Analysis and Prediction of Electric Motor Faults, for Ships using the Taguchi Approach

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Abstract: This paper focuses on identifying the key parameters that affect the frequency of electric motor faults on ships. First, a comprehensive field study was conducted to analyze the electric motor faults observed on various ships. Key factors examined included the age of the ships, carrying capacity, fault type and the year of fault occurrence. The effects of these factors on the frequency of electric motor faults were evaluated using the L18(43) orthogonal array in conjunction with the Taguchi design of experiments approach. The findings revealed that the most significant factors influencing fault frequency are the type of fault and the age of the ship. This study also demonstrated that the Taguchi approach provides an effective and practical method for the analysis of large data sets. This approach has shown that the electrical fault frequencies of ships with different characteristics can be reliably predicted with this approach.

Keywords: ship; electric motor; Taguchi approach

1 Introduction

Electric motors play a fundamental role in the global economy and serve as indispensable components across various industries, including industrial production and transportation. A significant portion of electrical energy consumption in industrial sectors worldwide is attributed to electric motor systems. According to data from the International Energy Agency (IEA), transportation equipment accounts for approximately 44% of total energy use in industrial sub-sectors, with around 18% of this consumption specifically attributed to motor-driven systems [1]. This statistic underscores the widespread use of electric motors in the transportation industry and highlights their substantial share in energy consumption. Electric motors are extensively utilized on ships, particularly in auxiliary systems, pumping systems, cooling and ventilation units, cranes, and other load-lifting mechanisms. These motors not only enhance the operational efficiency of ships but also ensure the safe functioning of onboard systems. Consequently, the reliable operation of electric motors is critical for maintaining the overall operational efficiency of the ship. Faults in electric motors can significantly disrupt the ship's operational processes. For instance, a malfunction in the electric motor of a cooling pump could lead to the fault of cooling systems, resulting in the overheating of the ship's main engine. This situation could potentially force the ship to shut down or even lead to a major accident. Such unexpected stoppages, especially on the high seas, can incur substantial costs, including increased logistics expenses and heightened safety risks. Therefore, the prompt and effective resolution of electric motor faults is essential to mitigate operational disruptions and associated risks. One effective method for enhancing the performance of this operational process is the Taguchi approach. Developed by Japanese engineer Genichi Taguchi, this statistical method aims to improve product quality and process performance. It emphasizes minimizing variation and creating systems that are robust against external noise factors. By employing design of experiments and orthogonal arrays, the Taguchi method facilitates efficient experimentation with fewer trials, enabling the identification of the most influential factors affecting performance. The goal is to achieve high quality at a low cost by optimizing controllable parameters. Due to its' simplicity, effectiveness and potential for cost savings, the Taguchi method is widely utilized in manufacturing, engineering and product development [2] [3].

The literature indicates that electric motor faults and the Taguchi approach have been examined from various perspectives. D'Urso et al. [4] compared the Military Standard and Svenska Kullagerfabriken techniques for diagnosing bearing faults, while Zhukovskiy et al. [5] employed failure probability prediction methods to enhance the accuracy of fault diagnosis in electric motors. In addition to general electric motor faults, research on electric motor faults in maritime applications has also been included in the literature. While Pandya et al. [6] emphasized the significance of fuzzy logic and K-means clustering methods for the early detection of electric motor faults on ships, Jayaswal et al. [7] focused on the design of a predictive maintenance system. Aizpurua et al. [8] and Çabuk [9] presented machine learning and Internet of Things (IoT)-based systems to forecast the performance of ship electric motors, respectively.

The literature also indicates that the Taguchi approach can be effectively utilized to analyze the parameters influencing the performance of electric motors. Jin and Chow [10] applied the Mahalanobis-Taguchi system for early-stage fault detection in induction motors, while Khoualdia et al. [11] combined the Taguchi method with grey relational analysis for fault classification. Additionally, Cui et al. [12] employed the Taguchi approach for the design optimization of permanent magnet synchronous motors. The Taguchi approach is also utilized to evaluate various systems on ships. Liu et al. [13] introduced the Adaptive Dynamic Weighted Hybrid Distance-Taguchi method for fault detection in ship diesel engines. Anh Tran [14] developed strategies to enhance the environmental and economic performance of ship operations using the Taguchi approach. Okanminiwei and Oke [15] examined the Taguchi, Taguchi-Pareto, and Taguchi-ABC methods to optimize the maintenance time of port equipment. Sii et al. [16] noted that concepts such as signal-to-noise ratio (SNR) and analysis of variance (ANOVA) expressed in Taguchi approaches, can be integrated into maritime safety engineering studies.

In addition to research on electric motor faults, successful modeling approaches have been applied across various disciplines. For instance, Pozna and Precup [17] presented the basis of an alternative modelling approach to observation process modelling within the framework of cognitive processes. Pozna et al. [18] also proposed a new pose estimation model for robotic navigation that effectively handles nonlinear uncertainties in dynamic environments. Venczel et al. [19] developed a physical viscosity model for the calculation of the filling process in visco-dampers. Szakács T. [20] presented the system model for pneumatic piston control. Abramov et al. [21] proposed a new modeling approach called the new opportunities model to predict coronavirus disease trends, which reflects the utility of adaptive modeling in variable systems. Grosu et al. [22] developed a model that uses active learning principles to develop metamodels to mimic circuit behavior for circuit design applications. Such studies reveal the importance of data-driven and system-specific modeling techniques. In this context, this study analyses how ship parameters affect electric motor faults using the Taguchi approach. Thus, the motivation of the study is revealed by combining classical statistical design and modeling approaches. With this structured experimental framework, the study aims to model fault behavior in a nonlinear ship operational environment, similar to the strategies used in the above-mentioned studies. As seen in the literature, it can also be said that the Taguchi approach is used more widely in other sectors than the maritime sector. While some research has been undertaken on ships, particularly concerning the enhancement of electrical systems, there is a notable lack of comprehensive studies evaluating electric motor faults on ships using the Taguchi approach. Therefore, the objective of this paper is to contribute to the existing literature and provide practical assessments of electric motor faults occurring on ships. Specifically, this study aims to identify the parameters influencing the frequency of electric motor faults on ships through the application of the Taguchi approach. In this context, the effects of factors such as ship age, carrying capacity, fault year, and fault type on the frequency of electrical faults in electric motors were analyzed using Taguchi experimental design. The study evaluated the effect levels of parameters influencing electric motor faults in ships through the Taguchi approach, aiming to identify an optimal solution in a practical manner. Furthermore, this research positions itself as one of the few studies that utilize the Taguchi approach specifically in the maritime industry. Therefore, this research seeks to address a significant gap in the existing literature regarding the optimization of electric motor faults in maritime applications. Additionally, the study is expected to make direct contributions to both academia and the maritime industry by providing actionable insights to enhance the operational safety of ships. The findings are anticipated to serve as a valuable guide for improving the reliability and performance of electric motor systems onboard ships.

The remainder of this paper is organized as follows: Section 2 introduces electric motor fault analysis ion ships and outlines the Taguchi approach employed in this study. Section 3 presents the experimental results and discussions. Section 4 summarizes the possible implications for electric motor fault prediction and maintenance optimization in ships and provides conclusions.

2 Analysis and Modeling Approach

Identifying the various types of electric motor faults that can occur on ships is crucial for their prevention. Generally, electric motor faults on ships can be categorized into three main types: Burn Out & Short Circuit, Bearing & Housing, and Low Insulation. In addition to understanding these faults, it is essential to monitor the changes in fault frequency over the years to predict future occurrences. Ships may exhibit different characteristics based on their year of manufacture, carrying capacity, quality of materials used, engineering standards, and technological advancements. This can significantly impact the ships' ability to withstand electrical faults and the frequency of such faults. The ships examined in this study range from approximately 12,000 to 40,000 DWT (Deadweight Tonnage) based on their carrying capacity. These ships were built during various periods between 1993 and 2017 and exhibit diverse configurations influenced by technological advancements and the year of built. Considering the built years and carrying capacities of ships currently operating in the market, numerous ship types with distinct features emerge. This diversity increases the likelihood that each ship will have different electrical systems, and consequently, varying fault frequencies. To conduct a comprehensive analysis of the fault frequency of electric motors, it is essential to obtain and compile reliable data from all existing ships. However, gathering detailed information from ship owners, operators, or relevant authorities to create an extensive data set can be a lengthy and labor-intensive process. The Taguchi approach represents an effective approach to minimizing the number of experiments needed to achieve desired results. This is accomplished by simultaneously analyzing multiple parameters, leading to a more efficient and cost-effective process [2] [3]. In contrast to traditional approaches, which often require numerous experiments to test each combination, Taguchi's orthogonal arrays (such as L_{18}) enable the study of parameter effects with minimal experimentation. This approach allows for the identification of the most significant parameters using only a few experiments from a comprehensive dataset that includes variables such as the year a ship was built, its' carrying capacity, fault duration, and types of faults. Furthermore, this approach offers solutions that are optimized to meet the specified requirements of the ship while ensuring the efficient use of resources and time. This means that high-quality results can be achieved with fewer combinations. For instance, experiments can be conducted with three factors (built year, DWT, and fault type) and 2-3 levels for each factor (such as ranges for the year of built, groups for DWT, and categories for fault types) using the L18 orthogonal array. This allows for a rapid analysis of the effects of these parameters on ship faults. Consequently, the search for the optimal solution is expedited, and unnecessary trials are eliminated.

When analyzing the ships in the dataset, it is seen that they are built to accommodate carrying capacities ranging from 12,000 to 39,000 DWT. To facilitate analysis based on ship capacity, the ships are categorized into three groups. Ships with a capacity of 12,000 to 17,000 DWT are classified as having an approximate carrying capacity of 15,000 DWT; ships with a capacity of 19,000 to 22,000 DWT are classified as carrying approximately 20,000 DWT; and ships with a capacity of 26,000 to 39,000 DWT are classified as carrying approximately 35,000 DWT. This classification is presented in Table 1.

Table 1
Carrying capacity and classification of ships

Carrying Capacity Group	**Lowest (DWT)**	**Highest (DWT)**	**Average (DWT)**	**Approximately (DWT)**
Low	12,184	17,307	14,786	15,000
Medium	19,325	22,178	20,274	20,000
High	26,001	39,479	35,307	35,000

In this study, ships were categorized into three groups based on their age to facilitate analysis. The 26-year ship category includes ships built in 1993, 1997, 2001, and 2002. The 18-year ship category comprises ships built in 2004, 2005, 2006, and 2008. The 12-year ship category consists of ships built in 2009, 2011, and 2017. The years of built and average ages of the ships evaluated in this study are presented in Table 2.

Table 2
Years of built and average age of ships

Age Category	**Average Age (Year)**	**Years of Built**
Old	26	1993, 1997, 2001, 2002
Middle Age	18	2004, 2005, 2006, 2008
Young	12	2009, 2011, 2017

Electric motor faults on ships are classified into three primary categories: Burn Out & Short Circuit, Bearing & Housing, and Low Insulation. To analyze the trends in these faults over the years, the observed fault frequencies from 2018-2019 and 2020-2022 were divided into two distinct periods. The factors and categories identified for this study are presented in Table 3.

Table 3
Determined parameters and their categories

Parameters	Category Level		
	Category 1	**Category 2**	**Category 3**
Ship Carrying Capacity (DWT)	15,000	20,000	35,000
Ship Age (Year)	12	18	26
Electric Motor Fault Year	2018-2019	2020-2022	-
Electric Motor Fault Type	Burn Out & Short Circuit	Bearing & Housing	Low Insulation

The Taguchi experimental design employs orthogonal arrays to systematically analyze the effects of various factors. This approach effectively reveals the main effects and interactions of parameters while requiring a minimal number of experiments. Orthogonal arrays provide different combinations for the identified factors and levels. In this study, the $L_{18}(4^3)$ orthogonal array was selected. The parameters listed in Table 3 were mapped to the $L_{18}(4^3)$ orthogonal array, as illustrated in Table 4. This approach resulted in 18 distinct combinations. For instance, Combination No. 1 indicates that the frequency of Burn Out & Short Circuit faults in ships with an average age of 26 years and a carrying capacity of approximately 15,000 DWT should be assessed for the period between 2018 and 2019.

Table 4
$L_{18}(4^3)$ array prepared according to parameter and category levels

Combination No	Ship Carrying Capacity (DWT)	Ship Age (Year)	Electric Motor Fault Year	Electric Motor Fault Type
1	15,000	26	2018-2019	Burn Out & Short Circuit
2	20,000	26	2018-2019	Bearing & Housing
3	35,000	26	2018-2019	Low Insulation
4	15,000	18	2018-2019	Burn Out & Short Circuit
5	20,000	18	2018-2019	Bearing & Housing
6	35,000	18	2018-2019	Low Insulation
7	20,000	12	2018-2019	Burn Out & Short Circuit
8	35,000	12	2018-2019	Bearing & Housing
9	15,000	12	2018-2019	Low Insulation
10	35,000	26	2020-2021	Burn Out & Short Circuit
11	15,000	26	2020-2021	Bearing & Housing
12	20,000	26	2020-2021	Low Insulation

13	20,000	18	2020-2021	Burn Out & Short Circuit
14	35,000	18	2020-2021	Bearing & Housing
15	15,000	18	2020-2021	Low Insulation
16	35,000	12	2020-2021	Burn Out & Short Circuit
17	15,000	12	2020-2021	Bearing & Housing
18	20,000	12	2020-2021	Low Insulation

Moreover, to analyze the results using the Taguchi approach, the data obtained from each combination must be evaluated according to quality characterization. The objective is to minimize the number of electric motor faults on ships. Consequently, in this study, signal-to-noise ratios were calculated using the is "lowest is best" quality characteristic formula proposed by Taguchi, as presented in Equation 1 [2] [3]:

$$\frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{1}$$

Where *S/N* is the signal-to-noise ratio, *n* is the number of observations, *y* is the observation value (fault frequency), and *i* is the observation level.

In order to make the results more realistic, S/N ratios were calculated separately using all ships determined for that combination, even though the number of ships in each combination was different. Thus, the electric motor fault frequencies of the ship parameters given in Table 4, which are suitable for the combinations within the scope of the study, were analyzed according to the Taguchi approach.

To analyze the results, an ANOVA table was constructed using the calculated *S/N* ratios and the formulas provided in Equations (2) to (10) [2] [3].

$$SS_T = \left[\sum_{I=1}^{N} yi^2\right] - \frac{T^2}{N} \tag{2}$$

$$SS_A = \left[\sum_{I=1}^{K_A}\left(\frac{Ai^2}{n_{A_i}}\right)\right] - \frac{T^2}{N} \tag{3}$$

$$v_T = N - 1 \tag{4}$$

$$V_A = \frac{SS_A}{v_B} \tag{5}$$

$$V_e = \frac{SS_e}{v_e} \tag{6}$$

$$F_A = \frac{V_A}{V_e} \tag{7}$$

Where SS_T represents the total sum of squares due to variation, N denotes the total number of experiments, SS_A indicates the sum of squares attributable to factor A, K_A refers to the number of levels for factor A, A_i signifies the sum of the total for the i^{th} level of factor A, T is the total sum of the *S/N* ratio across the experiments, V_A represents the variance associated with factor A, and F_A is the F ratio for the factor.

The predicted average fault frequencies and their confidence intervals were calculated for the conditions defined by Equations (8) to (10):

$$\check{\mu} = \overline{Ai} + \overline{Bi} + \overline{Ci} + \overline{Di} - 3\overline{T} \tag{8}$$

$$CI = \sqrt{\frac{F_{(f)} V_e}{n}} \tag{9}$$

$$\check{\mu} - CI \leq \mu \leq CI + \check{\mu} \tag{10}$$

In this context, $\check{\mu}$ represents the estimated average *S/N* value, μ denotes the validation test average *S/N* value, $F_{(f)}$ refers to the F ratio, V_e indicates the error variance, and n signifies the number of tests conducted under the specified conditions.

3 Results and Discussion

Table 5 shows the number of ships found for each combination as a result of the market research. In addition, the fault frequencies and averages obtained from the ships for the fault type and fault year in that combination are also shown. S/N ratios calculated for each combination are also presented in Table 5.

Table 5
Number of ships, electric motor fault frequencies, averages and S/N ratios for 18 different combinations

Combination No	Number of Ships	Frequency of Ships' Electric Motor Fault								Average Fault Frequency per Ship	S/N
1	8	6	5	0	1	4	2	6	3	3.38	-12.01
2	4	1	1	1	0					0.75	1.25
3	3	1	1	1						1.00	-1.25
4	4	1	2	1	1					1.25	-2.43
5	3	1	0	3						1.33	-5.23

6	6	0	0	0	0	0	1			0.17	7.78
7	4	2	2	3	1					2.00	-6.53
8	5	0	0	0	0	1				0.20	6.99
9	6	0	0	0	0	1	0			0.17	7.78
10	3	4	1	2						2.33	-7.53
11	8	4	0	1	1	1	0	1	3	1.38	-5.59
12	4	0	0	3	0					0.75	-3.52
13	3	3	2	3						2.67	-8.65
14	6	1	0	1	1	0	0			0.50	3.01
15	4	0	1	0	0					0.25	6.02
16	5	0	1	0	0	1				0.40	3.98
17	6	0	0	1	1	0	1			0.50	3.01
18	4	0	0	0	1					0.25	6.02

Table 5 shows that fault frequencies vary between 0 and 6 between 2018 and 2019 and 2020 and 2022, depending on fault types, built years and carrying capacities. The highest fault frequency was 3.38 on average in the 1st trial combination. The lowest fault frequency occurred in the 6th and 9th experimental combinations, with one fault occurring in six ships in both combinations. It is not clear from Table 5 which factor has the extent of influence on fault frequency. For this reason, a variance analysis table (ANOVA) was prepared using the S/N ratios specified in Table 5 according to the Taguchi approach. The results of the analysis of variance are given in Table 6.

Table 6

Variance analysis table (ANOVA)

Source of Change	Sum of Squares (S)	Degree of Freedom (f)	Mean of Squares	F (calculation)	F (table)	P %
Ship Carrying Capacity (DWT)	73.42	2	36.71	3.37*	2.86	11
Ship Age	209.46	2	104.73	9.63***	7.20	31
Electric Motor Fault Year (Pooling)	0.01	1	0.01	0	-	0
Electric Motor Fault Type	269.57	2	134.79	12.39***	7.20	40
Total	552.45	6	92.08			
Error (e)	119.69	11	10.88			18

* F Table for α = 0.10 is 2.86
** F Table for α = 0.05 is 3.98
*** F Table for α = 0.01 is 7.20

Table 6 presents to what extent which factor has an impact on the frequency of electric motor fault s. In addition, interaction situations of factors can also be analyzed. According to these results, the most effective factor on the frequency of electric motor fault on ships is the type of fault. If the F(calculation) value is greater than the F(table) value, it shows that these factors have significant effects on the fault frequency. Electric motor fault type, ship age and ship carrying capacity are the most important factors respectively. However, the electric motor fault year factor was excluded from the analysis as it did not show a significant effect (pooling method). In the percentage effect (P%) column, it was seen that the electric motor fault type had a 40% effect on the fault frequency, the ship age had a 31% effect, and the ship DWT capacity had an 11% effect. In addition, it was determined that fault type and ship age factors together affect fault frequency at 99% confidence level. Ship DWT capacity was found to be effective at 90% confidence level. As a result, it is understood that factors such as fault type and ship age should be taken into consideration in the studies to reduce electric motor faults, and DWT capacity also plays an important role. This analysis clearly indicates which factors should be given priority in preventing faults. According to the Taguchi approach, the influence graphs of the factors are also drawn to determine the optimum values of the factors.

Figures 1 and 2 illustrate the effect plots of the significant factors, constructed using the average fault frequencies and S/N ratios, respectively. These plots were created to visually identify the optimal levels of each factor.

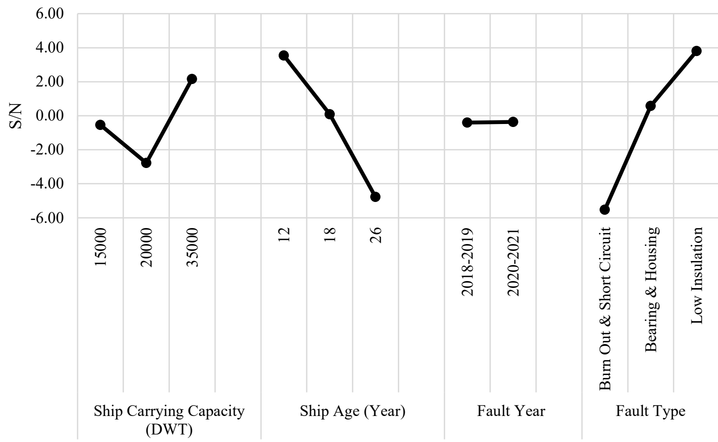

Figure 1

Effect graph of factors plotted according to S/N ratios

When the effect graph of ship age is analyzed in Figure 1, it is seen that the frequency of electric motor fault is higher for ships with higher ship age. This result shows that the frequency of fault increases as the ship ages. The possible reason for this may be that the technology used in older ships has become obsolete over time and the frequency of fault s has decreased in new ships produced with developing technology. When the effect of ship carrying capacity on fault frequency is analyzed in Figure 1, it is seen that ships with high carrying capacity have lower frequency of electric motor faults. This may be due to the use of more advanced and durable technological equipment in high-tonnage ships. In Figure 2, the effect of electric motor fault types on fault frequency is analyzed.

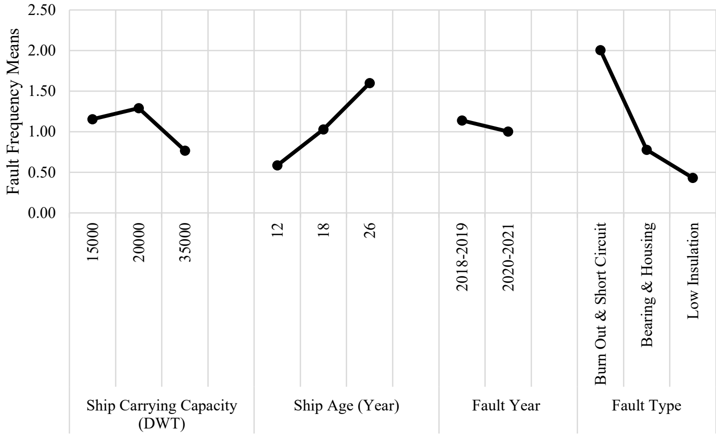

Figure 2

Effect graph of factors plotted according to the fault frequency means

Figure 2 shows that Low Insulation is the least common fault type and Burn Out & Short Circuit is the most common fault type. This may be due to the different quality of the equipment of the electric motor system. In addition, it is seen in the graphs that the frequency of electric motor fault does not show a significant change over the years. This means that the frequency of faults does not change over time.

In this study, the factors affecting the frequency of electric motor faults on ships were examined and fault types were evaluated according to different ship characteristics. According to the impact graph of the factors in Figure 1, the lowest fault frequency (with high S/N ratio) in the 2020-2021 period was observed as Low Insulation fault in ships with an average age of 12 years and a carrying capacity of 35,000 DWT. The highest fault frequency was observed in 26-year-old ships with a carrying capacity of 15,000 DWT and in the Burn Out & Short Circuit fault type in the 2018-2019 period. In order to test the accuracy of the study and these findings, it is recommended to conduct verification experiments according to the Taguchi approach. The accuracy of the study is determined by the S/N ratio obtained from the actual values within the estimated confidence interval. For validation experiments, ships with the highest, medium and lowest combination of electric motor fault frequencies were analyzed. The ships identified as a result of the analyses are coded and their electric motor fault frequencies and the actual S/N ratios calculated according to the fault frequencies are given in Table 7. In the last three columns of the table, the confidence intervals and means of the estimated S/N ratios calculated according to the specified conditions are presented. With this table, it can be easily tested whether the measured S/N ratios match the estimated confidence intervals.

Table 7
Combinations, ships and fault frequencies determined for verification experiments

<table>
<tr><th rowspan="2">Selected Combination</th><th rowspan="2">DWT</th><th rowspan="2">Ship Age</th><th rowspan="2">Fault Year</th><th rowspan="2">Fault Type</th><th rowspan="2">Ship Codes (D) and Fault Frequency</th><th rowspan="2">Average Fault Frequency per Ship</th><th rowspan="2">S/N</th><th colspan="3">Confidence Interval for α = 0.05</th></tr>
<tr><th>Min.</th><th>Avg.</th><th>Max.</th></tr>
<tr><td>Combination with Highest Fault Frequency</td><td>15,000</td><td>26</td><td>2018 - 2019</td><td>Burn Out & Short Circuit</td><td>D1=6
D2=5
D3=0
D4=1
D5=4
D6=2
D7=0
D8=3</td><td>2.63</td><td>-10.56</td><td>-13.9</td><td>-10.1</td><td>-6.3</td></tr>
<tr><td>Combination with Medium Fault Frequency</td><td>15,000</td><td>18</td><td>2020 - 2021</td><td>Bearing & Housing</td><td>D1=2
D2=1
D3=3
D4=0
D5=0
D6=0
D7=0
D8=0</td><td>0.75</td><td>-2.43</td><td>-5.13</td><td>-1.33</td><td>2.47</td></tr>
<tr><td>Combination with Lowest Fault Frequency</td><td>35,000</td><td>12</td><td>2020 - 2021</td><td>Low Insulation</td><td>D1=1
D2=0
D3=0
D4=0
D5=0
D6=0
D7=0
D8=0</td><td>0.13</td><td>9.03</td><td>6.5</td><td>10.3</td><td>14.1</td></tr>
</table>

Table 7 shows that the actual S/N ratios for all three combinations fall within the estimated confidence intervals and are close to the average S/N ratios. This result demonstrates the accuracy and validity of the analysis.

In this study, instead of examining all ships in the maritime industry, only ships in 18 combinations were examined using the Taguchi experimental design. Thus, the effects of factors such as ship carrying capacity, ship age, electric motor fault type and year are revealed quickly and effectively. The obtained data and validation experiments have shown that the frequency of electric motor faults on ships with different combinations and characteristics can be predicted within reliable limits. This proves that the approach is a successful approach for analyzing faults in the maritime industry. The outputs obtained reveal important findings in terms of the safety and efficiency of ship operations as a result of in-depth investigation of electric motor faults occurring on ships. In particular, determining the effects of parameters such as fault type and ship age on fault frequency directly contributes to both optimizing maintenance planning and reducing fault risks. Moreover, these analyses, through a robust experimental design, such as the Taguchi approach, stand out as a viable solution in the industry to obtain economical and reliable results on large data sets. In this context, the results provide an important roadmap for developing more effective and sustainable maintenance strategies for use within the maritime industry.

Conclusions

This study focused on determining the parameters that affect the frequency of electric motor faults for ships. The effects of factors such as ship age, carrying capacity, fault year and fault type on electric motor fault frequency, were analyzed using the Taguchi experimental design. Electric motor faults that occur on ships are categorized into three main types: Burnout & Short Circuit, Bearing & Housing, and Low Insulation.

In this study, the Taguchi approach was selected to analyze the minimum combination of the effects of different parameters, thereby reducing the number of combinations examined. Utilizing the $L_{18}(4^3)$ orthogonal array, variables such as ship age, carrying capacity and fault type were examined. Different levels were selected for each factor, which accelerated the search for optimal solutions. The outputs obtained are as follows:

1) As a result of the ANOVA analysis, it was determined that the most significant factor influencing the frequency of electric motor faults is the type of fault. The factors, in order of importance, are fault type, ship age, and ship carrying capacity. The fault year parameter was excluded from the analysis because it did not demonstrate a significant effect.
2) The influence of fault type on fault frequency was determined to be 40%, the influence of ship age was 31%, and the influence of ship carrying capacity was 11%. These factors were found to significantly impact the frequency of electric motor faults. Both ship age and fault type were identified as effective at a 99% confidence interval.
3) In the analyses conducted based on signal-to-noise (S/N) ratios, it was found that the lowest fault frequency occurred in the Low Insulation fault among ships with an average age of 12 years and a carrying capacity of 35,000 DWT. Conversely, the highest frequency of electric motor faults was identified in the Burn Out & Short Circuit faults in ships that were 26 years old and had a carrying capacity of 15,000 DWT.

4) In the impact graph analysis, it was observed that older ships exhibited a higher frequency of electric motor faults. Additionally, it was found that the frequency of faults was lower in ships with a high carrying capacity. The analysis revealed that the Low Insulation fault is less common, while the most prevalent fault type is Burn Out & Short Circuit.
5) As a result of the verification experiments conducted using the Taguchi approach, it was determined that the actual S/N ratios obtained for ships with high, medium, and low fault frequencies align with the estimated confidence intervals. These analyses demonstrate that the electric motor fault frequencies that may occur in ships with various combinations can be predicted within reliable limits. This finding reinforces the accuracy and reliability of the model.
6) In the study, it was determined that the most significant factors influencing the frequency of electric motor faults on ships are the type of fault and the age of the ship. These analyses offer valuable insights for preventing faults and optimizing maintenance efforts. The Taguchi approach minimizes the number of experiments required when dealing with large data sets, demonstrating that it is an economical and practical approach that can be widely applied in the industry.

References

[1] International Energy Agency (IEA): Motor-driven system electricity use as a share of electricity use by industry subsector, 2020 Paris. Accessed: November 11, 2024, Available: https://www.iea.org/data-and-statistics/charts/motor-driven-system-electricity-use-as-a-share-of-electricity-use-by-industry-subsector

[2] Harris, L. N.: Taguchi techniques for Quality Engineering, Philip J. Ross, McGraw-Hill Book Company, 1988, Quality and Reliability Engineering International, 5 (3), 1989, pp. 249-249

[3] Propst, A. L. et al.: Designing for quality, an introduction to the best of Taguchi and Western Methods of Statistical Experimental Design. Technometrics, 34 (1), 1992, p. 100

[4] D'Urso, D. et al.: Dynamic Failure Rate Model of an electric motor comparing the military standard and Svenska Kullagerfabriken (SKF) methods. Procedia Computer Science, 180, 2021, pp. 456-465

[5] Zhukovskiy, Y. L. et al.: The probability estimate of the defects of the asynchronous motors based on the complex method of Diagnostics. IOP Conference Series: Earth and Environmental Science, 87, 2017, p. 032055

[6] Pandya, V. et al.: Early fault detection for rotating machinery onboard ships motor using fuzzy logic and K-means. Lecture Notes in Networks and Systems, 2023, pp. 567-580

[7] Jayaswal, B. et al.: Predictive maintenance system for rotating machinery onboard ships for detecting performance degradation. Scalable Computing: Practice and Experience, 24 (4), 2023, pp. 1231-1240

[8] Aizpurua, J. I. et al.: Integrated machine learning and probabilistic degradation approach for vessel electric motor prognostics. Ocean Engineering, 275, 2023, p. 114153

[9] Sinan Cabuk, A.: Experimental IOT study on fault detection and preventive apparatus using node-red ship's main engine cooling water pump motor. Engineering Failure Analysis, 138, 2022, p. 106310

[10] Jin, X., Chow, T. W. S.: Anomaly detection of cooling fan and fault classification of Induction Motor Using Mahalanobis–Taguchi System. Expert Systems with Applications, 40 (15), 2013, pp. 5787-5795

[11] Khoualdia, T. et al.: Multi-objective optimization of ann fault diagnosis model for rotating machinery using grey rational analysis in Taguchi method. The International Journal of Advanced Manufacturing Technology, 89 (9-12), 2016, pp. 3009-3020

[12] Cui, J. et al.: Multi-objective design optimization of the DPMSM using RSM, Taguchi Method, and improved Taguchi Method. Journal of Electrical Engineering & Technology, 19 (3), 2023, pp. 1343-1357

[13] Liu, G. et al.: Fault diagnosis of diesel engine information fusion based on adaptive dynamic weighted hybrid distance-taguchi method (ADWHD-T). Applied Intelligence, 52 (9), 2022, pp. 10307-10329

[14] Anh Tran, T.: A research on the Energy Efficiency Operational Indicator EEOI using Taguchi optimization method for bulk carriers: A case of study in Vietnam. Journal of Engineering and Applied Sciences, 14 (10), 2019, pp. 3472-3481

[15] Okanminiwei, L., Oke, S. A.: Optimization of maintenance downtime for handling equipment in a container terminal using Taguchi Scheme, Taguchi-Pareto method and Taguchi-ABC Method. IJIEM - Indonesian Journal of Industrial Engineering and Management, 1 (2), 2020, p. 69

[16] Sii, H. S. et al.: Taguchi concepts and their applications in Marine and Offshore Safety Studies. Journal of Engineering Design, 12 (4), 2001, pp. 331-358

[17] Pozna C., Precup, R. E.: Aspects concerning the observation process modelling in the framework of cognition processes, Acta Polytechnica Hungarica, 9(1), 2012, pp. 203-223

[18] Pozna, C. et al.: A novel pose estimation algorithm for robotic navigation. Robotics and Autonomous Systems, 63, 2015, pp. 10-21

[19] Venczel, M. et al.: Development of a viscosity model and an application, for the filling process calculation in Visco-dampers. Acta Polytechnica Hungarica, 20 (7), 2023, pp. 7-27

[20] Szakács, T.: Pneumatic piston control modelling and optimization. Acta Polytechnica Hungarica, 20 (6), 2023, pp. 249-265

[21] Abramov, S. et al.: New opportunities model for monitoring, analyzing and forecasting the official statistics on coronavirus disease pandemic. Romanian Journal of Information Science and Technology, 2023 (1), 2023, pp. 49-64

[22] Grosu, V. et al.: On the modelling possibilities of integrated circuits behavior using active learning principles. Romanian Journal of Information Science and Technology, 27 (2), 2024, pp. 183-195