Ship Fuel Consumption Prediction with Machine Learning

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Abstract

Like every sector, the maritime sector also has problems and needs to be solved within itself. Fuel consumption on ships and reduction of emissions are the most important expenses for shipping. In addition to IMO, states and other international organizations work on decreasing the fuel consumption on ships and reducing the amount of harmful gases emitted from ships on the one hand, by putting various rules and audits on to solve these two problems.

In order to reduce fuel consumption on the ships, maritime companies are working essentially to determine the fuel used during the voyage. Various methods have been proposed in the past. In this study, artificial intelligence methods were used to estimate the fuel spent by the ship during the voyage. At first, noon report which is vessel data was taken from a commercial ship. The data in this report were analyzed and divided into two parts as training and test data. Some of the data were taught to the computer as a training data. It was then asked to estimate the non-taught part by using multiple linear regression method from the computer. Finally, this prediction made by machine learning are compared with real data on a graph and the success of the estimation has examined.

Keywords: Maritime, fuel-consumption, machine learning, multiple linear regression

1. INTRODUCTION

Recently, the fuel saving applications for ships has been increasingly addressed by IMO (International Maritime Organization) and other international societies. The IMO consented upon the objective of reduce the sector's total gas emissions by at least 50% as part of a continuing pathway of reduction by 2050. Especially, studies aiming to reduce emissions from the ships are important for the researches for these reasons [1, 2].

The maritime sector is also affected by oil prices, like all other industrial sectors. Fuel costs for the maritime industry are the most important expenditure item. Each sector is looking for ways to increase fuel efficiency by making innovation moves in itself due to the high fuel prices. The fuel consumptions of the vessels are controlled by daily noon reports during voyage and via survey companies perform this service on behalf of the shipping agencies. The maritime industry is focused on the fuel efficiency through methods such as waste heat recovery, load optimization, maintenance and efficient ship hull design [3]. In addition to all these methods, fuel consumption prediction applications are also very important to optimize the conditions. The fuel consumption estimations in vessels are difficult to process because of variable operational and environmental conditions as well as the operation of power and drive systems [4].

In the last decade, fuel saving methods has been proposed for prediction ship energy efficiency. In one of these methods, the actual data from the reports related to fuel consumption were examined and the consumption forecasting was tried to achieve [5, 6]. There is also fuel consumption estimation has been made based on the weather forecasts of the vessels' voyage route [7] and accomplished by using Automatic Identification System (AIS) [8]. Even though there are many studies about this topic, generally internal and external factors such as, environmental conditions, wind, waves, currents, main engine rpm, ship speed etc. are neglected. The multiple linear regressions method can be used to find the relationship between multiple variables which are mentioned above. This method has proven its success by being used in various prediction applications. For instance, the multiple linear regressions could be used to find the relationship between the variables and especially the estimation of energy consumption [9, 10, 11].

In this paper, the actual voyage data obtained from the ship were examined and the internal and external factors that affect the fuel consumption of the ship were analyzed. In order to understand the effect of these elements on the fuel consumption of the vessel during the voyage, noon report was used. Then data were divided into two parts as training and test data. Finally, the data is taught to the computer using multiple-linear regression method. Based on this data, the artificial intelligence was asked to estimate the data stored as test data.

2. MATERIAL AND METHOD

Machine learning algorithms and data science have improved in recent years. In this study, fuel consumption values are estimated based on real voyage data for a vessel by using machine learning and data science. Firstly, the noon report (for 35 days of voyage) was taken from a commercial ship. These data are divided into two parts as random as test (1/3) and train (2/3) data. Equation 1 shows the multiple-linear regression method used for this study. The dependent variable is y. The independent variable is x. The coefficients are shown as b_i for i = 0 to n.

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \quad (1)$$

Table 1 and Table 2 show the randomly selected part (2/3) of data and used as the train data. Table 3 and Table 4 show data part (1/3) used as test data.

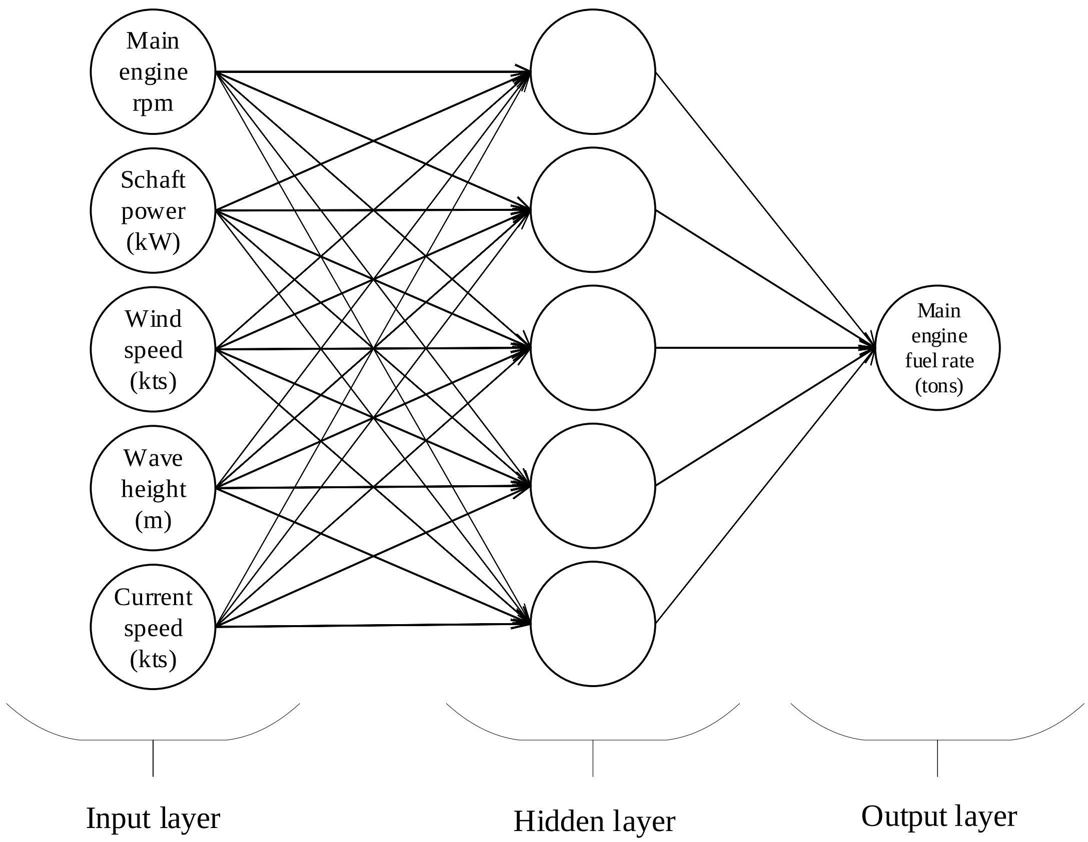

Figure 1: Fuel consumption estimation machine learning scheme

Table 1: Train data 1

Index day	Main engine (rpm)	Schaft power (kW)	Wind speed (kts)	Wave height (m)	Current speed (kts)
32	73.19	4302.17	21.9	1.5	0.405564
26	75.13	4235.38	21.9	2	0.811409
30	73.56	4014.71	21.9	2	0.201876
8	0	0	10.9	0	0
13	70.19	9824.72	6.9	0	0.200559
5	47.97	2134.75	16.9	0	0
17	71.44	3845.96	21.9	0	0.402248
34	0	0	6.9	1	0
31	74.01	4212.46	21.9	1.5	0.604309
24	73.28	4136.74	16.9	1	1.41422
1	39.06	817	10.9	1	0.602004
12	0	0	6.9	0	0
6	0	0	6.9	0	0
23	75.32	4440.17	21.9	2	1.71329
4	0	0	16.9	0	0
18	74.92	4366.54	16.9	0	0.504639
21	74.32	4290.17	16.9	2	0.303715

19	74.98	4511.46	27.9	2	0.807749
9	0	0	10.9	0	0
7	0	0	6.9	0	0
33	75.15	4458.76	16.9	1.5	0
3	72	3926.73	16.9	0	0.508077
0	69.65	3498.42	16.9	0	0.201473

Table 2: Train data 2

Index day	Main engine fuel rate (tons)
32	18.5
26	18.45
30	18.45
8	0
13	15.26
5	2.25
17	18.1
34	15.8
31	18.46
24	18.42
1	4.2
12	4.24
6	9.01
23	18.45
4	0.75
18	18.45
21	17.67
19	18.47
9	0
7	0
33	18.31
3	17.02
0	15.8

Table 3: Test data 1

Index day	Main engine (rpm)	Schaft power (kW)	Wind speed (kts)	Wave height (m)	Current speed (kts)
29	73.24	3999.42	21.9	2	0.100938
20	74.83	4404	27.9	2	0.303405
16	71.04	3763.54	16.9	0	0.702778
28	73.13	4211.21	16.9	2	0.710105
22	74.93	4443.63	27.9	2	0.806253
15	71.83	3624.42	33.9	0	0.811661
10	0	0	6.9	0	0

2	69.36	2227.04	21.9	0	0.304846
11	0	0	6.9	0	0
27	74.08	4304.04	27.9	2	0.201067
25	73.98	4186.21	16.9	2	1.01065
34	0	0	6.9	1	0

Table 4: Test data 2

Index day	Real fuel oil consumption (tons)
29	18.46
20	18.49
16	18.6
28	18.48
22	19.25
15	18.4
10	1.12
2	15.2
11	0.0
27	18.47
25	18.5
34	0.17

3. SIMULATION RESULTS

In this section, the voyage's day numbers and the data of that day were taught to computer in a random manner. Then, it was as asked to the computer to estimate test data. Table 5 shows the fuel consumption and actual consumption values estimated by the computer. Figure 2 shows the actual fuel consumption (blue) and the values that predicted (red) by the machine learning.

Table 5: Comparison between real fuel oil consumption with prediction data

Index day	Real fuel oil consumption (tons)	Predicted fuel oil consumption (tons)
29	18.46	17.94185934
20	18.49	17.94185934
16	18.6	15.3626487
28	18.48	18.42122925
22	19.25	18.75303289
15	18.4	15.34644149
10	1.12	1.5439226
2	15.2	14.27951698
11	0.0	1.5439226
27	18.47	18.18497189
25	18.5	18.74665971
34	0.17	2.81843676

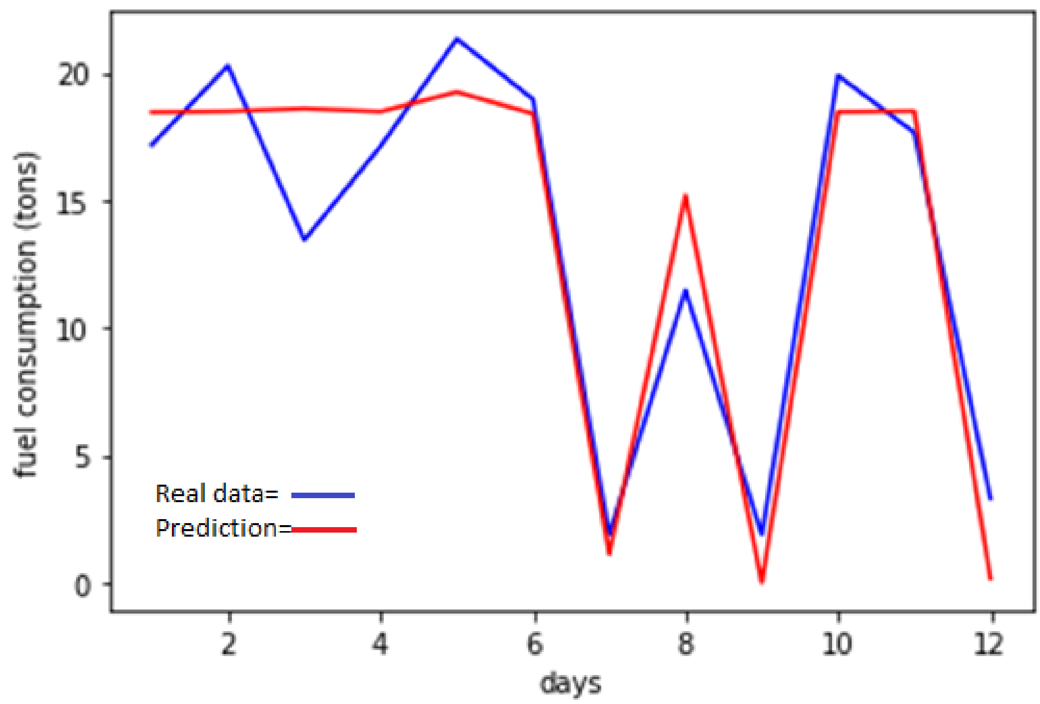

Figure 2: Real vs. predicted fuel oil consumption

4. CONCLUSION

In this study, a 23-day portion of the 35-day voyage data of a commercial ship was taught to the computer via machine learning. From the data learned, the computer estimated the 12-day portion that was not taught to him. The actual values and the computer predicted values are shown in Figure 2 in order to evaluate the success of this estimation process. The 12-day voyage portion of the chart was successfully estimated by the machine learning, even from just 23 days of data. As a result, estimation of the fuel consumption for a ship has been successfully carried out, taking into account internal factors and external factors. It should be kept in mind that the success rate of the estimates made by increasing the number of voyage days will increase.

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