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An Investigation into the Operational Characteristics of High-Speed Crew Boat Based on Artificial Neural Network

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Abstract. Estimating shaft power of a crew boat is very important to be analysed because it has high-speed operational characteristics along with limited routes. To understand the phenomena, 3 sister crew-boats with operational distance about 40-60 nautical miles every day are investigated. The daily operational time is 8 hours and the configurations are: 4.04% full speed, 13.63% economical speed, 1.81% slow speed, 7.65% snatching, 1.25% manoeuvring, 5.29% idle, and the remaining time is in standby condition.

The crew boats are fitted with a monitoring system namely SHIMOS®, in which data is sent to a server in the centre office every 2 minutes. The data consists of time capture, boat position (latitude and longitude), speed, left and right RPM engine, left and right flow-meter data engine, and average of fuel consumption data in everyday operation. Three years of data has been collected for the vessel.

The present study proposed characteristics of crew-boat shaft power, which affected by external factors using Artificial Neural Network (ANN) back propagation method and optimisation in 4 hidden layers and 40 neurons with relative error 6.2%. The results demonstrates good agreement with previous popular method that using statistical models

1. Introduction

The use of energy from fossil fuels has increased excessively in the past 50 years and continues to increase considering the development of the human population to date in accordance with data on world population prospects 2019 reaching 7.7 billion [1]. In accordance with BP Energy outlook data in the 2019 edition [2], energy demand along with the amount of pollution also increases. In line with the study which was study conducted by IMO conducted in 2014 that air pollution was estimated at 2.2% of CO2 emissions and this would increase between 50% to 250% at 2050 [3]. Therefore, providing a roadmap to develop thoroughly strategy to reduce emissions from ships is very important.

In the process of getting speed results with the appropriate power estimation, there are margin factors in the form of roughness, fouling, and weather [4]. Nonetheless, obtaining this margin from the results of the design process is not easy. Globally explained in a study carried out by Molland et al [5], there

are many factors that affect the emissions of ships, including the hull shape that affects resistance, propulsion system, ship operations (weather routing, trim, and speed), and the design procedures related to the economic factors of the ship. Gorski et al [6] the factors affecting the operation of the ship in relation to fuel consumption, which is not easy to explain in a simple formula. The linkages of factors include the condition of the ship, the ship's trim, and the bow's shape. Peterson et al. [7] carry out analysis for ship propulsion efficiency using statistical modelling and compared the results using artificial neural networks (ANN) and Gaussian processes. There are similarities in the results, but further work must be done for different ships types.

Parkes, et al [8] did the research by using the neural network method for a ship with displacement type. That ship has very long operation route with the constant velocity which is supported by ship's noon data report. In this study the neural network method is applied for different ship type, planning hull type. The planning hull ship types has a short route, so that by using the neural network method it is possible to simulate the shaft power that the ship needs. This research results can become a references to the ship operator providing suggestion on ship's performance.

2. Crew Boat Operational

2.1. Crew boat specification

A crew boat is a vessel type with specialized in the transport of offshore support personnel, deck cargo, and below-deck cargo such as fuel and potable water to and from offshore installations such as oil platforms, drilling rigs, drill and dive ships. There are many shipping companies that rent crew boat to offshore platform operators. The propulsion system is a waterjet, the jet unit involves fluid into hull through an intake and discharging it above water at high velocity. The benefit of this type of propulsion is no underwater appendage which can be used in rivers, deltas, and lower drafts. Detail picture shown in Figure 1 and principal dimensions shown in Table 1.

Figure 1. The crew boat has monitoring by SHIMOS®

Table 1. Principal dimensions of the analyzed crew boat

Princapal Dimension		Ship	
Length Over All	(LOA)	19.50	m
Breadth	(B)	4.50	m
Draft	(T)	0.95	m
Speed max	(Knot)	35.0	Kn
Engine Power	(Hp)	2 x 880	Hp
Waterjet	(kW)	2 x 1324	kW
Deadweight	(Tonne)	12.56	tonne

2.2. Operational crew boat
2.2.1. Route of operation
In crew boat operations there are rules aimed at ensuring a high level of safety. The pattern of the route is not fixed permanently, but follows the operational needs. As seen in Figure 2 an image that discription about 3 operational zones.

- Zone A is the highest level of safety because there is an offshore platform, with a radius of about 100 meters. In this zone the crew boat must be careful and controlled, this is indicated by its speed must not exceed 3 knots.

- Zone B has a radius of 500 meters from the jetty home base. Limitation of speed is the same as with Zone A. In the jetty area, low speed is needed so that the effects of the ship's movement do not cause high waves.

- Zone C is a common area so that it does not have a speed limit. Operating in general areas following general shipping requirements, vessel movements must take into account wave and wind factors.
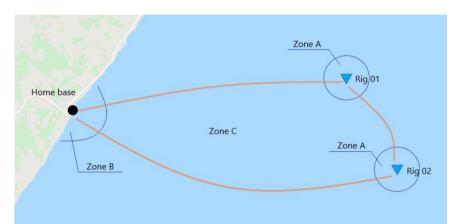

Figure 2. Route of crew boat from home base to offshore plateform with safety zone identification.

2.2.2. Category of operation
With the crew boat operational route as described above, it causes different engine load. The parameter of engine load is indicated in the performance of the engine speed (RPM). Category of conditional regulation shown in below:

- Standby is condition of vessel when engine starts and kept on without clutch in the water jet.
- Idle is condition of engine vessel condition run in minimal idle speed when the engine is uncoupled from the drivetrain and the throttle pedal is not depressed. In combustion engines, idle speed is generally measured in revolutions per minute (rpm) of the crankshaft. At idle speed, the engine generates enough power to run reasonably smoothly and operate its ancillaries (water pump, alternator, and power steering), but usually insufficient to perform useful work.
- Manoeuvre is the condition of the crew boat to change direction or path route. In this criteria when manoeuvring the captain must consider to the machinery, type propulsion, stability, and seakeeping. In this condition for exstreme must be done in low speed.
- Snatching condition or boat landing to secure transfer personal transfer from crew boat to offshore platform. As explanantion in news and magazine at website bourbon [9], the captain ensure the enviroment (wave and wind) for boat landing is safe. Commonly engine speed in 900

rpm until 1200 rpm or as suit condition to deliver enough power to remain position whe boat landing process for detail can see in Figure 3 and 4.

Figure 3. A crew boat snatching or mooring system to access an offshore platform

Figure 4. A crew boat snatching or mooring system to access an offshore platform

- Operational speed
  At an operational speed adjusted to the conditions of the contract made between the operator and the contractor, the indicator is with a speed of 7.2 knots to 20 knots.
- Full speed
  While at full speed is a condition with speeds above 20 knots. This speed is only allowed in the appropriate area and not in the area around the jetty area or in the offshore platform area.

2.2.3. Time of operation
crew-boat with operational distance approximately 40 to 60 nautical miles every day. The daily operational time is 24 hours and the configurations are: 4.04% full speed, 13.63% economical speed, 1.81% slow speed, 7.65% snatching, 1.25% manoeuvre, 5.29% idle, and the remaining are in standby condition.
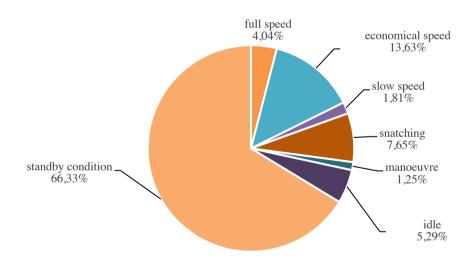
full speed
4,04%

economical speed
13,63%

slow speed
1,81%

snatching
7,65%

manoeuvre
1,25%

idle
5,29%

standby condition
66,33%

Figure 5. Pie chart distribution for operational condition time based generated from SHIMOS®.

2.3. Ship monitoring Vessel (SHIMOS®)
To get data on the results of vessel operations being reviewed, there is On-board data monitoring device inside the ship. SHIMOS® is product of development from Orela shipyard for monitoring vessel, and

used by PT. Pelayaran Nasional Ekalya Purnamasari. The data for the study are global positioning system (GPS) and fuel consumption from the main engine [10]. The equipment used to determine fuel consumption is a flow meter. Which will record the amount of fuel flowing towards the ship's engine. The flow meter data will be sent to the integrated. Data recording from system shown below:

- Id transmit
- Date & Time
- Position vessel (latitude and longitude)
- Speed (knot)
- Heading (degree)
- Rpm 1 (engine starboard) & Rpm 2 (engine portside)
- Flow meter 1 (liter) & Flow meter 1 (liter)
- Post Id

Based on the GPS receiver. Data parameters used in SHIMOS® are the position of the ship, the speed of the ship over the ground via GPS, the direction of the ship's course, also the engine rpm data is obtained from the ship engine panel on the engine speed sensor as shown in Figure 6.
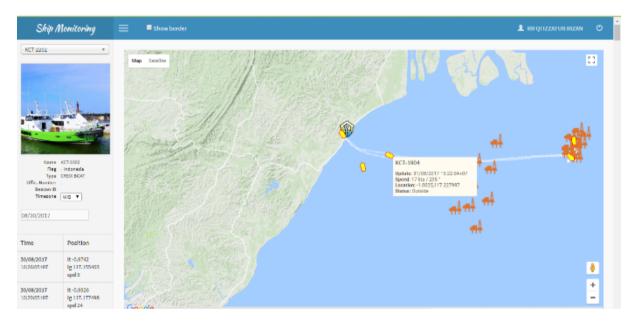

Figure. 6. Display tracking route and position from SHIMOS® [9]

3. Artificial neural network

Artificial Neural Network (ANN) is a method to process with performance characteristics of biological neural network. The component is input neuron which is grouped in layers with connected by weighted [11]. The NN model that is used in this study is shown in Figure 7. This method based on the back-propagation learning algorithm that is applied with n- hidden layer, n-weighted and activation function with bipolar sigmoid function-tanh hyperbolic function. That describe receive input from neuron I_1, I_2, I_n. Each neuron input is connected to neuron in hidden layer and connected to bias unit, then continue with connecting to the second hidden layer and the n-th hidden layer.
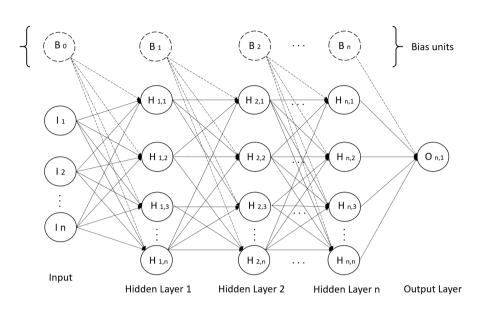
Figure.7 Schema of Neural Network with n hidden layers and n Neuron.

This study uses sigmoid for activation function. 2/3 of the data was uses for training network and 1/3 for testing final network. There were three main steps as outlined below:

3.1. Parameter Selection
The key to neural networks is that determined primarily by combination of the number of neural and hidden layers. As we knew in the iteration process that with more neurons and hidden layers it will take quite a long time but not sure can yield better results because it depends on the case characterization. The neural network variable that were used in this study are shown in Table 2.

Table 2. Parameter selection of Neural Network

Parameter Selection	
Parameter	Value
Number of epoch (iteration)	1000
Goal	0.001
Performance evaluation	mean square error
Training algorithm	scale conjugate gradient

3.2. Training & Validation
The training process in the back-propagation algorithm is supervised learning with the value of the conjugate gradient scale, which is between 0 and 1. Modelling the given function by modifying the internal weight of the input signal to produce the expected output shaft power. The system is trained using supervised learning methods, where errors between system outputs and expected outputs are known to be presented to the system and used to modify the internal state of the weight, neurons, and hidden layers. This process will repeat itself according to iteration by updating the weight, neurons and hidden layers based on the conjugate gradient until the expected error criteria is obtained.

In the validation process in order to obtain the results that are responsible for the results of the training that has been done and also so that iteration time is also efficient, the goal error is 0.001 and the

maximum iteration is 1000. During the validation process, the priority is the error value to the specified limit so that the iteration is stopped.

3.3. Testing
The next stage is testing the results of the training. And testing is not carried out as a training process. The testing process carried out directly on the network and there is no back propagation and iteration process.

4. Data Description

The data used for neural network training in this research uses 3 sister ships with the same design between 31 December 2016 to 5 March 2020. In accordance with the explanation in section 2.3 that data recording is done every 2 minutes. With the operational pattern of the crew boat in accordance with the explanation and configuration in accordance with the time operation. The total data obtained for each ship is 834,040 points, so the total data for 3 vessels is 2,502,120 points.

Training data for used to estimation of shaft power in kilowatts [12] [13] distribute to water jet of vessel. Torque data from full load performance curve engine conversion. Shaft power is product of Shaft Torque (T_{tq}) in torque (T), phi, and RPM (n) of the engine, is shown below:

$$P_{eff} = \frac{T_{tq} \,.\pi.n}{30} \qquad (1)$$

In this study the configuration of engine and water jet propulsion is direct connected. Gearbox to reduce RPM of engine include in package or water jet [14]. Shaft power is method to measure power engine transmit to water jet via shaft.
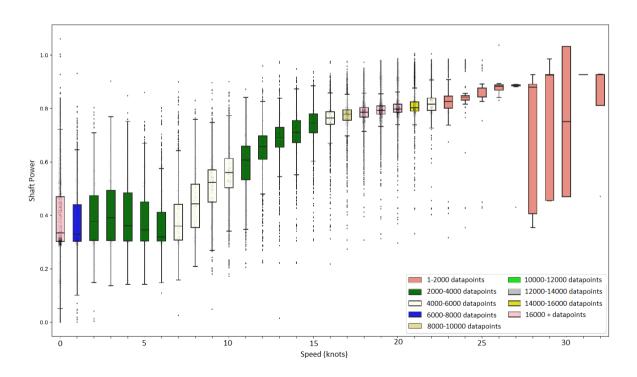

Figure 8. Box plot plotting at every recorded value of shaft power in scale at recorded speed.

Raw data shown with boxplot method is shown in Figure 8. The choice of using a boxplot is because in this method there are items that can show data characteristics. Namely outliers, upper extreme, upper

whisker, upper fourth, median, lower fourth, lower whisker, and lower extreme. This method divides the sorted data into 4 quartiles. The lowest value of the lower quartile (first quartile) is defined as the lower box boundary and the upper limit is the upper quartile (third quartile), in which there are parameters of the amount of data and the value of the quartile (second quartile) or median. The data used as the bottom outliner are 1.5 from the first quartile and the top outliner is 1.5 from the third quartile [15].

From the boxplot image, the highest data point value is obtained when the speed is 0 knots while the least data is the speed of 27 knots and above. The highest data point's value speed is 0 knot, second at range speed 18 knots to 20 knots, third is 21 knots which is the operational speed. Another speed range that is often used at speeds of 7 knots to 10 knots. While at speeds above 28 knots and above there are unstable results, as seen from the variation of the shaft power varies greatly. For 0 knot with the most data points because the effect of snatching.

The data selected to obtain the shaft power characteristics of the studied crew boat, displayed using a box plot. In Figure 8 there are uncommon things when compared to the speed chart that is planned in the design or sea trial. These unusual values include speeds of 0 knot and over speeds of 28 knots. It is seen at 0 knot that there is an indication of shaft power with a scale from 0 to 0.8, this is due to effect of the Snatching condition or boat landing operating patterns. Whereas, when the speed is above 28 knots there is an inconsistency in the shaft power. The engine power trend has reached 0.2. This phenomenon is due to the effect of the ship rolling acceleration, so that the speed increases, while from the operational decreases the engine power. The data that are used in this study for neural network training are the range of speeds from 1 knot to 27 knots, meanwhile for speed 0 knot the value of shaft power is zero. Finally, the total data used for neural network proses after filtering from 2,502,120 is 42,686 data. Data from Shimos® system process for ANN is speed (knot), post ID, heading, and rpm.
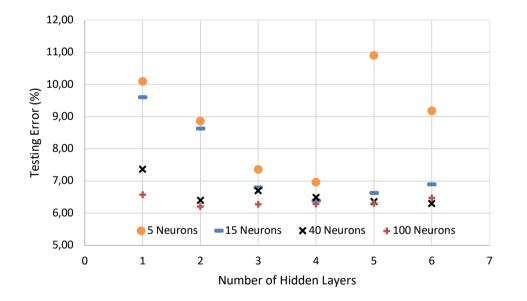

Figure 9. Hidden layers with testing error in percentage with variation of neurons plotting.

5. Neural network process

5. 1. Numbers of neurons

To obtain optimal results, this study does some variations of the initial neurons with 5, 15, 40, and 100 neurons. In accordance with Figure 9, it is found that with the smallest neuron that is 5 the maximum testing error results was 10.9% and a minimum was 6.93%. At 100 neurons, the maximum error result

was 6.58% and the smallest was 6.20%. However, in the process of getting these results requires quite a long time. In general, neurons 40 have a 6.3% error. Comparison of calculation time when compared with neurons 40 and 100, the most optimal is 40. The time needed is 2.5 times and the difference in error is only 0.1%. There are quite surprising results, namely in neurons 5 with hidden layers 5 and 6, the trend of results away from other neurons.

5. 2. Numbers of hidden layer
The performance of neural networks also depends on the hidden layer, which also produces weights result of its output. Simulation optimization of hidden layers combined with neurons. In accordance with Table 3. The results of the optimization depend on existing data. It is not necessarily the same when compared with other data. The simulation consists of hidden layer 1 in sequence up to 6 and combined with neurons 1, 50, and 100. In process, some data is used as training and part is used as testing in accordance with the previous explanation.

Table 3. Table shown test and training error with various layers and neurons

Layers	Neurons	Training Error (%)	Testing Error (%)
1	1	67.47	67.39
1	50	8.71	8.71
2	1	14.93	14.89
2	50	6.59	6.55
3	1	32.79	32.80
3	50	6.32	6.27
4	50	6.35	6.30
4	100	6.38	6.33
5	50	6.35	6.30
5	100	6.41	6.36
6	50	6.36	6.31
6	100	6.35	6.30

The highest value of training error occurs when hidden layer 1 and neuron 1 is 67.47%. Whereas the highest hidden layer is 6 with 100 neurons which is 6.35%. Overall, the smallest error training results were 6.32% occurred in hidden layers 3 and neurons 50. Although in hidden layers 6 and neurons 100 the difference was only 0.03% but it took a long time. The simulation results when compared with Figure 9 there is a similarity that is the lowest in hidden layers 2 neurons 100 has a smaller difference of 0.1%.

The results of the simulation in Table 3 are made into Figures 10 to 13. The subject used to investigate is the speed and direction of the ship against the shaft power and the trend of these results are observed.

The next stage, the simulation with graph output is made after knowing in the Table 3 that the consistency value found in the 50th neurons, the simulation of 40 neurons with number hidden layer variations are 1, 2, 3, and 4.

Figure 10 is the result of neural network training with hidden layer 1 and neuron 1. According to table 3, the training error is 67.47%. In the picture graph the speed and shaft power if it matches the reference [16] [17] [18] then at speeds of 0 knots to 7 knots is equal to Froude number 0.5, it looks incompatible with the general rules of displacement ships. The slope of the graph line at the beginning of the angle is very high when compared to displacement vessels that tend to be gentle.
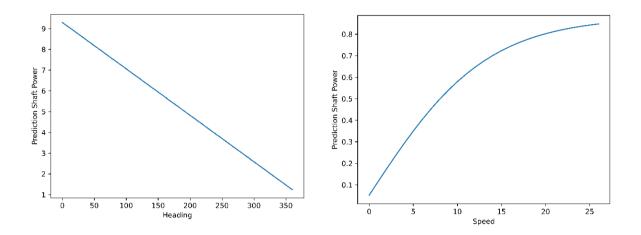
Figure 10. Simulation with 1 hidden Layer and 1 Neuron (heading and speed).

The Neural Network results with the process of 3 hidden layers and 40 neurons producing the configuration output heading and speeds shown in Figure 11. In the prediction chart of heading for speed simulation, there are random patterns cannot be used as a reference. This happens because the external factors affect crew boat operations have not been properly monitored. The simulation of shaft power with speed, describe quite similar to the previous simulation. In 5 knots graph speed that occurs horizontally, which then rises polynomial to the speed of 27 knots.
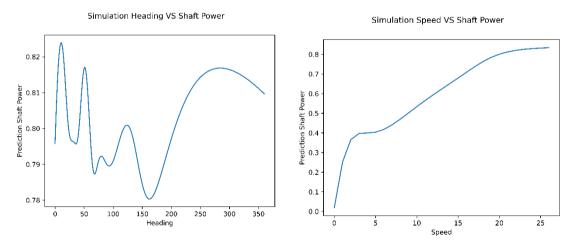

Figure 11. Simulation 3 hidden layers and 40 neurons (heading and speed).

In the simulation with 4 hidden layers and 40 neurons according to Figure 12, the heading chart with shaft power found that the highest movement is in the range of 10 ° to 30 ° and above 300 °. At a heading between 50° to 200° whereas the speed and shaft power graphs are similar to a graph with 3 hidden layers. From the speed of 0 knots to 3 knots, have a sharp slope / high gradient. Therefore, in general, to get the speed of 3 knots 40% shaft power is required. After that, the sloping graph decreases from 3 knots to 7 knots. Whereas at 7 knots and above the graph rises to a speed of 27 knots with a polynomial pattern.
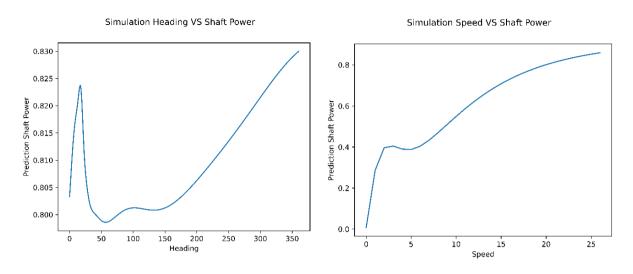
Figure 12. Simulation 4 hidden layers and 40 neurons (heading and speed).

In accordance with Figure 13.a, the plotting graph for hidden layers 2 with variations of neurons 2, 8, 25, and 60. In this figure, we can find out when the neurons 2 and 8 have similar graphs. The 2 neurons have quite different characters at speeds above 20 knots and above, whereas at 8 neurons at speeds below 4 knots there are differences. For neurons 25 and 60 the curve has almost the same trend and almost coincide with the graph, but at low speeds below 5 knots there is a difference in neurons 60 whose value is lower than neuron 25 for the value of the shaft power.

The same thing in Figure 13.b, neurons 2 and 4 have similar characteristics. The curve is parabolic, but neuron 2 has higher shaft power and at speeds above 20 knots the shaft power is lower. While neurons 25 and 60 have the same curve, there are differences in neurons 25 whose values are slightly higher than neurons 60.
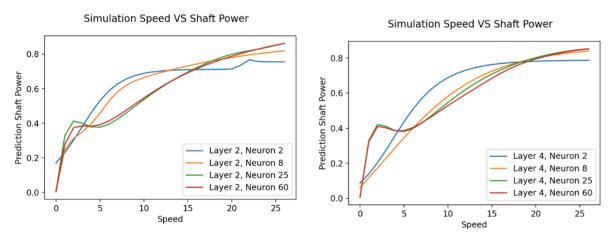

Figure 13. Simulation with range of neurons (Layer 2 and Layer 4).

From some simulations with variations above, we get 4 neurons and 40 hidden layers that we choose based on low errors and the simulation time is not too long. Seen in figure 14.a with neurons 40 and hidden layer variations from 1 to 7. Seen in the hidden layer above 2 have similar graphs. However, it appears hidden layer 4 has the optimal character of the error value 6.20% and simulation time. Thus, from 4 hidden layers and 40 neurons we compare them with linear regression of the data used in the

neural network process. It can be seen that in the regression results have not been able to preset exactly from existing data.
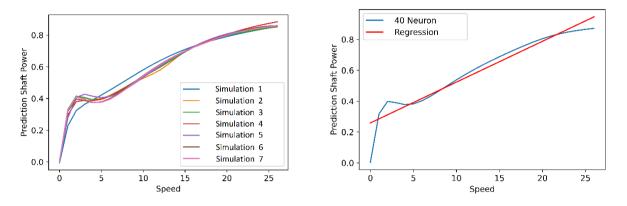

Figure 14. Simulation shaft power with 1-7 hidden layer with neuron 40 and simulation with range of 4 hidden layers 40 neurons with regression.

To get a comparison between the results of the simulation of neural network 4 hidden layers and 40 neutrons with data as much as 70% of the available data which we then compare in general with the histogram data in Figure 15 which is the overall data available. Obtained identical results so that the simulation results are reliable. At speeds of 0 knots to 3 knots there is accumulation of data that results in a drastic increase in simulation, which then decreases at 5 knots, continues up to a maximum of 20 knots, and tends to stagnate to 27 knots. Generally identical with operational frequency density.
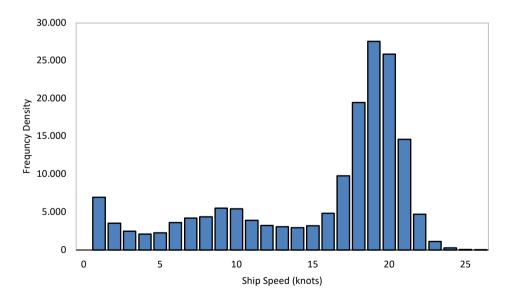

Figure 15. Frequency density of speed used in operational

6. Discussion & Conclusion

Improving cost efficiency is very important and is the main priority of operational costs. The contribution of fuel costs to direct expenses is around 8.79% according to general data [20]. To optimise these costs, what needs to be considered is the character of the existing operational patterns. These

components consist of selecting the ship and the transportation system, the route of the ship, the rules of operation, and the skills of the ship operator. External forces that influence and impact on crew boat operations need to be paired so that the analysis can be obtained thoroughly by installing motion sensors [21] and wind clippers.

By completing the ship with tools to monitor the ship itself, operational patterns or characters can be obtained. The noon report which is carried out every 2 minutes given 24 hours in this study is very helpful in getting accurate results to be examined. However, from the existing data before it is processed, a filter that is according to the existing conditions, according to the existing filter data, is 8.32% used. This happens because in actual operations there are times the ship is not operational due to the ship's shift schedule, maintenance, and routes.

In the process of analysis simulations with Neural Networks using shaft power prediction as the target. In the simulation, hidden layer and neuron variations are performed so that the most optimal is obtained with 4 hidden layers and 40 neurons, including testing with available data. The results of the simulation are compared with the regression and frequency density of the speed used. In general, the results of the neural network are as expected.

The results of this study are also compared with studies using neural network methods as in table 4. In the study conducted by Parker the amount of data used was around 10% of the available data and had a 7.8% relative error. By previously filtering data that affects the shaft power. However, from sheet data with different ship types and the operational patterns of the ship will give a different relative error character. Therefore, from this comparative picture we can get that according to logic.

Table 4. Comparison of variation data sheet with other data sheet used Neural Network application.

	Quantity data	Frequency	Coefficient of variation		Network Size	Relative Error (%)
			Ship Speed	Powering		
Crew Boat Data sheet	208,116	2 min	1	0.01	4L / 40N	6.2
Pederson and Larsen [19]	679	10 min	0.006	0.001	1L / 5-10N	2.7
Bal Besikci et al [20]	233	24 h		0.26	1L / 12N	6
Parkers et al [8]	45,983	5 min	0.3	0.59	3L / 50N	7.8

Ideally, it can be compared with the results of towing tests, CFD, or with sea trials so that you will get complete validation. Also, the existing data should also be given a response from existing conditions. In accordance with the results of the simulation with a neural network with back propagation with 4 hidden layers and 40 neurons ultimately has the prediction results of shaft power with an accuracy of 6.2%. Of course, with these conditions can provide input on operating patterns or provide power margins in accordance with operational conditions that described above.

7. Acknowledgments

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