective of reducing absolute emissions by at least 50% by 2050 compared to 2008 levels. To evaluate the extent to which a particular vessel is in line with climate goals, the yearly carbon intensity of the vessel is compared to the decarbonisation trajectory specific to its type and size category.

Science Based Targets Initiative (SBTi)¹⁰: The Maritime Guidance provided by the SBTi establishes targets that align with the objective of restricting the rise in average global surface air and sea surface temperatures, over a span of 30 years, to a level significantly below 2°C above pre-industrial levels. Additionally,

it encourages endeavours to limit this temperature increase to 1.5°C above pre-industrial levels. The SBTi has prioritised 1.5°C as the primary objective in its framework for establishing targets, surpassing the level of ambition outlined by IMO's trajectory¹¹.

The comparisons of different trajectories of IMO Revised Strategy 2023, PP and SBTi are shown in **Figure 2** .

IV. key metrics

From both maritime and financial regulatory frameworks, several crucial metrics have been identified. Adherence to maritime regulations is imperative for ship owners and operators, given that non-compliance can result in various consequences, ranging from port restrictions to the severe outcome of vessel detention, preventing it from sailing. The IMO is actively developing these regulations, and it is mandatory for all shipowners and operators to adhere to them. There have been recent developments in the European Union (EU) as well related to the Emission Trading Scheme and Monitoring, Reporting & Verification which will require the maritime industry to develop more efficient and structured data collection systems. The key metrics are discussed below:

A. IMO Data Collection System (DCS)

The Data Collection System (DCS) was adopted by the International Maritime Organization in 2019 and is now

Figure. 3 Connection between the DCS, CII and SEEMP Part III Figure. 4 EEXI Baseline

The maritime industry faces significant social issues, particularly regarding seafarers' well-being, including long work hours, poor living conditions, and low pay

an important database for multiple frameworks, such as PP, CBI, and Sustainability Linked Loan Principles (SLLP).

Ships of 5,000 Gross Tones or above are required to collect and report data, including fuel consumption, distance travelled and hours underway, to an IMO database after which the data is verified by an IMO verifier, such as Recognized Organization (RO) or Administration¹².

Verified data forms the basis for the calculation of CII ratings and enables the calculation of AER, which is required by PP and CBI. Similarly, borrowers under the SLLP¹³ must obtain verification of their performance against their Sustainability Performance Targets (SPTs) and

provide yearly verified reports to lenders. This generally includes (but is not limited to) DCS Data in the maritime sector. **Figure 3** shows the connection between DCS, CII and SEEMP Part III.

B. EEXI/EEDI

The IMO mandates the calculation of the Energy Efficiency Design Index (EEDI) and Energy Efficiency Existing Ship Index (EEXI) for ships of 400 gross tonnes and above to enhance global fleet energy efficiency. EEDI measures the energy efficiency of new ships based on annual CO2 emissions, transport capacity, and distance. EEXI assesses existing ships' energy efficiency by CO2 emissions per transport work, focusing solely on design parameters. Both indices must fall below a maximum threshold.

The baseline forming the requirement level was implemented in 2013, with the requirement getting stricter every 5 years starting from 2015, as seen in **Figure 4**. Existing ships that do not meet the requirements will need to make technical modifications to their ships to improve their energy efficiency, using methods such as installing more efficient engines, propellers, and rudders.

C. CII

IMO requires all ships of 5,000 gross tonnes and above to calculate and report their Carbon Intensity

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Indicator (CII)¹⁴. The CII measures a ship's operational carbon efficiency and is based on its fuel consumption, which is influenced by its technical efficiency, fuel type, and how it is operated.

Ships are assigned a CII rating of A, B, C, D, or E, with A being the best rating, as seen in **Figure 5**. The rating indicates the ship's performance relative to other ships of its type and size. Ships rated D for three consecutive years or E for one year must submit a corrective action plan to show how they will improve their CII rating to C or above.

– Inclusion of maritime industry

D. EU Emissions Trading System (ETS) Starting in January 2024, the EU plans to expand the scope of its Emissions Trading System (EU ETS) to include carbon dioxide emissions from all large ships (weighing 5,000 gross tonnage or more) that enter EU ports,

Half of the emissions from voyages starting or ending outside of the EU are subject to the third country's decision on how to address them.

regardless of their flag state¹⁶. As per the system:

- All emissions that take place between two EU ports and when ships are within EU ports are fully accounted for.
- There is a regulation on carbon dioxide, methane, and nitrous oxide emissions. However, the inclusion of methane and nitrous oxide emissions will only take effect starting in 2026.

Maritime transport emissions fall under the ETS cap, which limits greenhouse gas emissions. The cap decreases over time to ensure all sectors contribute to EU climate goals, promoting energy-efficient and low-carbon solutions, and reducing the price gap between alternative and conventional marine fuels.

E. MRV – Monitoring, Reporting and Verification (EU and UK)

In 2017, the EU implemented mandatory Monitoring, Reporting and Verification (MRV) as the initial phase of a broader initiative to gather and analyse data on

The CII measures a ship's operational carbon efficiency and is based on its fuel consumption, which is influenced by its technical efficiency, fuel type, and how it is operated

shipping emissions. Ships above 5,000 GT on EU-related voyages are subject to the EU MRV regulations¹⁷. Primary responsibilities for organisations that meet the criteria outlined in the MRV Maritime Regulation:

Monitoring Plan: As per the EU MRV regulation, it is required that a vessel's monitoring plan be verified by an independent and accredited verifier. The monitoring plan will provide a detailed description of the vessel and its combustion machinery, including the types of fuels used and the monitoring methods employed. It will also include any other pertinent information 18 .

Emissions Reporting: Companies are required to submit a verified emissions report for each ship that has engaged in maritime transport activities in the European Economic Area during the previous reporting period. This report must be submitted through THETIS MRV to the Commission and the flag States by 30 April of each year.

Document of Compliance: Every year, by 30 June, companies are required to ensure that all their ships, which have engaged in activities during the previous reporting period and are visiting ports in the European Economic Area, have a document of compliance on board. Inspections by authorities from Member States may be required¹⁹.

V. challenge: measure, monitor and report

The complexities of sustainability data challenges are numerous. The initial hurdle is identifying the specific data required to influence materiality, even before the commencement of data collection for a project. Subsequently, the issues of consolidating internal data and obtaining credible external data present themselves.

Here are some of the challenges specific to the shipping industry when it comes to data acquisition:

Identifying Data Sources: Finding reliable and relevant data sources for sustainability issues across the value chain.

Figure. 5. CII rating15 Figure. 6. Challenges of Sustainability Reporting

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No Clear KPI Definition: Lacking standardised and consistent definitions of key performance indicators for ESG metrics.

Non-Standardised Manual Data Collection Process: Collecting data in different ways and systems, resulting in data inconsistency and unreliability.

Lack of Company Data: Not having robust data collection and reporting systems or clear ownership of sustainability data within the organisation.

Much Data Needs After-Correction: Having errors and inaccuracies in the data that require validation and correction, leading to data inauthenticity and greenwashing.

High Cost of Automation: Facing significant costs and resource constraints to implement and maintain automated data collection and analysis systems.

Acquiring Scope-3 Data: Facing challenges in obtaining accurate and comprehensive data on upstream and downstream emissions throughout the value chain.

Less Quantitative Social and Governance Data: Dealing with subjective and proxy data on social and governance issues that are difficult to measure and connect to market performance.

Data Validation and Third-Party Assurance: Requiring external verification or assurance of ESG data and disclosures to avoid scrutiny and enhance credibility.

Anticipating Future Standards and Requirements: Keeping up with changing market trends and stakeholder expectations on ESG data and reporting.

Figure 6 describes common challenges in sustainability reporting and possible mitigation measures for each challenge.

VI. How AI can help

 The surge in data availability has posed a challenge for stakeholders to make balanced decisions when it comes to ESG issues. The implementation of artificial intelligence (AI) algorithms emerges as an optimal solution to expedite data processing and enhance the comprehension of the

information extracted²⁰. AI encompasses practical tools and methods such as machine learning (ML) and data analysis, which are apt for solving a variety of problems including correlation, optimisation, classification, and prediction. ML and deep learning (DL) methods have proven their efficacy in diverse areas and can be tailored to tackle ESG challenges. As per²¹, ML methods can contribute to achieving 79% of the Sustainable Development Goals (SDGs) in the UN Agenda, with 93% for ecology, 82% for society, and 70% for the economy.

A. AI in Materiality Assessment

AI can significantly enhance ESG materiality assessment in the shipping industry. Here are a couple of examples from industry reports and academic/research papers:

Baker Hughes, an energy technology enterprise, employed AI and Large Language Models (LLMs) to conduct ESG materiality assessments²². They initiated a trial program using C3 AI to analyse 3,500 stakeholder documents over a span of 9 weeks. The objective was to teach natural language processing and LLMs to accurately detect and categorise paragraphs related to ESG issues. This was achieved by utilising over 1,700 training labels. The project was swiftly implemented and resulted in a reduction of 30,000 hours in the two-year timeframe required to complete the ESG materiality assessment.

In 2021, Booz Allen began leveraging AI-powered risk analysis software Datamaran to complement their ESG management processes. This allowed them to power a continuous data-driven review of ESG-related risks and their regulatory, competitive, and operating contexts 23 . They used Datamaran to assess and prioritise the 27 ESG topics most commonly identified as material by companies in their sector.

B. AI in Sustainability Reporting

The advent of deep learning in the 2010s first focused on computer vision but rapidly expanded to include textual analysis24. Textual tools that utilise deep learning rely on the implementation of various word embedding

Figure. 7. Extractive Summarization by GPT-3.5 **Figure. 8. Text generation capabilities by GPT-3.5**

models. These models employ neural networks to map words from a dictionary to word vectors, which also capture semantic information about the words²⁵. The concept of word embeddings was advanced through the utilisation of the transformer architecture, which is employed by the majority of the latest cutting-edge Natural Language Processing (NLP) models, including Bidirectional Encoder Representations from Transformers (BERT)26 and Generative Pre-Trained Transformer 4 (GPT-3.5)27. GPT-3.5 is a highly effective tool for extracting and summarising valuable information from a company's disclosure. **Figure 7** is a demonstration showcasing how GPT-3.5 can accurately identify the significant actions taken by a company in the realm of ESG through text analysis. This excerpt is sourced from the CMA CGM sustainability report for 2022²⁸.

A second example showcases the impressive text generation capabilities of GPT-3.5. **Figure 8** displays the output generated by GPT-3.5 in response to a prompt about the challenges that maritime companies are currently encountering in relation to ESG. From the output, it is evident that GPT-3.5 provides a thorough analysis of the significant challenges that maritime companies encounter when transitioning to sustainable practices. The text generation capabilities of models like GPT-3.5 offer exciting opportunities for practical applications. One such application is the creation of initial draft sustainability guidelines for shipping companies.

A third utilisation of AI in sustainability reporting is creating data pipelines, automating data collection, monitoring the performance along different ESG impact topics, and creating reports along different requirements – regional regulatory frameworks and international guidelines. **Figure 9** shows a typical flowchart where AI automates the sustainability reporting system.

C. AI in MRV/DCS

AI plays a crucial role in optimising fuel consumption and emissions in the shipping industry. By analysing historical and real-time data on various factors like weather, sea conditions, vessel speed, and engine performance, AI can provide optimal routes and speeds for each voyage. This results in significant reductions in fuel consumption and CO2 emissions.

In addition to optimisation, AI improves the quality of data and reporting. It automates the collection, processing, and verification of data on fuel consumption and emissions from various sources, including onboard

Figure. 9. Architecture of Automated Sustainability Reporting System **Figure. 10. ESG Roadmap**

sensors, logbooks, and satellite AIS. This automation leads to the generation of standardised and accurate reports that comply with EU MRV and IMO DCS regulations. For example, PwC offers an AI-based solution for MRV reporting that integrates with existing systems and ensures data quality and reliability²⁹. Furthermore, AI enhances decision-making and risk management by providing insights and recommendations based on data analysis and predictive models. This helps shipping companies improve their performance, competitiveness, and sustainability. AI also identifies and mitigates potential risks, such as non-compliance, operational failures, or reputational damage. For instance, DeepSea uses AI to provide real-time alerts and guidance to ship operators and managers, enabling them to make informed decisions and reduce risks³⁰.

D. Use Case of AI: Hitachi Collaborated with Stena Line in 2018 to Integrate Digital Solutions in Maritime Operations

Stena Line, one of Europe's largest shipping companies, teamed up with Hitachi Europe Ltd., a subsidiary of Hitachi, Ltd. The collaboration aimed to deploy artificial intelligence technology on ships, with the objective of reducing fuel consumption costs. This initiative played a crucial part in their strategy to lessen environmental impact.

Environmental Impact: The primary goal of this partnership was to reduce fuel consumption costs, which directly translates to a reduction in CO2 emissions. This aligns with Hitachi's commitment to environmental sustainability and its focus on decarbonisation³¹.

Social Impact: By reducing fuel consumption, Hitachi and Stena Line are not only cutting costs but also minimising the environmental impact of shipping operations32. This contributes to the broader societal goal of sustainable development.

Governance: This initiative demonstrates Hitachi's proactive approach to sustainable management. It shows that Hitachi is taking responsibility for its environmental impact and is committed to implementing innovative solutions to reduce it.

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In summary, this partnership can be seen as a significant step in Hitachi's ESG journey. It showcases Hitachi's commitment to leveraging technology for environmental sustainability, contributing to societal goals, and maintaining strong governance practices.

E. AI tools and initiatives in the Shipping Industry

Several AI tools and initiatives are reshaping the ESG landscape in the shipping industry:

ESG Analytics: This AI engine delivers sentiment analysis on companies across the world³³.

SenseFolio ESG Framework: Utilises Natural Language Processing (NLP) and Machine Learning (ML) to monitor 20,000 companies' ESG ratings in real-time^{30.}

Accern: Provides a simplified solution to gathering insights from unstructured ESG data³⁰.

Generative AI powered by Large Language Models (LLMs): These AI tools can excel traditional AI applications in tasks such as recognising images, processing text, audio, video, and more. As a result, they can transform the way companies track, measure, and perform on ESG parameters³⁴.

F. DNV's journey towards AI

DNV, a leading risk management and assurance company, has been actively leveraging Artificial Intelligence (AI) in its operations. Their initiatives span from research and development in AI technologies to assuring AI-enabled systems and publishing recommended practices for safe AI application. They have also developed AI-based tools for various use cases such as corrosion monitoring, battery health verification, and x-ray film analysis. These efforts underscore DNV's commitment to harnessing AI to address complex challenges and ensure trust in AI systems.

Recommended Practices (RPs): DNV has published a suite of RPs that enable companies operating critical devices, assets, and infrastructure to safely apply AI. DNV's recommended practices (RPs) provide a framework for the safe application of AI, covering key building blocks like data, sensors, algorithms, and digital twins 35 . These RPs, informed by DNV's expertise in sectors like maritime, energy, and healthcare, offer practical guidance on the EU Artificial Intelligence Act, the world's first AI law. The law broadly defines AI and applies to any data-driven system deployed in the EU. The RPs address four main challenges:

- They adopt a systems approach to understand how AI components interact with other elements, humans, and the environment.
- They ensure continuous assurance to keep up with the dynamic nature of AI-enabled systems.
- They include stakeholder mapping to identify and balance competing interests.
- They promote collaboration through modular assurance claims, allowing each actor to assure their parts, thereby enabling system-wide assurance.

• These RPs serve as a valuable resource for companies to ensure compliance with relevant requirements.

AIS Business Intelligence Service: DNV's AIS (Automatic Identification System) Business Intelligence Service is a system that leverages Big Data to provide valuable insights in various areas³⁶. The AIS Business Intelligence Service helps ship operators and owners monitor vessel safety, sustainability, and performance by collecting and analysing Big Data. DNV GL experts use advanced models to analyse voyage management, port and bunker operations, and benchmark data. This tailored analysis offers advice on reducing operational costs, optimising voyages, and suggesting retrofit solutions. These insights benefit the entire maritime value chain, including ship operators, port authorities, insurance companies, commodity traders, and maritime service providers.

Research and Development: DNV has a dedicated focus on AI and smart industry technologies in their assurance offerings. They work on understanding how AI is regulated and how these technologies can be assured to be trustworthy³⁷. DNV is actively involved in several research

> **Stricter regulations demand innovative solutions for accurate Scope 3 emissions calculation, efficient supply chain evaluation and personalised decarbonisation plans**

and development projects related to AI in the shipping industry. One of them is the SAFE Maritime Autonomous Technology (SAFEMATE). This research project, run by DNV and their industry partners, is working on a system solution for autonomous shipping. SAFEMATE focuses on evolving a decision support system for safe navigation that can detect obstacles and threats in the marine environment, interpret this information, and communicate a routing solution to the onboard operator. A prototype system developed by project partner Kongsberg Maritime is now being tested in a pilot project on the operational ferry Bastø VI serving the route between Moss and Horten in Norway³⁸.

In addition to SAFEMATE, DNV is also focusing on the transition towards digitalisation and automation in the maritime industry.

They are leveraging digital technologies and solutions to increase competitiveness and enhance operational efficiency. Another significant initiative is the Autonomous Ship Technology Development. DNV has entered a memorandum of understanding (MoU) with Hyundai Heavy Industries (HHI), AVIKUS, and Liberian International Ship & Corporate Registry (LISCR) for the development of autonomous ship technology³⁹. DNV has been developing and testing high-fidelity and low-fidelity simulations to

assess various scenarios quickly and effectively. They have been working with augmentations to train AI algorithms to detect and adjust to various factors⁴⁰.

Assurance of AI-enabled Systems: DNV provides an integrated approach to assure AI-enabled systems by assessing the development process and using industryleading AI testing technologies1. They manage AI-related risks during the full life cycle of systems³⁴. Corrosion.ai is a tool that leverages AI and machine learning to provide a safer and more dynamic solution for the inspection and monitoring of corrosion on ships. Battery.ai uses both AI and empirical models for monitoring and verifying battery health in the short and long-term**.**

G. Use Case: ESG Roadmap for a Turbocharger manufacturing giant

One of the turbocharger manufacturing and repairing company teamed up with DNV to utilise AI to automate their sustainability reporting journey. The issue was not only limited to data collection but expanded to materialising the continuous improvement which includes regular materiality assessment and automated sustainability reporting. The process followed a series of steps conducting surveys focussing on key issues that stakeholders might face, risk assessments of potential impact on value chain at a corporate level, creating a matrix prioritising the key issues based on the result of surveys, creating data pipelines for automated data collection, utilising them to create reports based on different frameworks including TCFD, SASB etc and target setting based on different trajectories including SBTi. **Figure 10** represents the roadmap which utilises AI in different parts of ESG journey.

VII. Conclusion

Despite its fragmented structure and data challenges, the maritime industry faces rising pressure to achieve ambitious ESG goals. Stricter regulations demand innovative solutions for accurate Scope 3 emissions calculation, efficient supply chain evaluation and personalised decarbonisation plans. Machine Learning and Artificial Intelligence (AI) are proving to be powerful tools, bridging the technology gap with capabilities like filtering crucial ESG metrics from massive datasets and proactively reporting system malfunctions. This paper thus underscores the transformative role of AI in enhancing ESG disclosure's informativeness, relevance, and transparency, with DNV leading the way in leveraging AI for process streamlining and sustainable business practices in the maritime industry.

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Going Astern into MER Archives…

The Editorial talks of putting the
inland waterways into good use
for cargo carriage by inland inland waterways into good use for cargo carriage by inland vessels. It further propsoes that the Institute may host an all-India seminar and MER might reach out to the members requesting to extend any form of help for realising the idea. There is a mention about the Bhopal Gas Tragedy. It posits that had people covered their faces (noses & mouths) with wet towels, they could have been saved (it appears that the plant employees followed this wet-towel method whenever there was a leak in the plant).

de of Marine Engir or, Nimal, Natiman Point, Bombay 400 021

The OPINION section talks of including Design subject in the marine engineering curriculum. Interestingly, it divides engineers into two groups: makers and users; and former is more than the later in numbers. The makers must know

what the users are doing. So a Naval Architect must study the plant before he starts designing. Amen!

Repair & maintenance cloumns: The first article discusses few main engine failures and causes. Though informative, the photos from the old issue are not very clear (so could not copy and insert). This is followed by write-ups on repairs of engine components and maintenance management.

Then there is an article on newbuilding of 'Royal Princess', a cruise liner. The next discussion is on hull forms and propeller/propulsion efficiency.

The Transaction on modifications to the steam propulsion plant of large container ships gives an insight into the trends of the times. There are other discussions on data transmission via satellites and new Pielstick engine and other products.

The Letters to the Editor (from Indian mariners) might interest a few.

MARINE ENGINEERS REVIEW (INDIA)

December 2024

Dear Sir,
I wish to congratulate you on the excellent sel-I wish to congratulate you on the excellent sel-
ection of Walt-Whitman quotation on the cover of
your October, 1984 issue and the very fine con-
ception of the composition of the visual.
Your editorial of the issue also w Your edi[.]
written.

R. Ramamurthy, General Manager (Projects), Telelink Nicco
B-15/26,Kalyani 741235 West Bengal

Sir,
Letter to the editor in your October '84 issue
from Mr. G.K. Ramakrishnan made interesting read-
ing. It is heartening to see younger members
taking interest on vital issues pertaining to the

ing. It is heartening to see younger members
ing interestion viral issues pertaining to the profession.
profession. The profession is profession and profession and profession. Marine education/training, warrants further di

marine engineers, to keep abreast with other
disciplines of engineering in our own country and
modern developments in our field abroad. Lastly,
provide better career opportunities to those who
have cared to better their qu Tactifies are available in related disciplines,
In advanced shippuilding nations, with financial
assistance from international agencies. The need
of the hour Is to make ourselves eligible.
Our esteemed journal could be a f

Engineer Surveyor,
Indian Register of Shipping.

Sir,

in your editorial of the October 1984 MER Issue,

you have very laudibly mentioned that we profes-

sionals shall whole heartedly support the poli-

cles of our new prime minister, which will bring

about overdue re

studies. sary

sary studies.
Ultimately however, the two avenues of training
merge into qualifying them for appearing for the
MQ.T. Professional examination and a career as
Marine Engineers.

Marine Engineers.
Lacking a strong foundation, this cadre of future
marine engineers are rendered vulnerable. The
institute as a guardian of professional Marine
Engineers could influence a correction to this
situation. Und

n nammyc
R. Vaz
15 Madonna Building, Road No.10, Wadala
Bombay 400 031

We invite observations, discussion threads from readers, taking cues from these sepia-soaked MER pages. - Hon.Ed.

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