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Electricity Consumption Prediction during Ship Construction: A Machine Learning Approach

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ABSTRACT

In the maritime industry, estimating electricity consumption during ship construction is pivotal for establishing budgets and ensuring cost-effective project management and resource allocation. The research aims to develop a machine learning model that enables shipbuilders to estimate electricity consumption during the preliminary design phase of various vessel types, including container ships, bulk carriers, passenger vessels and oil tankers. The methodology involved calculating the welded area and volume of different sections of ship structure using specific drawings for each vessel type. Subsequently, the weight of welded metal was determined from the volume, considering the density of the metal. This was followed by calculating the required electrode consumption based on the weight of welded metal and the deposition rate. Finally, electricity consumption was calculated based on the electrode requirements for each ship. Leveraging advanced machine learning techniques, a linear regression model is constructed, utilizing multiple variables such as ship length, breadth, depth, and ship's type to establish a predictive relationship with electricity consumption. The model is cross-checked with field data and found consistent result with industry standard. It is hoped that this model will empower shipbuilders with a predictive tool during the preliminary design phase, aiding in estimating electricity consumption costs. By integrating this model into the shipbuilding process, stakeholders can proactively devise budgets and allocate resources more efficiently, thus optimizing the overall construction endeavor.

1. Introduction.

Bangladesh, spanning 1,66,000 square kilometers of sea, rich in rivers and has a glorious tradition of shipbuilding dating back to ancient times. Recently, this industry has gained renewed focus, becoming a key economic sector (Alam, 2004). Bangladesh has 700 rivers, making up 24,000 kilometers of waterways and 120 registered shipyards of varying size, located mostly on the river banks. Motivated by this topographical characteristic, the nation employs 150,000 semi-skilled and over 100,000 skilled people in the shipbuilding sector. Waterways in Bangladesh facilitate the transportation of about 90% of fuels, 70% of cargo, and 35% of passengers, resulting in a significant local need for vessels (BIDA - Shipbuilding, 2024).

The country currently has over 200 shipyards, primarily situated in Dhaka, Chattogram, Narayanganj, and Khulna, with a focus on constructing and repairing ocean-going vessels. Approximately 70% of these shipyards are concentrated in Dhaka and Narayanganj, specifically along the banks of the Buriganga, Shitalakha, and Meghna rivers. In the Chattogram division, around 20% of the shipyards are located along the Karnaphuli River, while 6% are positioned along the Poshur River in the

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Khulna division. The remaining 4% are distributed within the Barishal division (Zakaria et al., 2011). During recent years, the shipbuilding industry in Bangladesh has attracted considerable optimism, owing to the outstanding accomplishments of several indigenous entrepreneurs. By constructing and delivering ocean-going vessels to international clients, these individuals have effectively contributed to enhancing Bangladesh's standing as a nation with immense potential in this field. Encouraged by these accomplishments, the shipbuilding sector in Bangladesh has demonstrated unwavering progress, thereby presenting lucrative prospects for additional expansion and development. (Iqbqql et al., 2010).

All inland vessels in Bangladesh are constructed and repaired within local shipyards. Additionally, Bangladesh is home to the second-largest ship-breaking industry globally, which supplies raw materials such as plates, pipes, stiffeners, old engines, and generators to the local market (Zakaria et al., 2011).Therefore, it can be asserted that Bangladesh is a significant hub for shipbuilding. Consequently, it is essential to implement proper design strategies and make critical decisions for both shipyards and ship owners.

In Shipbuilding, cost estimation is a crucial part in ship designing phase. The ability to estimate best cost that suit for the commercial success of shipyard. Approximate cost estimation is essential not only for shipbuilders but also for shipowners, particularly within the contexts of contracts and tender bidding. Precise cost forecasts ensure financial viability and competitiveness, highlighting the importance of financial planning in advancing Bangladesh's shipbuilding industry. Accurately measuring the exact cost of a ship's construction is challenging. Traditionally, this is done using black book, parametric, standard ship, direct analysis approach. However, each ship is unique, so these estimates can be inaccurate. These methods rely on past consumption data to predict future demand, assuming historical patterns will continue. While somewhat useful, they often overlook unexpected developments and the complex interactions of various factors (Ross, 2002).

A significant amount of cost is focused on electricity for various operations, such as running cranes, cutting equipment, machining tools, welding, and other miscellaneous activities. Notably, electricity consumption in the welding field constitutes a substantial portion of these costs (Harish & Sunil, 2015). By predicting the electricity usage in welding, a considerable amount of these expenses can be managed and potentially reduced. Effective forecasting helps balance supply and demand, optimize electricity consumption, and reduce production costs. (Azhar & Kristiyono, 2022)

Many papers have been reviewed, and there is a significant lack of research on predicting the electricity consumption during ship construction using machine learning. This gap presents a unique opportunity for our study to have a meaningful impact.

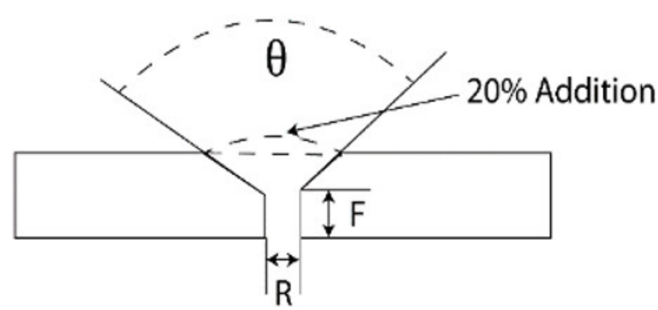
This paper tries to develop a machine learning model for predicting electricity consumption during ship construction, enables to calculate approximate manufacturing costs for specific ship types at preliminary design phase according to owner's requirements and to establish comprehensive relationships between electricity consumption and different types of parameters, like: Principal Particulars, Number of Bulkheads, Types of ship, Single Bottom, Double Bottom etc in shipbuilding.

2. Methodology.

The methodology of this paper involves several steps. Initially, identifying and documenting specific areas or processes within the shipyard that consume electricity, such as welding, workshops, cranes, offices, and other operational zones are done. As most electricity consumption occurs during the welding process, it is crucial to determine the welded area and length for precise calculations. To achieve this, ship drawings are indispensable tools. To facilitate this evaluation, three types of drawings are required: midship drawing, longitudinal construction drawing, and shell expansion drawing for a particular ship. From the drawings, the quantity of various component including longitudinal and transverse sections, frames, web frames, bulkheads, and others, welding length and thickness are evaluated. To assess electricity consumption during a particular ship construction, the welding zones were identified. Shielded metal arc welding (SMAW) has used in this ship. The SMAW is advantageous because of its versatility, portability, cost - effectiveness, and suitability for outdoor work (Shravan et al., 2024). This study followed butt welding for plate joining and fillet welding to connect vertical members. Welding was performed with a root gap of 3 mm and a root face of 2 mm, appropriate for plate thicknesses ranging from 5 to 12 mm (Mandal, 2017). E6010 mild steel electrodes were used in this study. During our study, an interview with a shipyard revealed that they generally use this electrode because it offers benefits such as high-quality weld, good ductility, and cost efficiency. (Bani-Melhem & Rasool Al-Kilani, 2023)

Now. The welding area was calculated using Equation (1) for the butt weld (Figure 1) and Equation (2) for the fillet weld (Figure 2).

Figure 1: Area of Butt Weld.



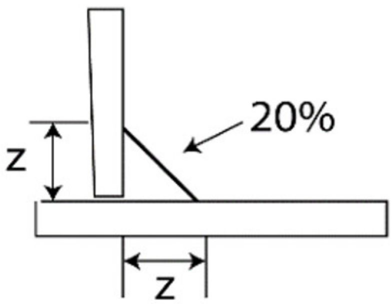
Source: Authors.

$$\begin{gathered}Cross\text{-}Sectional\ Area = (R \times T)(T - F)^2 + tan\tfrac{\theta}{2} \\ +20\%\ addition\ with\ final\ value\end{gathered} \tag{1}$$

(Calculation of the Welding Consumables Consumption, 2024.)

Where, R = Root Gap = 3 mm, F = Root Face = 2 mm, T = Thickness of Base Metal.

Figure 2: Area of Fillet Weld.



Source: Authors.

$$Cross\text{-}Sectional\ Area = \frac{z^2}{2} + 20\%\ addition\ of\ final\ value\ (reinforcement) \quad (2)$$

where z = Leg size.

The filler metal requirement was then calculated using Equation (3).

$$Filler\ Metal = \frac{Total\ Quantity \times Area \times Lenght \times Density}{Deposition\ Efficiency} \quad (3)$$

Using the deposition rate, total welding time, and power of the welding machine, the electricity consumption was calculated (Masmoudi et al., 2007). Furthermore, the electricity bill was determined based on the current electricity rate. Similarly, the electricity consumption for 21 different ships of four different types (Cargo, Container, Passenger, Oil Tanker) was calculated, as summarized in Table 1.

Table 1: Calculation of required electrode and electricity consumption of different types of ships during ship construction.

Length (m)	Breadth (m)	Depth (m)	Ship Type	Filler Metal (Ton)	Electricity Consumption (Kwh)
82.05	15.20	5.50	1	6.498	50141.341
82.56	16.00	5.50	1	6.656	51356.117
82.92	18.00	6.00	1	7.033	54266.980
87.00	18.00	6.20	1	7.927	61163.284
86.20	18.20	6.10	2	9.303	71787.033
87.00	18.00	6.20	4	12.304	94938.426
59.00	12.10	5.10	4	5.861	45224.563
58.60	12.00	4.90	4	5.831	44993.077
87.60	16.00	5.30	2	9.58	73925.413
85.40	15.60	5.20	2	9.084	70096.839
84.30	15.40	5.10	1	6.694	51655.090
81.76	15.00	5.00	1	6.128	47286.795
78.50	14.40	4.80	4	9.562	73782.744
74.22	12.50	3.50	3	6.795	52436.378
71.46	13.00	3.80	3	6.415	49501.649
69.56	12.70	4.20	2	5.3	40901.674
67.46	12.30	4.10	2	6.929	53466.101
65.00	11.50	3.80	1	3.079	23757.872
45.00	10.50	3.30	3	1.892	14598.327
55.60	10.00	3.80	3	3.834	29587.430

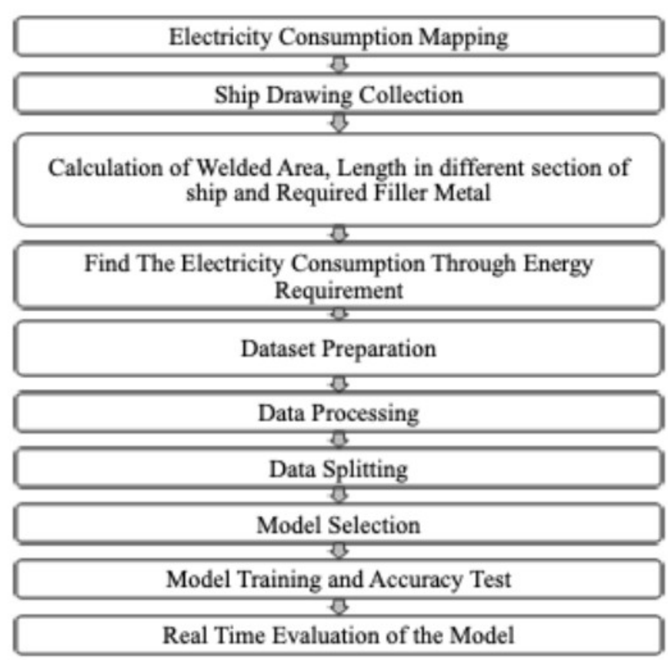
Source: Authors.

The table data served as the dataset for the machine learning model, consisting of variables such as length, breadth, depth, ship type, electrode (filler metal), and electricity consumption. Unnecessary data was removed to ensure relevance and accuracy. The data was standardized to place all variables on a similar scale. From this dataset, the most influential parameters independent (input) variables affecting electricity consumption were identified. The total electricity consumption was treated as the dependent (output) variable.

The dataset was divided into training and testing sets, with 80% allocated to the training set and 20% to the testing set. The training set was used to train the model, while the testing set was employed to evaluate the model's accuracy. An appropriate machine learning algorithm was selected, and since this is a prediction problem, a regression model was chosen. Multiple models were compared to identify the one with the best performance. The model with the highest accuracy was then selected.

After selecting the appropriate model, it was trained using the training dataset and tested with the testing dataset. The accuracy of the model was evaluated using a confusion matrix or other relevant libraries. At this stage, the model was prepared to predict electricity consumption during ship construction. A detailed discussion of the machine learning model is presented in the next section. Figure 3 illustrates the flowchart outlining the steps in this paper.

Figure 3: Flowchart outlining the steps in this paper.

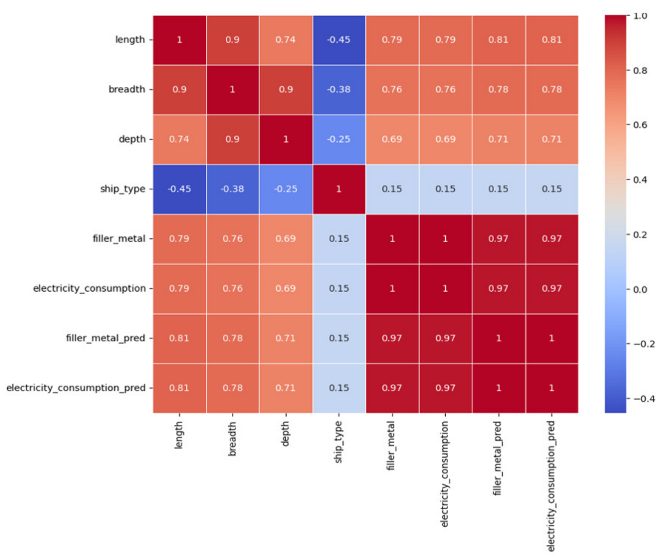


Source: Authors.

3. Machine Learning Model and Results.

In this paper, Linear regression model with multiple variables suits our datasets. The coefficients of the model directly represent the relationship between each independent variable (e.g., length, breadth, depth, type of ship) and the dependent variable (electricity consumption) (See Figure 4). Multiple linear regressions allow for the inclusion of several predictor variables, which can improve the explanatory power of the model compared to other models. This can help in identifying which factors are most significant and potentially guiding decisions or further research (Sucharita Barik et al., 2020).

Figure 4: Correlation Matrix.



Source: Authors.

The machine learning model developed in this research effectively predicts both electrode consumption and electricity consumption during ship construction based on ship dimensions and type. The equations derived from the model are as follows:

$$\begin{gathered}\textit{Electrode consumption} = \\ [0.18L + 0.08B + 0.2D + 1.28K - 11.524]\ \textit{Tonnes}\end{gathered} \tag{4}$$

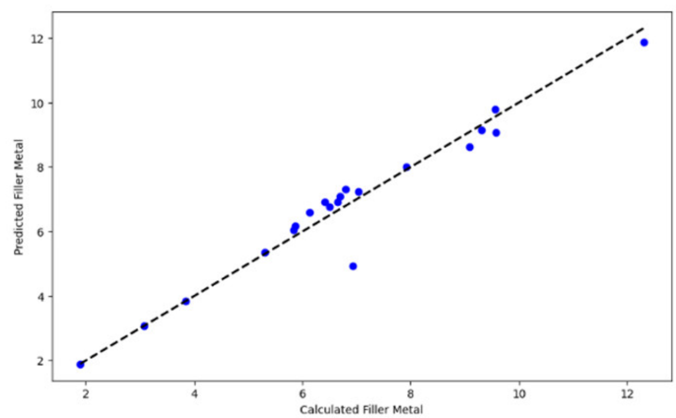
$$\begin{gathered}\textit{Electricity consumption} = \\ [1381.56L + 614.5B + 1542.05D + 9931.72K \\ -88921.64]\ \textit{KWh}\end{gathered} \tag{5}$$

Where, L = Length (m), B = Breadth (m), D = Depth (m), K= Ship's Type = 1,2,3,4 for Cargo Ship, Container, Oil Tanker, Container, Passenger Ship respectively.

Again, the scatter plots comparing the predicted values to the actual values for both the electrode (Figure 5) and electricity consumption (Figure 6) demonstrated a strong linear relationship, as indicated by the alignment of the data points along the dashed line. This line represents a perfect prediction, and the proximity of the points to this line suggests that the model performs well.

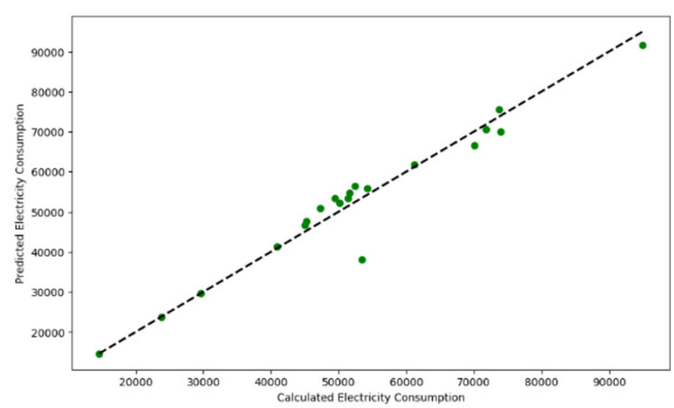
To validate the model, field data was cross-checked with the calculated data. An interview was conducted during the study at Karnafuly Shipyard, where ship data was provided. The shipyard representatives mentioned that at Karnafuly Ship Builders Limited, they use 6 packets of electrodes for welding 1 ton of steel, with each packet weighing 5 kg. Therefore, 30 kg of electrode is used for 1 ton of steel welding, resulting in an electrode consumption rate of 3%. Refer to Table 2 for detailed data.

Figure 5: Calculated vs Predicted Filler Metal (Ton).



Source: Authors.

Figure 6: Calculated vs Predicted Electricity Consumption (Kwh).



Source: Authors.

Table 2: Principal Particulars, Total Steel Weight and Total Weight of Electrode Used in A Passenger Vessel.

Particulars	**Value**
Length Overall (Meters)	56.00
Breadth (Meters)	12.50
Depth (Meters)	2.90
Total Steel Weight (Tonnes)	560
Total Electrode Weight (Tonnes)	16.80
Electrode Consumption Per Tonne of Steel in Percentage	3%

Source: Authors.

From a second shipyard visit, 3% electrode-to-steel weight ratio was reported. Similarly, data from third shipyard indicated an electrode consumption rate of 2-3% per tonne of steel. Additionally, according to Harish & Sunil, 2015, the electrode consumption is reported to be 35 kg per tonne of steel. Now, for verification of the model using the data from Table 2, it is found that electrode consumption per tonne of steel is 2.95% from equation (4) and electricity consumption per tonne is 228 Kwh from equation (5).

Since the calculated electrode consumption per tonne of steel is 2.95%, which falls within the 2-3% range reported by the shipyards, and the electricity consumption is 228 kWh/tonne, which is consistent with industry standards, the model is verified as accurate and satisfies the requirements for predicting electricity consumption in shipbuilding.

4. Discussion.

In this paper, a machine learning model was constructed to predict electricity consumption during ship construction. Variability in ship length, especially for very long vessels (length higher than 120 meters) & very small vessels (length less than 65 meters) might introduce errors in predictions due to the model's reliance on linear regression. The model is generated using data from 21 ships of 4 types: Cargo Ships, Oil Tankers, Passenger Vessels, and Container Ships. Therefore, other types of ships may generate errors in prediction. The model does not account for the complexity and variability of the ship's superstructure, which can significantly influence electricity consumption during construction. The model relies on precise measurements of length, breadth, depth, and ship type. Any deviations or inaccuracies in these measurements can affect the prediction accuracy.

Ensure that the input data (length, breadth, depth, and ship type) are measured accurately to reduce prediction errors. Incorporate the model early in the design phase to provide preliminary estimates of electricity consumption, allowing for better budget planning and resource allocation. Periodically update the model with new data from completed projects to improve its accuracy and reliability. This includes adjusting for any new variables that may become relevant over time.

Future models should aim to include factors related to the complexity and specific design elements of the ship's superstructure to enhance prediction accuracy. However, additional research is necessary to validate these findings, which would serve as a benchmark for electricity consumption estimation in various contexts.

Conclusions.

This study successfully demonstrated the application of machine learning techniques to predict the electricity consumption during the preliminary design phase of ship construction. By developing a linear regression model, this study provides shipbuilders with a powerful predictive tool that incorporates multiple ship parameters including length, breadth, depth, and type. 21 Ships data were collected using the welding electrode consumption, and the electricity consumption was calculated. Using this data, a dataset was created and used in a linear regression model to develop the model. Field data were collected and cross-checked with the calculated data. The calculated electrode consumption per tonne of steel is 2.95%, which falls within the 2-3% range reported by the shipyards, and the electricity consumption is 228 kWh/tonne, which is consistent with industry standards, the model is verified as mostly accurate and satisfies the requirements for predicting electricity consumption in shipbuilding. The model offers a reliable method for estimating costs and will aid shipbuilders in better planning and budgeting of electricity consumption during construction.

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