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Predicting Preliminary Structural Strength Requirements of Cargo Vessels using Artificial Neural Network

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ABSTRACT

In the preliminary stage of a ship design, different classification societies rules are usually followed for predicting the structural strength after finalizing the principal particulars of the ship. Most of the formula for evaluating the requirements of structural strength of a ship using classification societies rules are empirical and the time required is very significant. In present study, an artificial neural network (ANN)-based method is proposed to predict the structural strength requirements for cargo vessels. Keel Plate Weight (KPW), Bottom Plate Weight (BPW), Inner Bottom Plate Weight (IBPW), Side Shell Plate Weight (SSPW), Bulkhead Weight (BW) and Main Deck Weight (MDW) is predicted as a function of ships' rule length (L), breadth (B) and draft (T). An ANN model was trained to achieve a root mean square error (RMSE) of less than 0.13. The R^2 of the trained model used to evaluate the new data is 0.998, which indicates that the various requirements of weights calculated by ANN model is in good agreement with the classification societies results.

1. Introduction.

Determining structural strength requirements has a significant impact on the preliminary ship design process because it effects the overall construction costs of the ship. Now-a-days structural strength requirements of a ship are calculated using the Finite Element Method (FEM) and Classification Societies rules. Classification societies rules are based on empirical formulas. However, there are several drawbacks in using FEM for preliminary structural strength analysis. For example, the accuracy of FEM solution highly depends on the initial boundary conditions. Furthermore, the high cost of FEM analysis, which is primarily due to the high computational power and the time required to generate many accurate structural strength analysis databases. Using classification societies empirical formula is time consuming and much effort is also required. Another drawback of using those formulas is that different classification societies have different rules [Kabir et.al. 2022]. Recently trained Artificial Neural Network (ANN) models have gained attention for learning the responses of large, complex, and nonlinear systems [Liu et.al. 2016]. Using ANN can significantly reduce the time requirements for determining the structural strength requirements.

Kabir et.al. 2022 calculated the variations of the structural strength requirements among classification societies such as RINA, BV, IRS and DoS for a coastal cargo vessel. In present study, required data set for ANN models is generated using the results of Kabir et.al. 2022.

2. Principal Particulars.

The General Arrangement (GA) plan and the principal particulars of the coastal cargo vessel used by Kabir et.al.[1] is mentioned in Fig.1. and Table 1 respectively.

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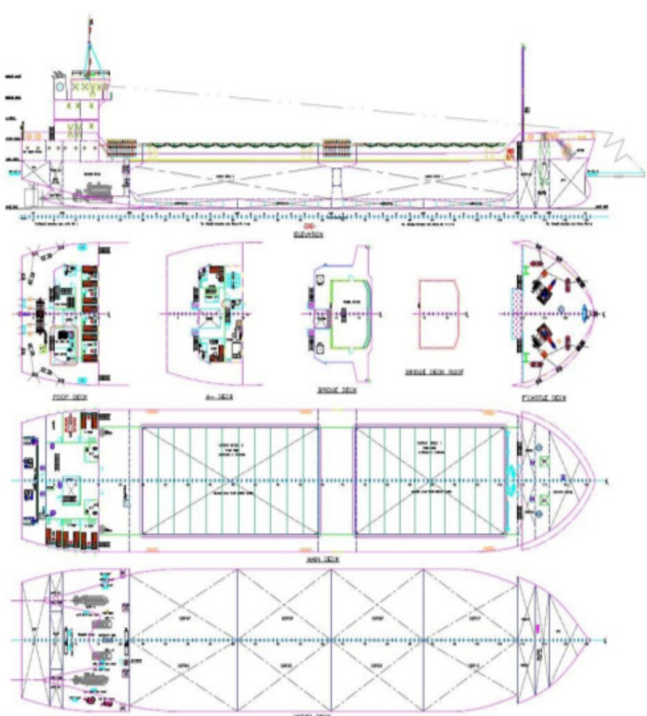
Table 1: Principal particulars of the coastal cargo vessel [Kabir et.al. 2022].

Particulars	Data	Unit
Length Overall	83.00	[meter]
Length LWL@ Scantling Draft	81.52	[meter]
Length BP@ Scantling Draft	79.90	[meter]
LWL extreme at scantling draft	81.52	[meter]
97% of above	79.075	[meter]
Rule length	79.075	[meter]
Breadth of the ship	18.000	[meter]
Depth, D	6.00	[meter]
Design Draft,	4.50	[meter]
Scantling Draft,	4.50	[meter]
Block co-efficient, C_b	0.84	[meter]
Service Speed,	10	[Kn]
Deadweight	4000	[Ton]

Source: Authors.

Figure 1: General Arrangement plan of a coastal cargo [Kabir et.al. 2022].



Source: Authors.

3. Formula for Structural Strength Requirements.

Various formula of classification societies for determining the structural strength requirements of a cargo vessels length ranging from 65.00 meter to 89.00 meter is presented in Table 2.

Table 2: Formula for the minimum net thickness of plating.

Location	Area	RINA	BV	IRS
Keel	-	$5.1+0.026LK^{1/2}+4.5s$	$3.8+0.040LK^{1/2}+4.5s$	$t=(t_o+0.03L)\sqrt{k}+2$
Bottom	Longitudinal framing Transverse framing	$3.2+0.018LK^{1/2}+4.5s$ $4.1+0.018LK^{1/2}+4.5s$	$1.9+0.032LK^{1/2}+4.5s$ $2.8+0.032LK^{1/2}+4.5s$	$t=(t_o+0.04L)\sqrt{k}$
Inner Bottom	Outside the engine room Engine room	$1.9+0.024LK^{1/2}+4.5s$ $3.0+0.024LK^{1/2}+4.5s$	$1.9+0.024LK^{1/2}+4.5s$ $3.0+0.024LK^{1/2}+4.5s$	$t=(t_o+0.03L)\sqrt{k}$
Side	Below freeboard deck Between freeboard deck and strength deck	$3.1+0.017LK^{1/2}+4.5s$ $3.0+0.004LK^{1/2}+4.5s$	$2.1+0.031LK^{1/2}+4.5s$ $2.1+0.013LK^{1/2}+4.5s$	$t_s=(5.0+c.L)\sqrt{k}$
Bulkhead	Transverse watertight Longitudinal watertight Tank and Wash	$1.3+0.004LK^{1/2}+4.5s$ $1.7+0.013LK^{1/2}+4.5s$ $1.7+0.013LK^{1/2}+4.5s$	$1.3+0.004LK^{1/2}+4.5s$ $1.7+0.013LK^{1/2}+4.5s$ $1.7+0.013LK^{1/2}+4.5s$	$t=(5.0+c.L)\sqrt{k}$
Main Deck	Area within 0.4 amidships: Longitudinal framing Transverse framing	$2.1+0.032LK^{1/2}+4.5s$ $2.1+0.032LK^{1/2}+4.5s$	$1.6+0.032LK^{1/2}+4.5s$ $1.6+0.032LK^{1/2}+4.5s$	$t=(6+0.02L)\sqrt{k}$

Source: Authors.

Where, L = Rule length, K = Material factor, s = Spacing of short side of the plate panel, c = Co efficient, t_0 = Constant.

Minimum thickness of various structural members without and with corrosion addition of the coastal cargo vessel for different classification societies calculated by Kabir et.al. 2022 is shown in Table 3 and Table 4 respectively. Table 5 represents the weight of various structural members of the coastal cargo vessel for different classification societies calculated by Kabir et.al. 2022.

Table 3: Minimum net thickness of plating without corrosion addition.

Location	Area	RINA (mm)	BV (mm)	IRS (mm)
Keel	-	9.766	9.573	10.163
Bottom	Longitudinal framing	7.391	7.198	8.163
	Transverse framing	8.448	8.225	
Inner Bottom	Outside the engine room	6.565	6.565	8.372
	Engine room	7.665	7.665	
Side	Below freeboard deck Between freeboard deck and strength deck	7.369 6.016	7.476 5.828	8.163
Bulkhead	Transverse watertight Longitudinal watertight Tank and Wash	4.384 5.653 5.653	4.384 5.653 5.653	5.791
	Area within 0.4 amidships:			
Main Deck	Longitudinal framing Transverse framing	7.398 8.188	6.898 7.055	7.582

Source: Authors.

Table 4: Minimum net thickness of plating with corrosion addition.

Location	Area	RINA Theoretical	Rounding	BV Theoretical	Rounding	IRS Theoretical	Rounding
Keel	-	10.766	11	10.573	11	12.163	12
Bottom	Longitudinal framing	8.391	8	8.198	8	10.163	10
	Transverse framing	9.448	9	9.225	9		
Inner Bottom	Outside the engine room	8.315	8	8.315	8	10.372	10
	Engine room	9.415	9	9.415	9		
Side	Below freeboard deck	9.119	9	9.226	9	10.633	11
	Between freeboard deck and strength deck	7.766	8	7.578	8		
Bulkhead	Transverse watertight Longitudinal watertight Tank and Wash	6.134 6.653 6.653	6 7 7	6.134 6.653 6.653	6 7 7	7.791	8
	Area within 0.4 amidships:						
Main Deck	Longitudinal framing Transverse framing	7.898 8.688	8 9	7.398 7.555	7 8	9.082	9

Source: Authors.

Table 5: Weight of plates in cargo hold area as per classification societies.

Location	RINA	BV	IRS
Keel	5.82 Tons	5.82 Tons	6.35 Tons
Bottom	64.91 Tons	64.91 Tons	81.14 Tons
Inner bottom	51.93 Tons	51.93 Tons	64.91 Tons
Side	37.58 Tons	37.58 Tons	45.94 Tons
bulkhead	10.51 Tons	10.51 Tons	14.02 Tons
Main Deck	23.73 Tons	20.76 Tons	26.69 Tons
Total	~195 Tons	~192 Tons	~239 Tons

Source: Authors.

4. Prediction using Neural Network.

Artificial neural networks (ANNs) are inspired by human brains. It can be created in a computer by mimicking the process of real neurons [Krogh, A. 2008]. Many types of problems can be learned to solve by ANNs [Basheer, 2000 and Abiodun et.al. 2019]. The main objective of designing an ANN model is that the model should make good predictions for new data or, in other words, the model should exhibit good generalization. The first step of designing such a network is creating a dataset.

4.1. Dataset preparation.

Ship rule length (L), Breadth (B), Draft (T), *KPW*, *BPW*, *IBPW*, *SSPW*, *BW* and *MDW* of different classification societies are the features of the dataset. RINA, BV, IRS and DOS is used to generate the total 5000 datapoints. 10% of the dataset is used as a test data and the remaining observations, 90% are used for training. 10% data are used to validate the model's accuracy after each epoch. A summary of the data breakdown is shown in Table 6.

Table 6: Partition of the dataset.

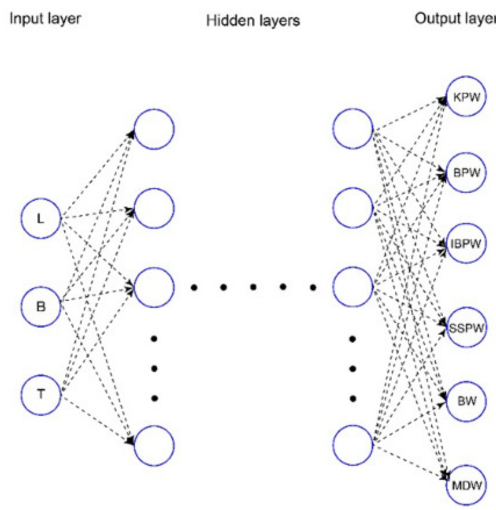
Dataset	Observations
Training data	4050
Validation data	450
Testing data	500

Source: Authors.

4.2. Network architecture.

The used ANN architecture is shown in Fig.2, consisting of an input layer, hidden layers, and an output layer with neurons in each layer. The input layer takes all the input features namely Ship rule length (L), Breadth (B), Draft (T) and then calculates the weighted sum of the inputs, and then the bias term is added. This linear combination goes through a non-linear activation function to output transformed features. The output of the input layer then goes to the next layer, and this process continues layer by layer until the last layer, which predicts the output features namely *KPW*, *BPW*, *IBPW*, *SSPW*, *BW* and *MDW* for RINA, BV, IRS, and DOS. Thus, the input features are mapped to the output features through a series of mappings.

Figure 2: ANN architecture used in the scantling requirements prediction network.

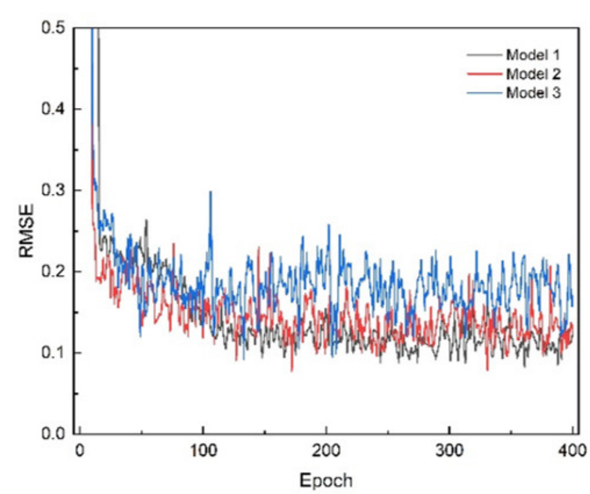


Source: Authors.

5. Results and Discussion.

In present study, three different ANN models are used for training. The models are trained for 400 epochs in which all the training data is fed to the network in batches of 32 observations before the weights are allowed to update using the root mean squared error (loss) of the batch. The model's training loss is shown in Fig. 3. RMSE of models along with network architectures is shown in Table 7. From Table 7 it is evident that model 1 with two hidden layers and eight nodes predicts better.

Figure 3: Training losses of ANNs after 400 epochs.



Source: Authors.

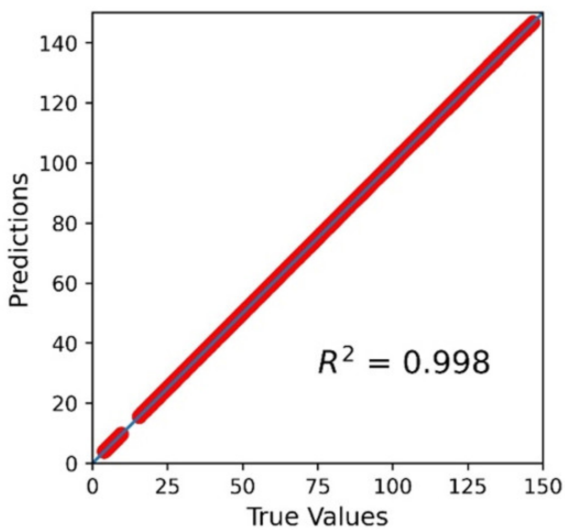
Table 7: ANN performance for 3 different models.

ANN model	No of hidden layers	No of nodes	RMSE
Model 1	2	8	0.126520
Model 2	2	16	0.128367
Model 3	3	8	0.170921

Source: Authors.

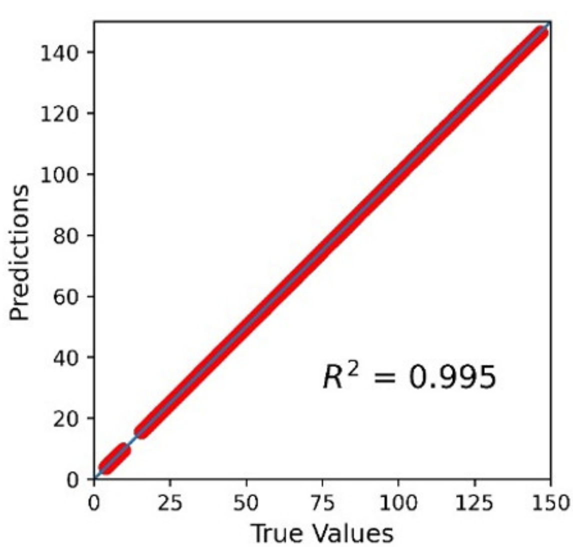
The R^2 values of the models were shown in Figs. 4~6. From Figs. 4~6, it is noticed that Model 1 has the highest R^2 value of 0.998 which is close to the maximum value of 1.0.

Figure 4: R^2 value of Model 1.



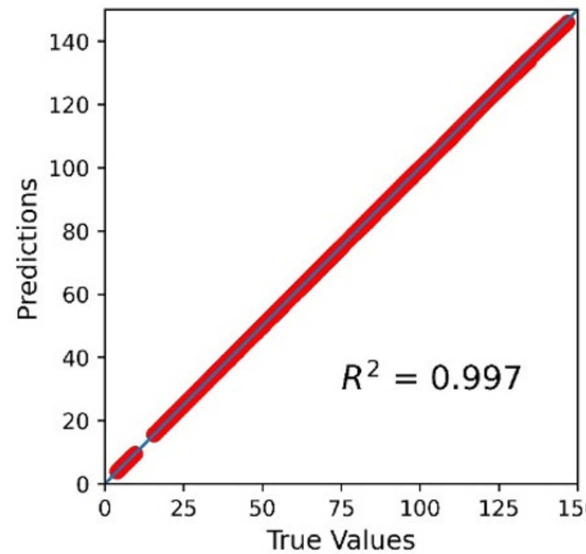
Source: Authors.

Figure 5: R^2 value of Model 2.



Source: Authors.

Figure 6: R^2 value of Model 3.



Source: Authors.

Conclusions.

The purpose of this study is to develop an ANN model to calculate the structural strength requirements of cargo vessels. Three different classification societies and DoS formula is used to generate the dataset for ANN. ANN models are trained and the results are found to be in good agreement with the classification societies results. Therefore, ANN can be used as an alternative to classification societies formula for predicting the structural strength of the cargo vessels in the preliminary design stage.

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