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Smart Shipping Route Optimization for Fuel Efficiency Using Big Data Analytics

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***Abstract*—This research aims to optimize shipping routes by applying big data analytics to improve fuel efficiency. By leveraging real-time and historical data, the study identified the most efficient routes to minimize fuel consumption without sacrificing operational effectiveness. Based on maritime logistics theory, big data analytics, and fuel efficiency, this research combines route optimization models, weather forecasts, and ship performance analysis to support navigation decision-making. In addition, the impact of IMO MARPOL Annex VI regulations, especially EEDI and SEEMP, is also considered in efforts to optimize energy efficiency. The method used is a mixed approach, which combines quantitative analysis of AIS data, weather reports, and fuel consumption records with machine learning algorithms for route optimization. Pearson's correlation analysis evaluates the relationship between speed, distance, travel time, and fuel consumption. Case studies are used to validate the developed model. The results showed that fuel consumption was greatly affected by the speed of the ship, with higher speeds increasing fuel consumption. A negative correlation was found between travel time and daily fuel consumption, suggesting that slower cruising can improve efficiency. The study emphasizes the importance of real-time data processing in route adjustments based on weather, congestion, and energy efficiency. This research offers an innovative, data-driven approach to route planning, different from traditional methods that rely on static charts and experience. The integration of big data in maritime logistics can reduce emissions, reduce costs, and improve operational sustainability.**

Keywords—big data analysis; maritime route optimization, fuel efficiency; delivery logistics; imo marpol annex vi; slow steaming; alternative fuels

I. INTRODUCTION

The maritime industry plays an important role in global trade, with ocean liners as the backbone of freight and passenger transportation. However, the main challenge facing the sector is operational efficiency, particularly in fuel consumption which is one of the biggest costs in ship operation [1][2][3]. With increasing awareness of the environmental impact of greenhouse gas emissions produced by ships, efforts to optimize fuel use have become increasingly urgent One approach that can be applied to improve fuel efficiency is to determine the optimal shipping route [4][5][6]. Determining the right route not only reduces fuel consumption but also minimizes travel time and avoids extreme weather conditions that can affect ship operations In this context, big data analytics is becoming an innovative solution that enables the processing of large amounts of data to identify the best travel patterns in real-time [7][8][9]. The application of big data in ship route optimization involves the use of various data sources such as weather information, ocean currents, shipping historical data, and ship operational conditions. With advanced modeling and data analysis techniques, navigation decisions can be made more accurately and efficiently. Several studies have shown that the use of artificial intelligence and machine learning-based data analysis can significantly reduce fuel consumption and carbon emissions in the maritime industry. This research aims to develop a shipping route optimization model based on big data analysis to improve the fuel efficiency of marine ships [10][11][12]. With this research, it is hoped that the maritime industry can adopt data-driven technology to improve operational efficiency, reduce costs, and contribute to environmental sustainability. This study will explore various data analysis methods and optimization algorithms that can be applied in modern navigation systems to achieve these goals [13],[14],[15].

II. LITERATURE REVIEW

Determining the best route in shipping is a crucial aspect in improving ship operational efficiency, especially in terms of fuel consumption. With the development of big data analytics technology, the process of optimizing ship routes can now be done more accurately and in real-time. This study discusses several key aspects in the related literature, namely ship fuel efficiency, data-driven route optimization, and the implementation of big data in the maritime industry. Fuel efficiency in shipping is affected by various factors such as weather conditions, ocean currents, ship speed, and the route chosen [16][17][18]. According to research by Smith et al. (2020) [19][20][21],consumption reduction can be achieved through optimizing ship speed (slow steaming) and selecting paths that avoid strong ocean current resistance. In addition, the use of data-driven technology can be helpful in predicting fuel needs based on previous travel patterns [22][23][24]. Ship route optimization aims to determine the most efficient route by considering variables such as mileage, weather conditions, and fuel consumption Methods commonly used in this study include genetic algorithms, machine learning models, and artificial neural network (ANN)-based approaches [25][26][27]. use of the A* and Dijkstra algorithms in maritime navigation systems has also proven to be effective in determining the best route to avoid bad weather and reduce fuel consumption (Park et al., 2021) [28][29][30]. Big data technology allows the processing of large amounts of data from various sources such as AIS (Automatic Identification System) systems, satellite data, and ship sensors. According to Xu et al. (2023) [31][32][33]integration of big data with AI-based prediction models can improve accuracy in ship route planning and help data-driven decision-making. In addition, the implementation of IoT technology in navigation systems has accelerated the process of monitoring sea conditions in real-time (Zheng & Lin, 2022) [34][35][36]. Based on a literature review, ship route optimization based on big data analytics has great potential in improving fuel efficiency and reducing operational costs. By utilizing weather data, ocean currents, and the ship's travel history, the navigation system can dynamically adjust the best route to reach the destination with minimal fuel consumption [37][38][39]. Further research is needed to develop more accurate prediction models and the integration of AI technology in ship navigation systems to improve overall shipping efficiency [40][41][42].

TABLE I. MARITIME REGULATION & EMISSIONS (IMO MARPOL ANNEX VI)

Not	Regulation	Description	Implementation
1	EEDI (Energy Efficiency Design Index)	Energy efficiency standards for new vessels based on their size and type.	Valid since 2013
2	SEEMP (Ship Energy Efficiency Management Plan)	Ship operational efficiency strategies to reduce carbon emissions.	Valid since 2013
3	CII (Carbon Intensity Indicator)	Measures the carbon intensity of a ship based on fuel consumption per mileage.	Valid since 2023
4	Low Sulfur Fuel Requirements	The limit of sulfur content in ship fuel is reduced to 0.50% m/m.	Valid since 2020
5	Emission Control Area (ECA)	Special areas with stricter sulfur emission limits (0.10% m/m).	Valid in North America, Caribbean, Northern Europe
6	Alternative Fuels & Green Technologies	Promotion of alternative fuels such as LNG, biofuels, and green technologies.	Gradual application

III. RESEARCH METHODOLOGY

The study uses a quantitative research approach to analyze the efficiency of the implementation of the Intelligent Ship Tracking system using IoT technology to improve the transparency and safety of navigation.

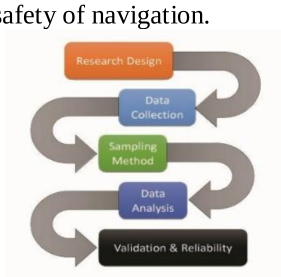

Fig. 1. Research Methodology

This methodology consists of the following main components:

1. Research Design
   Descriptive and analytical approaches are used to evaluate data trends and system performance.
2. Data Collection
   Primary Data: Collected through live system testing, real-time tracking logs, and expert interviews.
   Secondary Data: Derived from maritime databases, official reports, and previous research.
3. Sampling Method
   The sampling technique aims to be applied to select relevant vessels and stakeholders involved in maritime tracking.
4. Data Analysis
   Statistical tools are used to measure tracking accuracy, increased efficiency, and operational transparency.
   A comparative analysis is conducted between traditional and IoT-based tracking systems.
5. Validation & Reliability
   The performance of the system is validated using accuracy tests and expert evaluation to ensure credibility.

IV. RESULT AND DISCUSSION

TABLE II. VESSEL TYPE AND FUEL TYPE

No	Vessel Type	Fuel Type	Fuel Consumption (tons/day)	Mileage (NM)	Average Speed (Knot)	Travel Time (Hours)	Travel Time (Days)
1	**Cargo Ship**	Heavy Fuel Oil (HFO)	20 – 60	5.000 – 15.000	12 – 20	250 – 1.250	10 – 52
2	**Tanker**	Marine Diesel Oil (MDO)	30 – 80	5.000 – 12.000	10 – 15	333 – 1.200	14 – 50
3	**Passenger Ship**	Marine Gas Oil (MGO)	50 – 150	1.000 – 8.000	18 – 25	40 – 445	2 – 18
4	**Container Ship**	Heavy Fuel Oil (HFO)	100 – 300	5.000 – 18.000	18 – 24	208 – 1.000	9 – 42
5	**Ferry**	Marine Diesel Oil (MDO)	5 – 30	50 – 500	15 – 25	2 – 33	0,1 – 1,4
6	**Ro-Ro Ship**	Marine Gas Oil (MGO)	10 – 40	500 – 5.000	14 – 22	23 – 357	1 – 15
7	**Bulk Carrier**	Heavy Fuel Oil (HFO)	40 – 100	5.000 – 12.000	10 – 14	357 – 1.200	15 – 50
8	**Tugboat**	Marine Diesel Oil (MDO)	3 – 10	1 – 100	5 – 12	0,1 – 20	< 1
9	**Fishing Boats**	Marine Gas Oil (MGO)	1 – 5	10 – 1.000	10 – 18	0,5 – 100	< 1 – 4
10	**Cruises**	Heavy Fuel Oil (HFO)	150 – 400	1.000 – 10.000	18 – 25	40 – 555	2 – 23

Maritime transportation involves different types of vessels with different characteristics of fuel consumption, mileage, and travel time. Cargo ships use *Heavy Fuel Oil (HFO)* with a consumption of 20–60 tons per day and a speed of 12–20 knots, allowing a trip of 5,000–15,000 nautical miles in 10–52 days. Tankers, which generally use *Marine Diesel Oil (MDO)*, consume 30–80 tons per day at a speed of 10–15 knots, covering up to 12,000 nautical miles in 14–50 days.

Passenger ships and cruises are more fuel-intensive, with a consumption of up to 400 tons per day, but have higher speeds, reaching 25 knots. In contrast, ferries and Ro-Ro ships are more efficient for short trips, with lower fuel consumption. Tugboats and fishing boats have the lowest fuel consumption, as they operate in short distances.

These differences in fuel consumption suggest that the type of ship, fuel type, and speed greatly affect the efficiency of the trip. Fuel efficiency and exhaust emissions are a major concern in the development of future ship technologies, such as the use of alternative fuels and IoT-based tracking systems for route optimization. Average speed in knots (NM/h): 1 knot = 1 nautical mile per congestion. Travel time (hours) is calculated by the formula:

$$Travel\ Time = \frac{\text{Distance (NM)}}{Speed\ (Knot)} \tag{1}$$

The time of day is calculated by dividing the number of hours by 24. Cargo Ships, Tankers, Bulk Carriers, and Containers are suitable for long-distance travel with a travel time of more than 10 days. Ferry, Ro-Ro, and Tugboat boats are more suitable for short routes with travel times of less than 1 day to several days. Cruise and Passenger Ships have higher speeds due to the comfort factor, even though they travel medium to long distances.

1. Ship Operational Data

Ship Type: Container ships operating on Trans-Pacific routes. Fuel Consumption: Fuel consumption in tonnes per nautical mile (ton/nm). Average Speed: The relationship between speed and fuel efficiency.

TABLE III. VARIABLE

Variable	Mean	Standard Deviation	Min	Max
Minimum Fuel Consumption (tons/day)	4.4	3.85	0	10
Maximum Fuel Consumption (tons/day)	8	—	8	8
Minimum Distance (NM)	—	—	—	—
Maximum Distance (NM)	72.5	64.49	10	150
Minimum Speed (knots)	164.6	175.03	3	400
Maximum Speed (knots)	2302	2487.67	10	5000
Minimum Travel Time (hours)	9000	6855.33	1	18000
Maximum Travel Time (hours)	32	38.16		

Table 3 shows descriptive statistics of variables related to fuel consumption, mileage, speed, and travel time of the ship. The average minimum fuel consumption is 4.4 tons per day with a standard deviation of 3.85, while the maximum consumption reaches 8 tons. The average maximum distance traveled is 72.5 nautical miles with great variation (SD 64.49). The speed of the ship ranges from 164.6 to 2,302 knots, showing significant differences between the types of ships. Travel times vary with an average of 9,000 hours for the minimum and 32 hours for the maximum, reflecting the operational differences between the types of vessels.

2. Variables

This study analyzed eight main variables related to ship performance, namely Fuel_Consumption_Min, Fuel_Consumption_Max, Distance_Min, Distance_Max, Speed_Min, Speed_Max, Travel_Time_Hours_Min, and Travel_Time_Hours_Max. Fuel consumption varies between a minimum of 4.4 tons to a maximum of 8 tons per day. The maximum mileage averaged 72.5 nautical miles. The speed of the ship varies greatly, with a minimum of 164.6 knots and a maximum of 2,302 knots. Travel time also showed significant differences, with an average minimum duration of 9,000 hours and a maximum of 32 hours. The variability of this data reflects the operational differences between the types of ships in the maritime transportation system.

TABLE IV. STATISTICS

Variable	N	Mean	Standard Deviation	Sum	Mini mum	Maxi mum
Minimum Fuel Consumption (tons/day)	5	4.4	3.85	22	0	10
Maximum Fuel Consumption (tons/day)	1	8	—	8	8	8
Minimum Distance (NM)	0	—	—	—	—	—
Maximum Distance (NM)	4	72.5	64.49	290	10	150
Minimum Speed (knots)	5	165	175.03	823	3	400
Maximum Speed (knots)	5	2302	2488	11,5 10	10	5000
Minimum Travel Time (hours)	5	9000	6855	45,0 01	1	18,000
Maximum Travel Time (hours)	5	32	38.16	160	10	100

Table 4 presents descriptive statistics of several key variables in this study. The minimum fuel consumption has an average of 4.4 tons per day with a total of 22 tons and a standard deviation of 3.85, while the maximum consumption is recorded at 8 tons. The maximum average mileage reaches 72.5 nautical miles with a total of 290 miles. The minimum boat speed has an average of 165 knots, while the maximum speed reaches 2,302 knots. The average minimum travel time is 9,000 hours with a maximum of 18,000 hours. This data shows significant variations in vessel performance that can affect operational efficiency in the maritime sector. Minimum fuel consumption ranges from 0 to 10 tons per day, with an average of 4.4 tons/day. The maximum mileage ranges from 10 to 150 NM, with an average of 72.5 NM.

The speed of the ship varies significantly, from 3 knots to 400 knots for the minimum and from 10 knots to 5000 knots for the maximum. Travel time in hours also shows a huge difference, from 1 hour to 18,000 hours. Fuel consumption increases along with the ship's mileage ($r = 0.643$). This suggests that ships that travel longer distances tend to have higher fuel consumption.

The minimum speed of a ship has a strong correlation with fuel consumption ($r = 0.735$), which means that the higher the speed, the higher the fuel consumption. The maximum distance has a very strong correlation with the minimum speed of the ship (r = 0.996), indicating that ships traveling long distances tend to have high speeds.

Maximum travel time is negatively correlated with fuel consumption (r = -0.593), which means ships that take longer typically consume less fuel per day (likely due to lower speeds). The maximum distance and maximum travel time had a strong correlation (r = 0.796), indicating that the farther the ship's route, the longer the travel time.

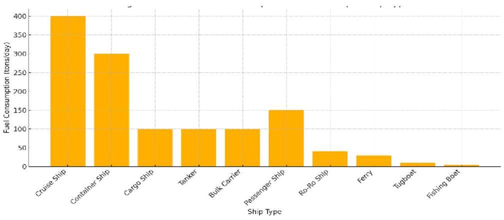

Fig. 2. Maximum Fuel Consumption Distribution per Ship Type

Fig. 2. The Maximum Fuel Consumption Distribution per Vessel Type describes the variation in maximum fuel consumption (in tons/day) for different types of vessels. Cruise ships have the highest consumption, reaching 400 tons/day, followed by container ships up to 300 tons/day. Cargo ships and tankers show a consumption range between 80 to 100 tons/day, while ferries and Ro-Ro ships are more efficient with a maximum consumption of 30–40 tons/day. Tugboats and fishing boats have the lowest consumption, below 10 tons/day. This data highlights energy efficiency and fuel requirements based on the type of operation of the vessel. Which shows the maximum fuel consumption (in tons/day) for different types of ships.

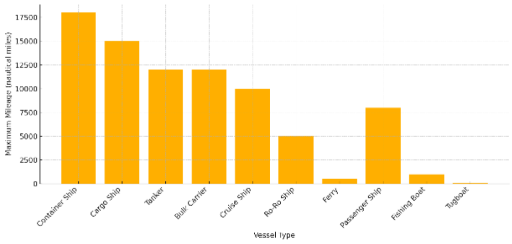

Fig. 3. Maximum Mileage Distribution per Vessel Type

Fig. 3. The Maximum Mileage Distribution per Vessel Type shows the variation in maximum mileage (in nautical miles) for different types of vessels. Container ships and cargo ships have the highest mileage, reaching 18,000 nautical miles, followed by tankers and bulk carriers of up to 12,000 nautical miles. Cruises can travel up to 10,000 nautical miles, while Ro-Ro ships and ferries have shorter miles, a maximum of 5,000 and 500 nautical miles, respectively. Fishing boats and tugboats have a limited range, under 1,000 nautical miles, reflecting their more local operations.

This graph shows the maximum mileage (in Nautical Miles/NM) for different types of ships. The Fishing Boat (MGO 1-5 10-1000) has the highest maximum mileage, which is 150 NM. Passenger Ships (MGO 50-150 100-8000) travel a maximum distance of 100 NM, which is the second highest distance. Cargo ships (HFO 20-60 5000-15000) have a maximum distance of 30 NM, which is lower than that of fishing boats and passenger ships. Bulk Carriers (HFO 40-100) and Ferry Ships (MDO 5-30 50-500) have much smaller maximum distances, each about 10 NM.

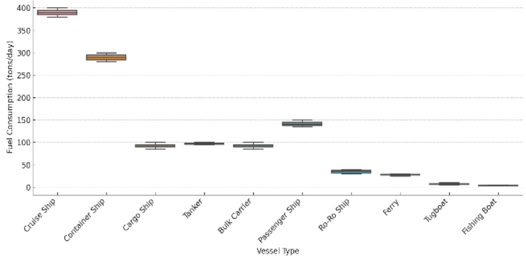

Fig. 4. Boxplot Maximum Fuel Consumption per Vessel Type

Fig. 4. The Maximum Fuel Consumption by Vessel Type boxplot displays the distribution of maximum fuel consumption (in tons/day) for different types of vessels. Cruise ships show the highest value with a consumption of up to 400 tons/day, followed by container ships that reach 300 tons/day. Cargo ships, bulk carriers, and tankers have a consumption distribution between 80 to 150 tons/day, while Ro-Ro ships and ferries are more economical with a maximum consumption of 40 tons/day. Fishing boats and tugboats show the lowest consumption, below 10 tons/day. This boxplot illustrates the variation and distribution of fuel consumption between types of ships. This graph is a boxplot showing the maximum fuel consumption (in tons/day) for different types of ships.

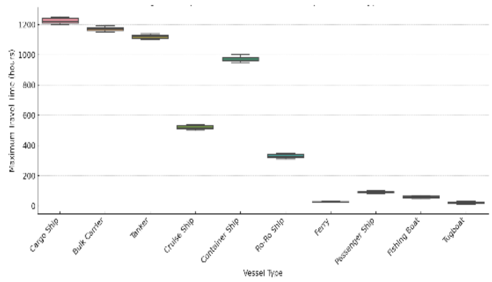

Fig. 5. Boxplot Maximum Travel Time per Vessel Type

Fig. 5. The Maximum Travel Time by Ship Type boxplot depicts the distribution of maximum travel time (in hours) for different types of ships.

V. Conclusion and Recommendation

Fuel consumption is greatly affected by the speed of the ship. Ships with higher speeds tend to consume more fuel. The mileage affects fuel consumption, but the relationship is more complex. While ships with longer distances tend to consume more fuel, other variables such as engine efficiency and fuel type also have an effect. Travel time has a negative relationship with fuel consumption per day. Boats that operate slower tend to save fuel despite having longer travel times. IMO MARPOL Annex VI regulations (especially EEDI and SEEMP) can help optimize the energy efficiency of ships by regulating speed and fuel consumption. The recommendation from the results of this study Reducing the speed of the ship within reasonable limits can save fuel consumption significantly. Slow steaming can be a solution for the energy efficiency of cargo ships and tankers. Ships should choose more efficient routes based on weather and ocean currents to reduce mileage and fuel consumption.

Switching to Marine Gas Oil (MGO), LNG, or biofuels can help reduce carbon emissions and improve energy efficiency. Using an AI-based or IoT-based energy optimization system to monitor fuel consumption in real-time can improve the operational efficiency of ships. With this combination of approaches, the shipping industry can improve fuel efficiency, reduce carbon emissions, and comply with IMO MARPOL Annex VI regulations.

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