BACHELOR THESIS & COLLOQUIUM – ME 184841

PREDICTION OF SHIP FUEL CONSUMPTION AT MV MERATUS WAINGAPU USING AUTOMATED MACHINE LEARNING

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DOUBLE DEGREE PROGRAM
DEPARTMENT OF MARINE ENGINEERING
FACULTY OF MARINE TECHNOLOGY
INSTITUT TEKNOLOGI SEPULUH NOPEMBER
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APPROVAL FORM

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BACHELOR THESIS

Submitted to Comply One of The Requirement to Obtain a Bachelor Engineering Degree

On
Digital Marine Operation and Maintenance (DMOM)
Bachelor Program Department of Marine Engineering
Faculty of Marine Technology
Institut Teknologi Sepuluh Nopember

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Sepuluh Nopember Institute of Technology

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AGUSTUS, 2020

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Bachelor Thesis Title	:	Prediction of Ship Fuel Consumption at MV Waingapu Using Automated Machine Learning
Department	:	Marine Engineering

If there is a plagiarism act in the future, I will fully responsible and receive the penalty given by ITS according to the regulation applied.

Surabaya, July 2020

Fernanda Rizqi Wijanarko

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ABSTRACT

Nowdays with the ship industry move towards digitalization, there is increasing number of automation and self monitoring in ship operation that allow the machine to analyze and diagnose issue. That's why, to increase the efficiency of shipping operation, the operation cost itself need to be forecast beforehand to support decision-making process. In this study, an accurate regression model for the fuel consumption of the main engine using automated machine learning was propose to find the most accurate way to estimate the fuel consumption. This method is done by data collecting, data cleaning, and data processing. The automation process is done by python library TPOT which is a Python Automated Machine Learning tool that optimizes machine learning pipelines using genetic programming The expected result in this thesis is the fuel prediciton model that generate the predicted value as close as posible to the real data. The analysis is done with data taken from MV. Meratus Waingapu deck log and engine room log. To measure how good the data perform RMSE (Root Mean Square Error) which is the standard deviation value of the residual (prediction errors). Beside that measurement, R-squared value also used, this value indicate a correlation coefficient between target and output values obtained from regression models. In this study, the best performing model is got from model with 4 feature which is: speed, engine load, displacement and sea condition with RMSE value of 127.05 which means that 68,2% of prediction error is within 127.05 ton and R-squared value of 0.845. the worst performing model is got from model using 1 feature which is sea condition with RMSE value of 326.93 and R-Squared value of -0.019.

Keywords: Machine Learning, Fuel Oil Consumption prediction

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PREDIKSI KONSUMSI BAHAN BAKAR KAPAL PADA KM MERATUS WAINGAPU DENGAN MENGGUNAKAN *AUTOMATED MACHINE LEARNING*

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ABSTRAK

Saat ini dengan industri kapal bergerak menuju era digitalisasi, dimana terdapat peningkatan jumlah otomatisasi dan *self-monitoring* dalam operasi kapal yang memungkinkan mesin untuk menganalisis dan mendiagnosis masalah. Karena itulah, untuk meningkatkan efisiensi operasi pengiriman, biaya operasi itu sendiri harus diramalkan sebelumnya untuk mendukung proses pengambilan keputusan. Dalam studi ini, model regresi yang akurat untuk konsumsi bahan bakar mesin utama menggunakan *automated machine learning* diusulkan untuk menemukan cara paling akurat untuk memperkirakan konsumsi bahan bakar. Metode ini dilakukan dengan pengumpulan data, pembersihan data, dan pengolahan data. Proses otomasi dilakukan dengan *python library* TPOT yang merupakan alat Python *Automated Machine Learning* yang mengoptimalkan *pipeline machine learning* menggunakan pemrograman genetik. Hasil yang diharapkan dalam tesis ini adalah model prediksi bahan bakar yang menghasilkan nilai prediksi sedekat mungkin dengan data sebenarnya. Analisis dilakukan dengan data yang diambil dari KM. Meratus Waingapu. Untuk mengukur seberapa baik data memprediksi konsumsi bahan bakar, *RMSE (Root Mean Square Error)* digunakan. RMSE merupakan nilai standar deviasi antara prediktor dan targetnya. Selain RMSE, nilai *R-squared* juga digunakan, nilai ini menunjukkan koefisien korelasi antara nilai target dan nilai sebenarnya yang diperoleh dari model regresi. Pada studi ini, model berperforma terbaik didapat dari model dengan 4 fitur yaitu: kecepatan, beban mesin, perpindahan dan kondisi laut dengan nilai RMSE 127.05 yang berarti 68,2% error prediksi berada pada kisaran 127.05 ton dan nilai *R-squared* 0,845. model berperforma terburuk didapat dari model menggunakan 1 fitur yaitu kondisi laut dengan nilai RMSE 326,93 dan nilai *R-Squared* -0,019.

Kata kunci: Machine Learning, prediksi konsumsi bahan bakar

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PREFACE

All praise to the Almighty God, for all his blessings, the author can start, work, finish this bachelor thesis.

For the author, this bachelor thesis represents an attempt to contribute to efforts in reducing fuel consumption. Nowadays, global warming and climate change have become a major issue that we face together. By predicting fuel consumption of the ship, author hope that it will also reducing not only the cost for shipping company, but also prolong planet sustainability for the next generation to come.

This thesis could not be completed without helps from others. The author would like to acknowledge people who helped and contributed in the process of this bachelor thesis completion, among others:

1. The author's beloved parents, for all their unconditional love, prayers, and supports.
2. Ir. Hari Prastowo, M.Sc., and Dr. Eng. Trika Pitana, S.T., M.Sc. as supervisors that have spent the time giving guidance and direction in this thesis completion.
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5. Mr. Idi Rambe and Mr. Muhammad Fahrudin, as the Fleet Division of PT. Meratus Line who helped the author to access shipping data..
6. Member of Digital Marine Operational and Maintenance Lab who always give advises and supports since the day one.
7. All Marine Engineering Students batch 2016 (Voyage 2016) for all their supports and advice.

The author hopes that the writing of the Final Project Proposal can be useful and provide information to the reader. Because of the limitations of the author, constructive criticisms and suggestions are indispensable for perfection in this report.

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CHAPTER I
INTRODUCTION

1.1 Background

The shipping industry is really important in this era of globalization. The ship in shipping industry ship food and all sort of technologies maritime transport, a vector of globalisation, Nowdays, shipping industry become the types of transportation that hace the lowest price compared to other type of transportation. Allowing for economies of scale and low cost of transportation, shipping industry has become the flagship mode given it can transport over long distancet and has he large capacity of either cargo and passanger. (Corbett & Winebrake, 2008)

The maritime sector is heavily affected by the price of oil and where most of the ship owner money spent in the ship operation (World Shipping Council, 2008). That's why, the most important expenditure item cost in shipping industry is fuel and in today market, the competitiveness of the maritime business is getting tigther making the profit margin is lower for the ship owner. So in order to get profit ship owner need to increase the volume of sales and increasing the efficiency of ship operation to cutting the cost of each trip. In order to reduce the cost and fuel consumption, the fuel used estimation can be one of the solution. With fuel estimation, the ship owner can decide and sort out which voyage is the most profitable. this also can help with decision making and adjustment for the ship master and crew during the operation.

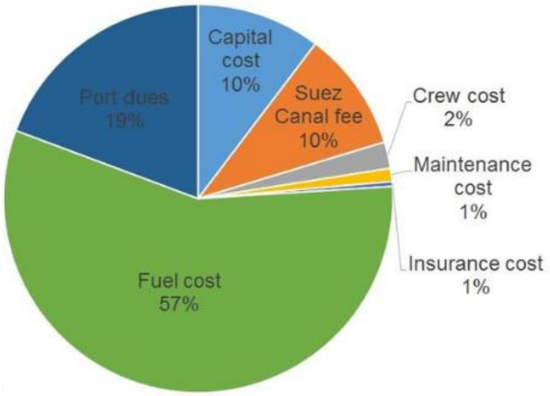

Figure 1.1: Ship Operating Cost

Source: (Furuichi et al, 2015)

To help ship owner estimate the ship fuel, nowdays the data that acquired form the ship can be processed by adaptive system called machine learning (Becchi, 2019) . Effective ship operation management for engine monitoring, route optimization and ship diagnosing and decision making based on the data can be manage using machine learning. Data analysis of ship performance monitoring has been broadened so that it will improve the ship operation efficiency from the connection with ship and maritime data (Jeon, Noh, Jeon, Lee, & Lee, 2019). In this study, machine learning will be use to create model for predicting ship's fuel oil consumption to make accurate prediction of ship performance

which will reduce ship fuel consumption and maximizing the fuel efficiency. This prediction is done by performing big data analysis towards the ship and its data.
To increase the efficiency of shipping operation, the operation decision itself need to be forecast beforehand. This forecasting process is important as a guidance of the ship operation by providing a support for decision-making process for the ship owner but to execute this process, a lot of data is needed to acquire a significant accuracy. This data processing is the problem right now, where according to article by NASA researcher, the increase of data in term of volume, velocity and variety causing the data to be difficult and nearly impossible to process using traditional method and was becoming an issue for computer systems at that time (Elsworth, 1997).
Machine learning used various statistical methods such as linear regression, logistic regression, K-neares neighbor, etc. this statistical method is used in all data processing step of machine learning. This data processing include preprocessing and post processing. Data preprocessing includes removing missing value, removing outlier and scaling, whereas data post-processing includes data expansion, data regeneration, and integration verification.data regeneration. In order to achieve the desired accuracy, combining and and tweak them in any way that would work for a set of problems is needed.

1.2 Problem Statement

Based from the background, the problem that will be discussed in this study are:
1. how the model from automated machine learning perform?
2. what variable are significant in determining the fuel usage at the ship?
3. which of the statistical method that will yield the least error in predicting the ship fuel consumption?

1.3 Aim and Objectives

The aim of this study are:
1. To know how the model from automated machine learning perform
2. To know which variable is more significant than others to predict ship fuel consumption
3. To know which statistical method is the most suitable machine learning tools that optimize ship operational effectiveness and performance.

1.4 Benefit

The benefit of this study are:
1. The model of this machine learning can be further improve by having real ship data as the input which mean the data that is used is real time data of the ship.
2. Can be used as a scientific reference about ship operation efficiency and ship fuel estimation.

1.5 Scope and Limitation

The scope and limitation of this bachelor thesis are:

1. Prediction of the ship fuel consumption is done with machine learning algorithm using python programming language.
2. there is limitation of minimum and maximum value of data that can be predicted based on the given data
3. Data that is used in this research come from ship log.

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CHAPTER II
LITERATURE REVIEW

2.1 Ship Fuel Consumption

Nowdays, most trade ships run on either Heavy Fuel Oil (HFO) or Marine Diesel Oil (MDO). Average consumption depends on the ship's type & engine power(and therefore speed), as well as their size. Ship fuel consumption is a function of both propulsion and non-propulsion (auxiliary) power. Some of these function are; function such as size, speed, weight, draft, resistance, etc. all these correlation is not linear. It is well known that a ship's fuel consumption generally increases with speed squared. In passage operation, the propulsion power is the dominant one and about 80% of commercial cargo ship's fuel consumption is due to the need for propulsion (IMO Train the Trainer (TTT) Course, 2016). The estimation formula of these function are:

$$Propulsive\ power\ \approx (ship\ speed)^3$$

$$Fuel\ consumption\ \approx (ship\ speed)^3$$

$$Fuel\ consumption\ per\ nautical\ mile\ \approx (ship\ speed)^2$$

2.3 Machine Learning

Machine learning is a subset of AI technique which use statistical methods to enable machines to improve with experience and make data driven decision to carry out certain task. This alogarithm program in a certain way that they can learn and improve overtime when expose to new data (Cakmak & Das, 2018). Machine learning algorithms can figure out how to perform important tasks by generalizing from examples Unlike a system that performs a task by following explicit rules, a machine learning system learns from experience. Whereas a rule-based system will perform a task the same way every time (for better or worse), the performance of a machine learning system can be improved through training, by exposing the algorithm to more data. However, there is more than one types of machine learning seen form how the machine learn, which is supervised learning and unsupervised learning.

2.3.1 supervise learning

As the name suggests, the learning process is supervised based on a specified target/outcome. The objective of supervised ML models is to learn and discover the patterns that can correctly predict the outcome. In case of supervised learning, there is always a labeled historical dataset with a target attribute. All attributes other than the target are termed as predictors/features.

2.3.2 unsupervised learning

In the case of unsupervised learning, there is no target attribute. The objective of unsupervised learning is to identify patterns by deducing structures and the relations of the features in the input dataset. It can be used to discover rules that collectively define a group, such as topic generation, partitioning—such as customer segmentation or determining the internal structure of the data such as gene clustering. Examples of unsupervised learning algorithms include association rule mining and clustering algorithms.

2.4 Statistical Method

2.4.1 Linear Regression

Is the traditional and most-used regression analysis. A linear regression is a linear approximation of a cause; relationship between two or more variables. The term linear suggests there is a fundamental assumption that the underlying data exhibits a linear relationship (Géron, 2019). Regression models are highly valuable as they are one of the most common ways to make inferences and predictions. The process for this regression is to get a sample data then design a model that work for that sample to make predictions for the whole population.
This method is used when the goal is to either predict or forecast and used to build a predictive model to a recognized dataset of dependent and independent values. Beside that if the goal of the model is to determine the strength of each relationship between the predictor and target variables, it can be applied to quantify the change in *Y* for a given value of *X*. the basic formula of linear regression is:

$$Y = F\ (\ x1,\ x2,\ \ldots.,\ xn)$$

In which: Y = Dependent variable or the predicted

X = Independent variable or the predictors

The dependent variable y is a function of the independent variable x

Essentially, linear regression is the "best guess" at using a set of data to make some kind of prediction. It's fitting a set of points to a graph.

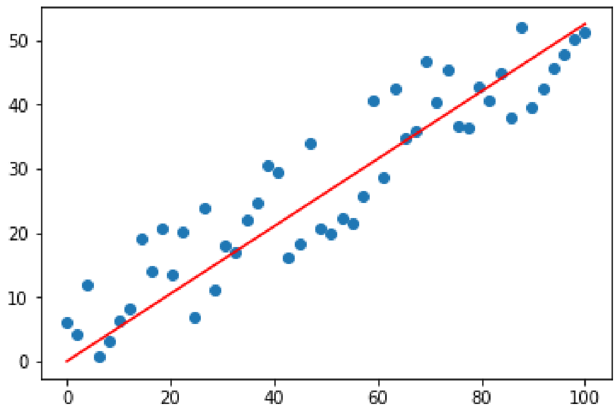


Figure 2.1 Simple linear regression scatter plot

Source: (https://gilberttanner.com/)

The simplest regression model is simple linear regression model as it involves only one predictor (x) and one target (y). with the formula:

$$y = \beta 0 + \beta 1 x 1$$

In which: y = dependent variable

x = independent variable

β = coefficient or the slope of line

$\beta 0$ = constant or the intercept of the best-fit regression line.

Another regression model is multiple linear regression. This regression is address the higher complexity problem compared to simple linear regression. The population model for this regression are:

$$y = \beta 0 + \beta 1 x 1 + \beta 2 x 2 + \cdots + \beta n x n$$

2.4.2 Ordinary Least Squares (OLS)

OLS is the most common method to estimate the linear regression equation and to find the best fit line. Least square stand for minimum squares error (SSE). This method aims to find the line which minimizes the sum of the squared errors, the OLS determines the one with the smallest error (Kenney, 1962). Graphically it is the one closest to all point simultaneously. The formula of the OLS estimator is:

$$OLS = (y - xb)^T (y - xb)$$

Where: T = denotes the matrix transpose

x = independent variables

y = dependent variables

However, this simplicity that this method have comes with a restriction. This restriction that OLS method have is adhering to its several fundamental assumptions. All of these assumptions about the data should hold true to reap the benefits of the OLS regression techniques:

- Linearity: assumes linearity, the true underlying relationship between X and Y is linear.
- No endogeneity: mathematically this is expressed as the covariance of the eror and the x is zero for any error or x.
- Homoscedastic: The variance of residuals must be constant. The residual is the difference between the observed value and predictive value of the target.
- Normality: The residuals/errors should be normally distributed.

- No or little multicollinearity: two or more variable have high correlation between each other.

2.4.3 Scaling

Scaling is a term for standardization in machine learning. these techniques is use so that the numerical features used in the model are weighted equally. this ensure that all the machine learning algotrihm doesnt prioritize on feature higher than others because of the numerical value of the feature (Cakmak & Das, 2018).
the technique that used for this standardization is Z- score standardization, the data is rescaled with a mean of zero and standard deviation of one The formula for this standardization is:

$$Z = \frac{X - X0}{\sigma}$$

Where: z = standaritation score

X = independent variable

$X0$ = mean of the value

σ = standard deviation

2.4.4 Log Transformation

This statical method helps meet the assumptions of linear regression models in a way that it decrease the spreadness and skeness of the distribution model. Several types of Log transformation are log transformation, log-log transformation and square root transformation (Cakmak & Das, 2018).
For each observation and the dependent variable, calculate its natural log and then create a regression between the log Y and the independent X. For example in linear regression where the formula is $y = \beta 0 + \beta 1 x 1$ as X is increases by 1 unit, y also increase by 1, when log transform is used on the model, it become log $y = \beta 0 + \beta 1 (log x 1)$, which means that as X increases by 1 percent, y also increases by 1 percent.

2.4.5 Logistic regression

Is a classification technique that instead predicting the value, it predicting probability of an occurrence and it used to model the probability of a certain class or event existing such as fail/pass , on/off, dead/alive or sick/healthy (Bonaccorso, 2017). Logistic regression is applied in the case of discrete target variables such as binary responses. In such scenarios, some of the assumptions of linear regression, such as target attribute and features, don't follow a linear relationship, the residuals might not be normally distributed, or the error terms are heteroscedastic.

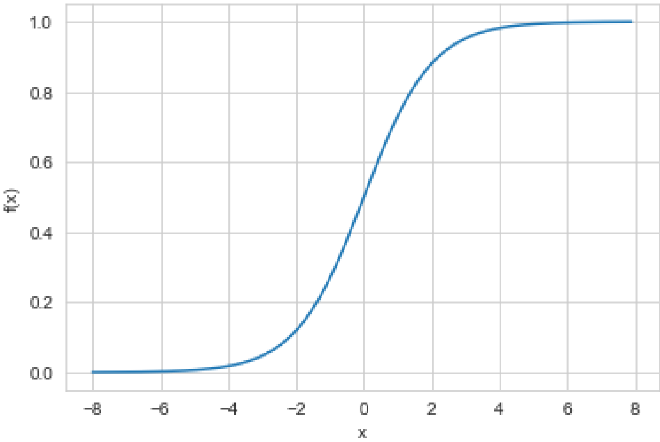


Figure 2. 2 Logistic regression graph

Source: (https://towardsdatascience.com)

This probability of occurrence goes between 0 and 1 so there is no infinite stretching line because there is some threshold passed some point. This is done by sigmoid function to get a probabilistic class value;

$$p = \frac{1}{1+e^{-(b0+b1x)}}$$

Where: p = probability

b = dependent variable

x = independent variable

2.4.6 K-Nearest Neighbors

It is a statical method that can make predictions using the training dataset directly.It predict new data besd on distance similarity measure to apply this method, first the number of K neighbors need to be choosen then take the KNN value of the new data point according to Euclidean distance. After that count the number of data points in each category. Next, assign the new data point to the category where you counted the most neighbors. Euclidean distance is calculated as the square root of the sum of the squared differences between two points (Altman, 1991).

$$Euclidean\ Distance = \sqrt{}sum((xi - yi)^2)$$

Where: Xi = Difference between Xn and Xn-1

Yi = Difference between Yn and Yn-1

This method is use to solve classification problems. This problem include, identifying which data set belong to which category when a new observation is done. to determine this, KNN use the the data set that have been trained and its category.

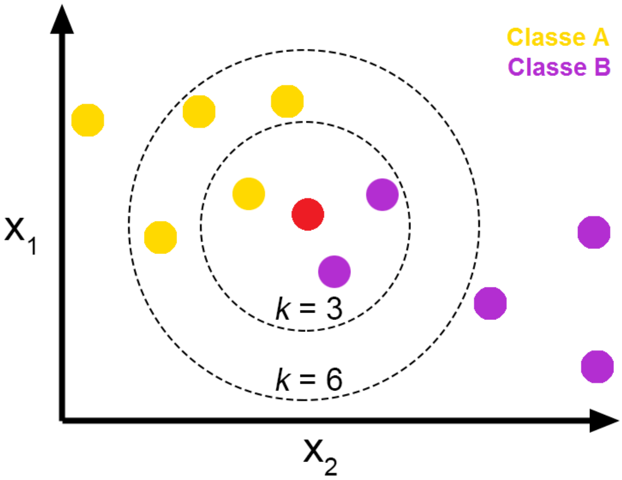


Figure 2. 3 KNN graph

Source: (https://medium.com)

2.4.7 K-fold Cross Validation

Cross-validation is a re-examine process that is used to evaluate a model in machine learning on limited data sample. This process has a single parameter which is “K” that refers to the number of how many the data sample will be split into K-fold Cross validation is use to fix the variance problem form the model after the data set is split into training set and test set. This method fix the problem by splitting the training set into K “folds” of equal size and then train the model K-1 times after that its tested on the remaining fold. The model performance accuracy is taken based on the average of different accuracies (Brownlee, 2019).

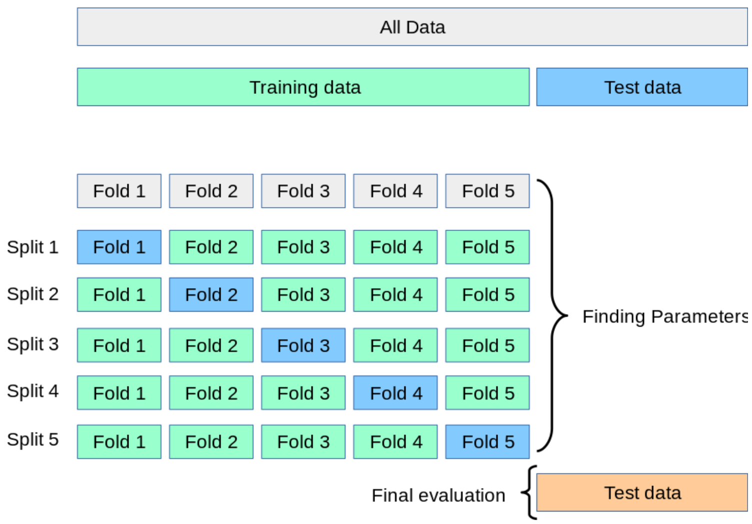


Figure 2. 4 K-fold Cross Validation Process

Source : Scikit-Learn.org

2.4.8 Principal Component Analysis

Principal Component Analysis (PCA) transforms the data in the high-dimensional space to a space of fewer dimensions. This method reduce the dimensionality of the data that make it possible to identify correlations and patterns in a data set so that it can be transformed into a data set of significantly lower feature without the loss of any significant information. PCA also provides an efficient way to reduce the dimensionality by forming various principal components that explain the variability of the data in a reduced dimensional space (Cakmak & Das, 2018).

2.4.9 R-squared

R-squared is a statistical measure of how imminent the data are to the fitted regression line. is a metric that is often interpreted as the proportion of variation in the target that is predictable or explained by the model. It is a number that can go from 1 for a model that explains 100% of the variation in the target, to 0 (a model that just predicts the average), and it can get even worse, although a negative R^2 would indicate that the model is so bad that it would be better just to always predict the average.. (Fuentes, 2018)

$$R^2 = \frac{SS\ res}{SStot}$$

Where: SSres = Explained variation

SSTot = Total variation

R-squared is always between 0 and 1. 0 indicates that the model explains none of the variability. 1 indicates that the model explains all the variability of the predictable data.

2.4.10 Lasso Regression

The Lasso Regression this is a method for regularization and for avoiding overfitting.

$$\textit{the sum of squared residuals} + \lambda|\text{slope}|$$

Here, the term $\lambda|\text{slope}|$ is a shrinkage penalty for the Lasso regression. The Lasso regression penalty term, using the absolute value forces some coefficients to be exactly equal to zero, if λ is large enough. In practice, Lasso automatically performs a real selection of variables (Ciaburro, 2018).

2.4.11 Ridge Regression

Ridge regression is very similar to least squares, except that the Ridge coefficients are estimated by minimizing a slightly different quantity. In particular, the Ridge regression coefficients β are the values that minimize the following quantity:

$$\textit{the sum of squared residuals} + \lambda(\text{slope})^2$$

Here, the term $\lambda(\text{slope})^2$ is a shrinkage penalty for the ridge regression. Small positive values of λ improve the conditioning of the problem and reduce the variance of the estimates. While biased, the reduced variance of Ridge estimates often result in a smaller mean square error when compared to least squares estimates (Ciaburro, 2018).

2.4.12 Elastic net Regression

Elastic net regression combines the strengths of lasso and ridge regression now the formula will be:

$$\textit{the sum of squared residuals} + \lambda|\text{slope}| + \lambda(\text{slope})^2$$

Here, the regression combine the penalty from both ridge regression and lasso regression. This kind of regression is use when there is model with a lot of variables.

2.4.13 Random Forest Regression

In random forest regression, multiple decision tree is used. This is done because one decision tree have a tendency to overfit, especially if we don't set limits on how far they can grow. this overfitting issue can bee addresed with a random forest, which is a bagging algorithm where we train many decision trees in parallel using bootstrap samples of input data and aggregate the output (Molin, 2019).

2.4.14 Gradient Boosting Regression

Gradient boosting build an ensemble trees regression in sequence with each tree improving and learning on the previous one. The main idea of gradient boosting is to add new models to the model sequentially so the model can improve its prediction each time a tree regression is added (Boehmke & Greenwell, 2020).

$$Fm(x) = Fm - 1(x) + v \sum_{j=}^{Jm} \gamma jmI(x \in Rjm)$$

Where: $F_{m-1}(X)$ = previous prediction

v = learning rate

$\sum_{j=}^{Jm} \gamma jmI(x \in Rjm)$ = output value from the tree

2.4.15 K-Neighbor Regressor

it's one of the simplest classification methods because the classification is done by just looking at the K-closest examples in the training set (in terms of Euclidean distance or some other kind of distance) in the case that we want to classify. Then, given the K-similar examples, the most popular target (majority voting) is chosen as the classification label. Two parameters are mandatory for this algorithm: the neighborhood cardinality (K), and the measure to evaluate the similarity. (Boschetti & Massaron, 2018)

2.4.16 Root Mean Squared Error (RMSE)

RMSE is The average of the squared error that is used as the loss function for least squares. It is the sum, over all the data points, of the square of the difference between the predicted and actual target variables, divided by the number of data points (Dua, Ghotra, & Pentreath, 2017). The formaulsa is:

$$\sqrt{\sum (\boldsymbol{Yt} - \boldsymbol{yt})^2}$$

Where: $\boldsymbol{Y}$ = real value

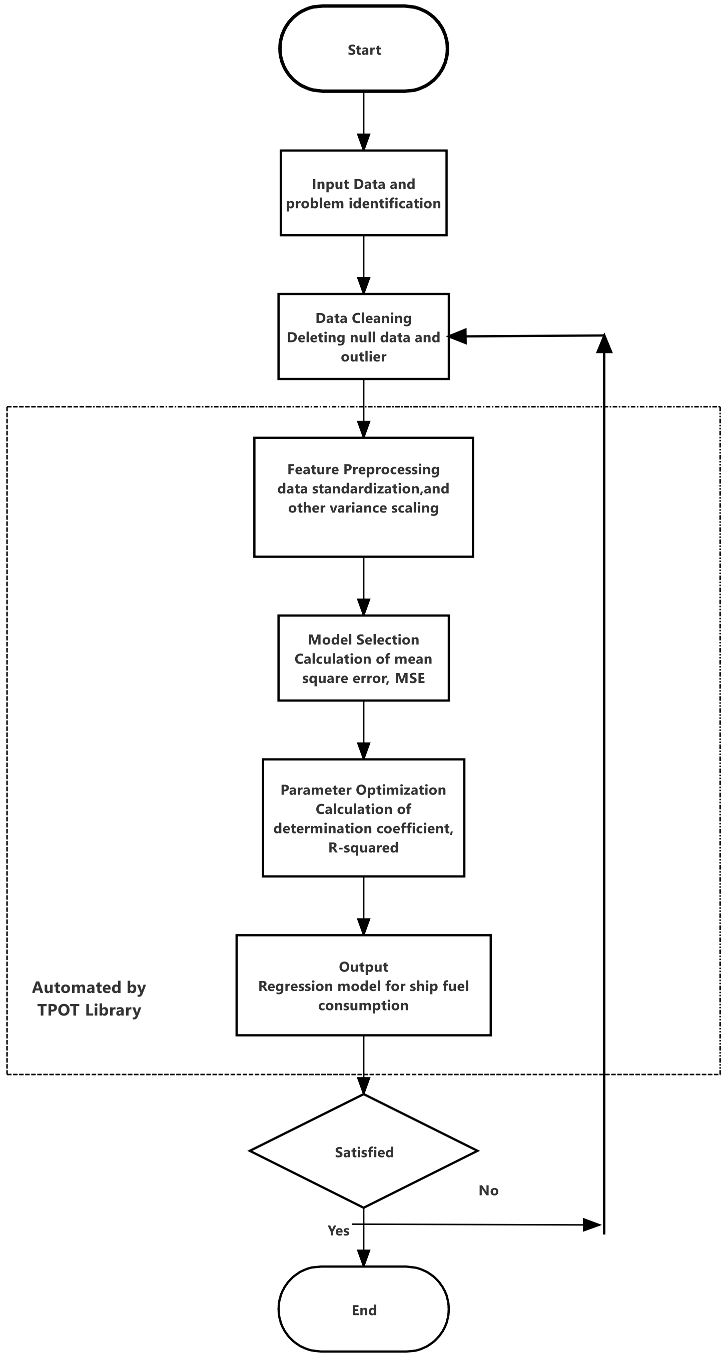
$\boldsymbol{y}$ = Predictor

2.5 Programming tool / programming language

Python is a popular programming language. It was created by Guido van Rossum, and released in 1991. Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. Beside that, python is one of the open-source meaning its free of charge which makes it accessible for a wide range of computing platforms. In the industry, python is used for web development, software development, mathematics and system scripting. Python supports the use of modules and packages, which means that programs can be designed in a modular style and code can be reused across a variety of projects. Once you've developed a module or package you need, it can be scaled for use in other projects, and its as to import or export these modules (Rossum, 1995). The liblary that is used for this reasearch is TPOT (Tree-based Pipeline Optimization Tool) TPOT is a Python Automated Machine Learning tool that optimizes machine learning pipelines using genetic programming (Olson, 2016). That is based on library called sk-learn (Pedregosa, et al., 2011).

CHAPTER III
WRITING METHODOLODY

3.1 Flow Chart



3.2 Input data and problem Identification

Problem identification is the first step to begin this writing method. In this process a list of specified problems is created and also create the suitable basis for identifying the solution of the problem both from now and in the future. The main problem is identified from the lack of data and information from maritime industry in industry in which led to increase of uncertainity and decrease of efficiency on ship voyage and operation that also increase the cost of ship operation. Collecting data is important for this research especially because everything about this research is about data and how the author process it. Beside that, the quantity and the quality of the data collected will dictate how accurate the model become. The data need to be collected that needed for further calculation is:

a. Noon report
b. Onboard logging data
c. Ship engine log data
d. Ship operation data

3.3 Data Cleaning

In this process to prepare the data before becoming the input of the model selection, model denoising or data cleaning is need to be done so that it remove duplicates, minimize errors, deal with missing values, etc. this process also the most important step to construct a good model. To made a good data, some of the things that can be done is transform the data, select the feature, and reduce the dimensionality of the data. In this process also the data is scaled, the missing values is to be taken care of and the outliers is removed. In feature selection, the variable that has low variance will be removed and information gain from the variable is measured. After that, the data will be split. The purpose of this so the model have 2 kinds of data, data that is used for training the model and data that is used for evalution of the model this is done to add the randomness of the data so the error of the model is known. If the same data for training is used for evaluating the data, then the error of the model won,t be valid.

3.4 Feature Processing

In this process after the data is clean, it will go trough standarization to normalize the data so that all variable in different feature can be treated equally.

3.5 Model Selection

finding the best performing statistical for problem and the corresponding configuration because different algorithms are for different tasks. After the model has been selected, the data that already been split is used to improve the model ability. The purpose of this training is to answer a question and make the error in prediction as little as possible.

3.6 Parameter Optimization

In this process the model will be test against the data from the data that is left after being split. The goal of this process is to measure the objective performance and the error of the model with the previously unseen data. With this data, the evaluation result also representative of model performance in the real world. In this process, the model will guess some number then wait for the number to train itself on some data then reassess wether the result were ideal or not if the result were not ideal, then the model redo the process until it get a better guess, in other word it is a process of trial and error until the model of error is small enough and the performance of the model will be improved.

3.7 Make Prediction

In this process, the output model will be used to predict the data in the real world.

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CHAPTER IV
RESULT AND DISCUSSION

4.1 Data acquisition

The data that is used for this paper was collected manually from the ship by photographing the engine log book and ship deck logbook. 9 month worth of data is collected from the log book from 17 June 2019 to 25 February 2020.

The study was conducted on the cruise ship m/v waingapu. the ship have the length of 146 m, breadth of 24 m, gross tonnage of 9942 tons, and deadweight at summer of 14798 tons. The vessel is powered by a two stroke diesel engine Mitsubishi 6UEC33LSE with capacity of 3990 kW and rotation speed of 133.3 rpm. The extracted dataset consist of ship speed (knot) ,ship displacement (m^3), distance traveled, (Nm) and sea condition from ship deck logbook. Other data such as engine load (%) and fuel consumption(Ton) are obtained from engine log book. The reading of this data is done by ship crew then these data written manually in ship logbook in a 4 hours interval. The data then manually convert to Microsoft excel file so the phyton library can read the dataset. The ship have 4 different cycle route which is, between Jakarta to Surabaya, Surabaya to bitung, bitung to gorontalo, an Gorontalo to Jakarta. Beside ship log, this research also use data from the noon report.

4.2 Preprocessing

The process of model training depending on the quality of the data that is inserted. Hence, if the model is trained on the wrong data, it will try to reduce the error in that dataset and the model will not be optimized. There are no data for displacement from 18/6/19 to 07/08/19, so that time period is filtered out and was replaced to NaN (not a number), and not to be counted into the data set.   the data that will included in the model consist of: engine load, speed, displacement, and sea condition as the input and fuel consumption as the output.

The data is written to the log book by the crew who manually recorded the measurement every 4 hours, this implies a large uncertainty of each hours of consumption. As this process in not automated, the results of the reading it can differ quite significant in exact time of the day. Because of this if the ship stop before the fourth hour, then the measurement value still written in the fourth hour. After analyzing existing data, the minimum limit set for fuel consumption to be included in dataset is 1300 ton.

An outlier is an observation that lies an abnormal distance from other values in a random sample from a population. Its decided that to leave the 5% data furthest from the mean value as an outlier and will be drop from the dataset. Inconsistency from data mostly come from human reading eror.

4.3 Model training

The MSE and regression R-squared values were used to check how well the regression model fits the datasets. These different activation values then compared to determine how good and accurate the estimation from the regression model.

The data used to construct the regression model came from training and testing datasets. The model then fitted to the training dataset so that the parameters such as weight and bias were estimated base on this dataset. The testing dataset is used to evaluates the performance of the model created by the training dataset. These datasets were used in the different stages of model creation. these dataset also selected randomly.

The model then tested using the help of automated machine learning, which chose the best parameter and method given the training dataset. And the auto machine learning that is used in this study are the Tree Pipeline Optimisation Tool (TPOT) library. in TPOT library there is some parameter to determine how much pipeline is used to create a model. the first parameter is generations which is number of iterations to the run pipeline optimization process the second parameter is population size which is generations is number of iterations to the run pipeline optimization process generally TPOT will work better with the increase value of both of this parameter. In this study the parameter that used are 10 for generation and 100 for population size, this parameter will generate 1100 pipeline. This parameter is chosen because there is no more significant decrease in model errors.

The RMSE and R values are shown to demonstrate the accuracy of the regression model. The mean squared error tells the dtandard value of a model. It does this by taking the average squared difference between the estimated values and what is estimated. R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression.

No.	Feature	RMSE	R-squared	Method
1	Speed	226.87	0.508	Kneighbor regressor, Lasso Regression
2	Engine Load	170.52	0.722	Lasso Regression, Extra trees regressor
3	Displacement	206.5	0.593	Elastic net Regressor, K neighbor regressor
4	Sea Condition	326.93	-0.019	Extra Trees Regressor
5	Speed, Engine Load	156.25	0.767	Ridge regression, extra trees regressor
6	Engine Load, Displacement	148.73	0.788	Random Forest Regressor, Kneighbors regressor
7	Displacement, Speed	158.25	0.761	ExtraTrees Regressor, Linear Regression
8	Speed , Sea Condition	218.32	0.545	Elastic Net Regressor
9	Engine Load, Sea Condition	162.22	0.748	Random Forest Regressor, Decision Tree Regressor
10	Displacement, Sea Condition	207.33	0.589	Kneighbor regressor
11	Speed, Engine Load, Displacement	134.75	0.826	Random Forest Regressor, Elascitc net Regressor
12	Speed , Engine Load , Sea Condition	149.28	0.787	Random Forest Regressor, Elascitc net Regressor
13	Speed, Displacment, Sea Condition	159.07	0.758	Gradient Boosting Regressor, K neighbor regressor
14	Engine Load, Displacement, Sea Condition	129.97	0.838	Random Forest Regressor, Extra Tree Regressor
15	Speed, Engine Load, Displacement, Sea Condition	127.05	0.845	Extra Tree Regressor, K neighbor regressor

Table 4. 1 Regression analysis result using automated machine learning

in table above, it is shown the RMSE value of its model with its own feature that inputted to the TPOT automl along with the method that is used to achieve these RMSE value. It also shown that on average, the more feature that its inputted on the models, the smaller the RMSE value in which mean the better the model to predict. the method column has a list of method that is used to produce the model. multiple method in column indicate that the model not only use one method but several of method stacked on each other with the first method on the list being the final estimator.

stacked regression consists in stacking the output of individual estimator and use a regressor to compute the final prediction. Stacking allows to use the strength of each individual estimator by using their output as input of a final estimator. stacked regression is intended to combining estimators to reduce their biases.

the way TPOT library decide which method is the best for each features are by scoring each iteration using cross validation in which the output will be mean square error (MSE). In comparing the performance of one feature with another, RMSE (root mean square error) and R value become benchmark to determine how good the model perform against each other. it shown from the table 4.1 that model with feature speed, engine load, displacement and sea condition have the lowest value of RMSE along with highest value of R. which mean that this model has the lowest amount of error and the best correlation between target and output values obtained. As the number of feature included increases, the average accuracy of the regression model also improves. Calculation of the R-squared values and RMSE values for each dataset shows that the learning performance of each training dataset is different from all other datasets.

It also can be seen from table 4.1 that the best performing model is model with 4 features. for worst model performance is model with one feature: sea condition in which the R value is minus it indicate that the sea condition model fits worse than a horizontal line and that model does not follow the trend of the data. As shown in figure 4.27 it can be seen that the model is so bad that according to its R value this model has RMSE bigger than that of a model which only predict the mean of the fuel oil consumption.

By looking the best performance model at n-features, it can be seen which of the features have the highest importance among the other features. In 3 features model, model which have the lowest RMSE and highest R-value is speed, engine load, and displacement. In 2 features model, the best performing model is engine load and ship displacement. In 1 feature model, the best performing model is engine load. It can be deducted that engine load is the most significance feature to predict the ship fuel consumption.

4.3.1 using 4 features : Speed, Engine Load, Displacement, and Sea Condition

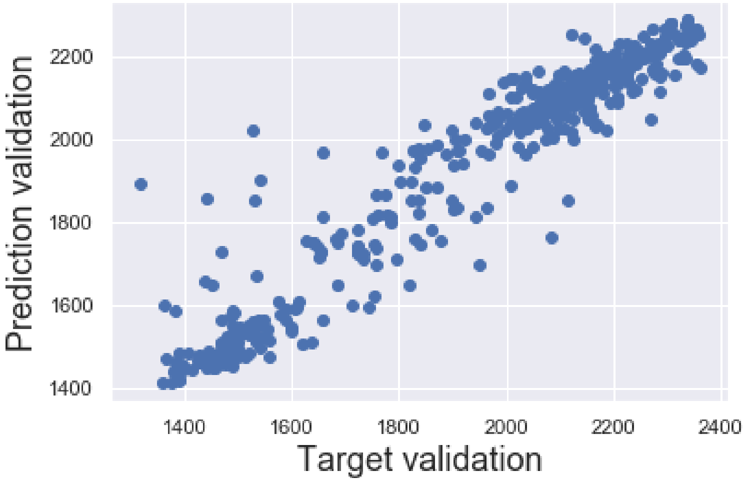


Figure 4. 1 scatter plot of model validation using speed, engine load, displacement, and sea condition as a feature

this model is acquired using 4 feature which is speed, engine load, displacement, and sea condition. the model made using KNeighbor regressor as its estimator and random forest regressor as its final estimator. random forest regressor create a tree-like structure to predict the output called regression tree by making multiple of this tree, the inaccuracy will be minimize compared to using one regression tree. This training data set consist of 80% of the entire data set.this dataset which TPOT library score and use to chose which model that have the best performance and tuned the parameter but to check if the model have high bias or overfitting, the model need to be faced against unknown data, that's why test dataset is needed. which in this model 20% of the entire data set is used as testing data. The real performance of this model can be seen in figure 4 where the model is face against unknown data from testing data set. The fit line give general idea how good the model is, the closer the fit line to 45^{o} degree angle the better the model. This model resulted in mean absolute difference of 4.95%.

from table 4.1 it can be seen that this method produces the lowest amount of RMSE which is 127.05 and the highest R-squared value of 0.845. in scatter plot above, it can be seen how close the prediction of fuel consumption in training data set. but to check if the model have high bias or overfitting, the model need to be faced against unknown data, that's why test dataset is needed. which in this model 20% of the total data is used as testing data.

Figure 4. 2 scatter plot of model testing using speed, engine load, displacement and sea condition as a feature

The scatter plot above is correlation between the predicted data of testing dataset with the prediction made with model created by automl. the X-axis is the target or the real fuel consumption value from the testing dataset that previously splitted. Y-axis is the value of predicted fuel consumption done by the model. as visualized by the scatter plot, the difference betwen the target and prediction ranges between 0.01% as the lowest and 48.59% as the highest.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1933.37 + 195.02 (Engine load percentage) + 102.64 (speed in knot) + 6.99 (displacement tonnage) + sea condition (21.34 for moderate sea , 2.94 for moderate sea to swell, 11.064 for rippled, 88.26 for slight sea , 23.94 for slight to moderate sea, 8.88for slight to swell, 75.77 for smooth sea , 31.8 for smooth to slight, 14.54 for smooth to swell, 0.39 for swell sea , -2.52 for very smooth).

With RMSE value of 154.3 and R-value of 0.73. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1924.094584	4.950605	4.956981
std	325.243011	276.257304	127.544399	5.929757
min	1328.744275	1425.388759	-599.221948	0.002949
25%	1568.869565	1620.692246	-58.310224	1.951610
50%	2036.642633	2066.712340	12.768311	3.845383
75%	2230.525963	2144.179791	88.493864	6.252375
max	2358.236842	2250.301000	215.554673	44.552193

Table 4. 2 Result analysis of model using speed, engine load, displacement and sea condition as a feature

in this model, the difference between the target and prediction ranges between 0.002% as the lowest and 44.55% as the highest. The mean absolute error value is 4.95%.

Table 4. 3 Model Prediction on Testing dataset using 4 features: engine load, speed, displacement and sea condition

No.	engine load	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
1	52.00	12.62	15257.60	smooth sea	2245.93	2246.17	-0.24	0.01
2	51.00	13.25	15623.00	slight sea	2248.05	2245.74	2.31	0.10
3	53.00	12.87	14837.80	smooth sea	2248.61	2245.08	3.53	0.16
4	51.00	13.00	14795.00	smooth sea	2248.16	2252.66	-4.50	0.20
5	53.00	13.37	18375.20	smooth sea	2274.09	2278.80	-4.71	0.21
6	51.00	12.75	16094.00	smooth sea	2156.40	2161.10	-4.70	0.22
7	41.00	12.00	15720.14	smooth sea	1564.38	1569.24	-4.86	0.31
8	40.00	11.12	14839.39	smooth sea	1504.10	1509.39	-5.29	0.35
9	50.00	13.00	15623.00	smooth sea	2131.55	2139.11	-7.56	0.35

No.	engine load	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
10	51.00	12.50	16644.60	slight sea	2169.89	2177.75	-7.86	0.36
11	51.00	11.00	13725.00	slight sea	1904.08	1912.11	-8.03	0.42
12	52.00	12.25	15623.00	slight sea	2073.91	2083.01	-9.10	0.44
13	42.00	11.25	12557.00	slight sea	1522.12	1514.08	8.05	0.53
14	53.00	13.25	16094.00	slight sea	2250.97	2263.75	-12.78	0.57
15	52.00	12.75	14400.80	slight sea	2265.59	2251.74	13.86	0.61
16	40.00	0.75	15103.29	slight sea	1542.09	1532.31	9.78	0.63
17	39.00	10.75	15096.20	smooth sea	1443.26	1432.57	10.70	0.74
18	52.00	10.50	18375.20	slight sea	1856.36	1870.57	-14.22	0.77
19	53.00	12.00	15255.00	smooth sea	2115.10	2098.89	16.21	0.77
20	41.00	11.25	15720.14	slight sea	1466.61	1453.20	13.41	0.91
21	54.00	11.87	18442.00	slight sea	2148.75	2173.41	-24.65	1.15
22	53.00	12.75	18255.00	smooth sea	2104.63	2079.77	24.87	1.18
23	52.00	12.50	15257.60	smooth sea	2223.70	2250.14	-26.44	1.19
24	54.00	12.50	16767.00	smooth sea	2232.65	2263.21	-30.56	1.37
25	42.00	12.12	15103.29	smooth sea	1568.87	1590.45	-21.58	1.38
26	40.00	11.00	14839.39	smooth sea	1487.20	1508.08	-20.88	1.40
27	52.00	11.75	15257.60	smooth sea	2090.28	2060.76	29.51	1.41
28	53.00	12.50	16644.60	slight sea	2150.16	2181.05	-30.89	1.44
29	42.00	11.25	12077.00	slight sea	1474.81	1498.73	-23.91	1.62
30	53.00	12.25	12209.80	smooth sea	2214.33	2176.12	38.21	1.73

No.	engine load	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
31	40.00	11.30	15726.47	smooth sea	1490.02	1461.93	28.09	1.89
32	51.00	12.50	14900.60	slight sea	2233.45	2189.74	43.70	1.96
33	53.00	12.81	14900.60	slight sea	2300.45	2253.63	46.82	2.04
34	50.00	12.50	15623.00	smooth to slight	2120.81	2076.40	44.41	2.09
35	50.00	13.00	13725.00	slight sea	2059.78	2104.37	-44.59	2.16
36	50.00	12.75	13725.00	slight sea	2036.64	2082.45	-45.80	2.25
37	55.00	12.62	14048.00	smooth sea	2303.94	2251.69	52.25	2.27
38	55.00	12.00	18090.52	slight sea	2191.27	2139.48	51.79	2.36
39	40.00	10.75	14839.39	smooth sea	1480.52	1444.95	35.57	2.40
40	52.00	12.25	12209.80	smooth sea	2230.53	2174.79	55.74	2.50
41	53.00	13.00	18255.00	slight sea	2238.40	2181.98	56.42	2.52
42	52.00	13.25	18090.52	smooth sea	2129.56	2187.04	-57.49	2.70
43	55.00	11.75	18442.00	slight sea	2284.80	2221.21	63.59	2.78
44	51.00	12.30	18375.20	slight sea	2078.49	2140.16	-61.67	2.97
45	44.00	12.25	12791.00	slight sea	1717.00	1768.21	-51.21	2.98
46	55.00	12.75	15255.00	smooth sea	2247.30	2179.58	67.71	3.01
47	42.00	12.15	18255.00	smooth sea	1915.55	1857.09	58.46	3.05
48	50.00	12.75	15255.00	slight sea	2205.33	2137.19	68.13	3.09
49	45.00	11.50	16335.00	slight sea	1729.81	1784.15	-54.34	3.14
50	39.00	11.50	14839.39	smooth sea	1628.62	1576.71	51.92	3.19

No.	engine load	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
51	45.00	12.25	12791.00	swell sea	1750.00	1806.75	-56.75	3.24
52	41.00	11.00	15720.14	smooth sea	1491.45	1442.87	48.58	3.26
53	58.00	13.50	12232.00	slight sea	2123.64	2194.74	-71.10	3.35
54	52.00	12.50	13725.00	slight sea	2111.27	2182.97	-71.70	3.40
55	30.00	12.00	15726.47	smooth sea	1536.00	1591.07	-55.07	3.59
56	54.00	12.10	18263.50	slight sea	2227.86	2146.78	81.08	3.64
57	51.00	11.50	15623.00	slight sea	1951.14	1877.33	73.81	3.78
58	55.00	13.50	16767.00	slight sea	2358.24	2267.00	91.23	3.87
59	39.00	10.62	14839.39	smooth to slight	1504.71	1443.09	61.62	4.09
60	55.00	12.75	14048.00	slight sea	2327.68	2231.93	95.75	4.11
61	53.00	12.75	18090.52	slight sea	2261.83	2168.54	93.29	4.12
62	44.00	12.40	12022.00	slight sea	1776.43	1850.85	-74.42	4.19
63	53.00	12.50	15255.00	smooth sea	2091.98	2180.92	-88.94	4.25
64	52.00	12.30	16644.60	slight sea	2273.47	2168.70	104.77	4.61
65	41.00	10.75	15726.47	smooth sea	1376.00	1441.64	-65.64	4.77
66	45.00	11.60	16335.00	smooth sea	1748.61	1832.73	-84.12	4.81
67	52.00	12.25	13725.00	smooth sea	2069.05	2171.99	-102.94	4.98
68	42.00	11.00	12557.00	smooth to slight	1488.30	1562.80	-74.51	5.01
69	55.00	12.40	18255.00	smooth sea	2289.91	2172.48	117.42	5.13
70	52.00	11.75	13725.00	slight sea	2033.90	2142.15	-108.25	5.32

No.	engine load	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
71	51.00	13.00	15623.00	slight sea	2327.86	2203.26	124.60	5.35
72	39.00	12.12	15096.20	smooth sea	1523.89	1611.15	-87.26	5.73
73	53.00	12.50	16644.60	slight sea	2319.86	2181.05	138.81	5.98
74	40.00	10.50	12557.00	slight sea	1471.79	1564.20	-92.41	6.28
75	50.00	12.25	12557.00	smooth sea	2004.50	2135.98	-131.48	6.56
76	52.00	12.62	12209.80	smooth to swell	2282.12	2132.12	150.00	6.57
77	40.00	0.75	15103.29	moderate sea	1419.00	1513.05	-94.05	6.63
78	40.00	11.60	15096.20	smooth sea	1560.74	1454.32	106.42	6.82
79	42.00	11.28	18255.00	smooth sea	1937.07	1802.77	134.31	6.93
80	49.00	10.62	12077.00	slight to moderate sea	2073.19	1928.43	144.77	6.98
81	54.00	12.50	12803.00	slight sea	2182.83	2020.66	162.17	7.43
82	40.00	10.87	15103.29	slight sea	1407.13	1514.34	-107.21	7.62
83	52.00	12.50	18263.50	smooth sea	2296.76	2117.31	179.45	7.81
84	53.00	12.50	18090.52	slight sea	2009.02	2166.55	-157.53	7.84
85	52.00	13.00	12557.00	slight sea	2310.89	2128.73	182.17	7.88
86	55.00	11.50	18442.00	slight sea	2236.18	2059.56	176.63	7.90
87	53.00	11.50	16094.00	smooth sea	1953.67	2116.49	-162.81	8.33
88	49.00	10.75	12077.00	slight to moderate sea	2097.58	1920.03	177.55	8.46
89	51.00	12.24	14900.60	slight sea	2322.01	2124.88	197.13	8.49

No.	engine load	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
90	44.00	9.13	14213.20	slight sea	1541.75	1673.87	-132.12	8.57
91	45.00	10.50	14213.20	smooth sea	1635.62	1776.52	-140.89	8.61
92	53.00	12.75	12803.00	slight sea	2226.48	2033.66	192.83	8.66
93	40.00	11.75	14839.39	smooth sea	1581.98	1719.25	-137.28	8.68
94	54.00	12.00	15255.00	smooth sea	2332.03	2127.16	204.87	8.78
95	41.00	11.08	12077.00	smooth sea	1818.94	1650.97	167.96	9.23
96	40.00	11.12	14130.97	smooth sea	1461.81	1597.29	-135.48	9.27
97	41.00	10.00	14213.20	smooth sea	1600.00	1450.54	149.46	9.34
98	41.00	11.37	16839.68	moderate sea	2030.33	1839.41	190.92	9.40
99	40.00	11.20	15720.14	smooth sea	1328.74	1456.04	-127.29	9.58
100	45.00	11.97	12791.00	slight sea	1826.42	1643.83	182.59	10.00
101	40.00	11.61	15103.29	smooth sea	1374.78	1513.05	-138.27	10.06
102	42.00	11.37	16839.68	slight sea	2030.33	1793.17	237.16	11.68
103	42.00	11.75	16839.68	smooth to slight	1729.09	1941.55	-212.46	12.29
104	40.00	10.50	14839.39	smooth sea	1635.46	1432.77	202.69	12.39
105	52.00	12.00	16644.60	slight sea	1909.51	2158.04	-248.53	13.02
106	40.00	11.80	15103.29	slight sea	1407.13	1597.29	-190.16	13.51
107	52.00	12.43	18255.00	smooth sea	1958.60	2253.89	-295.30	15.08
108	54.00	11.00	18263.50	slight sea	1415.47	1879.97	-464.50	32.82
109	54.00	12.00	16094.00	moderate sea	1344.99	1998.54	-653.55	48.59

4.3.2. Using 3 feature: speed, engine load, and displacement

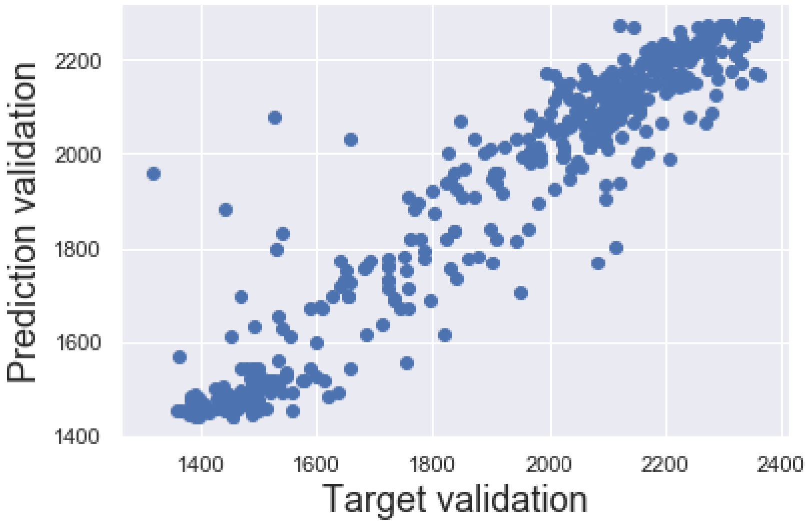


Figure 4. 3 scatter plot of model validation using speed, engine load, and displacement as a feature

this model is acquired using 3 feature which is speed, engine load, and displacement. the model made using elastic net regressor as its estimator and random forest regressor as its final estimator.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1932.61 + 192.88 (Engine load percentage) + 104.32 (speed in knot) + 5.24 (displacement tonnage)

with RMSE value of 156.8 and R-value of 0.723. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

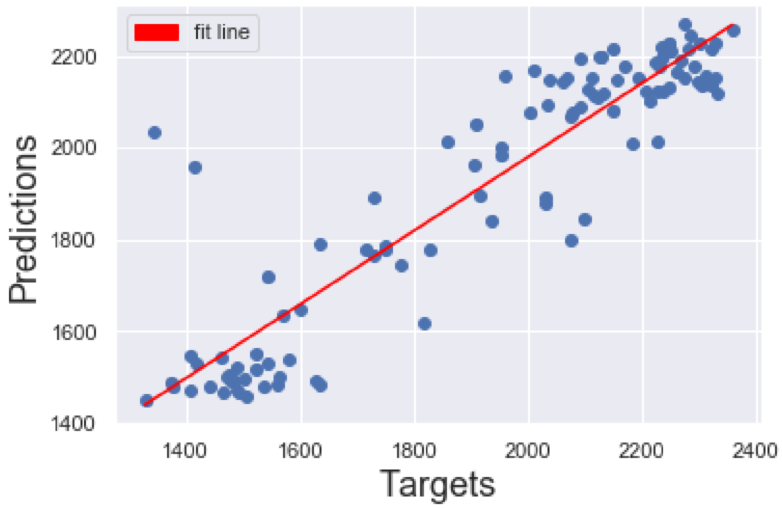


Figure 4. 4 scatter plot of model testing using speed, engine load, and displacement as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1922.279927	6.765262	4.846731
std	325.243011	285.504775	130.393731	6.381454
min	1328.744275	1449.742490	-687.670521	0.074934
25%	1568.869565	1616.681067	-56.662527	1.621428
50%	2036.642633	2067.528190	13.000834	3.429293
75%	2230.525963	2154.480907	78.374934	6.696729
max	2358.236842	2270.660715	273.158534	51.128350

Table 4. 4 Result analysis of model using speed, engine load, and displacement as a feature

in this model, the difference between the target and prediction ranges between 0.07% as the lowest and 51.12% as the highest. The mean absolute error value is 4.84%.

Table 4. 5 Model Prediction on Testing dataset using 3 features: engine load, speed, and displacement

No.	engine load	speed	displace ment	Target	Predictio n	Residua l	Differe nce%
1	40.00	11.00	14839.39	1487.20	1488.39	-1.19	0.08
2	41.00	11.25	15720.14	1466.61	1467.90	-1.29	0.09
3	51.00	12.75	16094.00	2156.40	2154.08	2.32	0.11
4	45.00	12.25	12791.00	1750.00	1748.07	1.93	0.11
5	52.00	11.75	13725.00	2033.90	2030.36	3.54	0.17
6	40.00	10.75	14839.39	1480.52	1476.94	3.58	0.24
7	54.00	12.50	16767.00	2232.65	2225.58	7.06	0.32
8	50.00	12.50	15623.00	2120.81	2113.98	6.83	0.32
9	45.00	11.60	16335.00	1748.61	1754.91	-6.30	0.36
10	52.00	11.75	15257.60	2090.28	2100.14	-9.86	0.47
11	51.00	12.30	18375.20	2078.49	2068.61	9.89	0.48
12	55.00	11.50	18442.00	2236.18	2247.14	-10.96	0.49
13	52.00	12.25	15623.00	2073.91	2086.50	-12.58	0.61
14	40.00	11.30	15726.47	1490.02	1480.72	9.30	0.62
15	40.00	11.12	14839.39	1504.10	1494.61	9.49	0.63
16	53.00	12.50	16644.60	2150.16	2164.08	-13.91	0.65
17	40.00	0.75	15103.29	1542.09	1552.45	-10.36	0.67
18	51.00	13.25	15623.00	2248.05	2231.65	16.41	0.73
19	51.00	12.50	16644.60	2169.89	2185.79	-15.90	0.73
20	53.00	12.00	15255.00	2115.10	2095.51	19.59	0.93
21	40.00	11.75	14839.39	1581.98	1565.70	16.27	1.03
22	42.00	11.28	18255.00	1937.07	1915.02	22.05	1.14
23	53.00	13.37	18375.20	2274.09	2247.74	26.36	1.16
24	51.00	11.50	15623.00	1951.14	1978.21	-27.07	1.39
25	50.00	13.00	15623.00	2131.55	2162.03	-30.47	1.43
26	39.00	10.62	14839.39	1504.71	1482.68	22.03	1.46
27	45.00	11.50	16335.00	1729.81	1755.87	-26.06	1.51
28	42.00	11.25	12557.00	1522.12	1546.13	-24.01	1.58
29	55.00	11.75	18442.00	2284.80	2248.44	36.36	1.59
30	58.00	13.50	12232.00	2123.64	2087.89	35.75	1.68
31	41.00	10.00	14213.20	1600.00	1637.17	-37.17	2.32
32	52.00	12.62	12209.80	2282.12	2228.91	53.20	2.33
33	53.00	12.87	14837.80	2248.61	2196.09	52.51	2.34

No.	engine load	speed	displacement	Target	Prediction	Residual	Difference%
34	44.00	12.40	12022.00	1776.43	1734.54	41.89	2.36
35	44.00	12.25	12791.00	1717.00	1757.64	-40.64	2.37
36	50.00	12.75	15255.00	2205.33	2151.25	54.08	2.45
37	41.00	11.00	15720.14	1491.45	1451.73	39.71	2.66
38	52.00	13.25	18090.52	2129.56	2187.87	-58.31	2.74
39	55.00	12.75	15255.00	2247.30	2185.05	62.25	2.77
40	40.00	11.60	15096.20	1560.74	1515.57	45.17	2.89
41	53.00	13.00	18255.00	2238.40	2172.56	65.84	2.94
42	50.00	13.00	13725.00	2059.78	2122.70	-62.92	3.05
43	52.00	12.62	15257.60	2245.93	2177.19	68.74	3.06
44	42.00	12.12	15103.29	1568.87	1617.00	-48.13	3.07
45	51.00	13.00	14795.00	2248.16	2177.91	70.25	3.12
46	53.00	13.25	16094.00	2250.97	2179.12	71.85	3.19
47	55.00	12.00	18090.52	2191.27	2118.01	73.26	3.34
48	52.00	12.75	14400.80	2265.59	2189.05	76.54	3.38
49	53.00	12.75	18255.00	2104.63	2177.55	-72.92	3.46
50	49.00	10.62	12077.00	2073.19	2000.15	73.04	3.52
51	39.00	10.75	15096.20	1443.26	1494.84	-51.58	3.57
52	52.00	12.50	13725.00	2111.27	2187.31	-76.03	3.60
53	53.00	12.75	12803.00	2226.48	2144.42	82.06	3.69
54	42.00	11.25	12077.00	1474.81	1529.87	-55.06	3.73
55	53.00	11.50	16094.00	1953.67	2029.64	-75.97	3.89
56	42.00	12.15	18255.00	1915.55	1992.54	-76.99	4.02
57	51.00	12.50	14900.60	2233.45	2142.21	91.23	4.08
58	52.00	12.00	16644.60	1909.51	1987.51	-78.01	4.09
59	53.00	12.75	18090.52	2261.83	2169.00	92.83	4.10
60	45.00	11.97	12791.00	1826.42	1748.69	77.73	4.26
61	49.00	10.75	12077.00	2097.58	2007.71	89.87	4.28
62	52.00	12.50	15257.60	2223.70	2126.28	97.41	4.38
63	52.00	12.25	12209.80	2230.53	2132.61	97.91	4.39
64	52.00	12.25	13725.00	2069.05	2161.70	-92.65	4.48
65	50.00	12.25	12557.00	2004.50	2095.57	-91.07	4.54
66	50.00	12.75	13725.00	2036.64	2131.88	-95.24	4.68
67	51.00	13.00	15623.00	2327.86	2216.13	111.73	4.80
68	53.00	12.81	14900.60	2300.45	2189.79	110.65	4.81
69	41.00	11.37	16839.68	2030.33	1924.12	106.21	5.23

No.	engine load	speed	displace ment	Target	Predictio n	Residua l	Differe nce%
70	40.00	10.87	15103.29	1407.13	1481.98	-74.85	5.32
71	55.00	13.50	16767.00	2358.24	2232.34	125.90	5.34
72	53.00	12.50	15255.00	2091.98	2208.43	-116.46	5.57
73	39.00	11.50	14839.39	1628.62	1535.74	92.89	5.70
74	54.00	12.10	18263.50	2227.86	2099.46	128.40	5.76
75	41.00	10.75	15726.47	1376.00	1459.28	-83.28	6.05
76	42.00	11.00	12557.00	1488.30	1580.23	-91.93	6.18
77	40.00	11.12	14130.97	1461.81	1552.41	-90.60	6.20
78	42.00	11.37	16839.68	2030.33	1902.08	128.25	6.32
79	53.00	12.50	18090.52	2009.02	2140.05	-131.03	6.52
80	52.00	13.00	12557.00	2310.89	2159.20	151.70	6.56
81	52.00	12.30	16644.60	2273.47	2121.29	152.17	6.69
82	53.00	12.50	16644.60	2319.86	2164.08	155.78	6.72
83	51.00	11.00	13725.00	1904.08	2039.53	-135.45	7.11
84	41.00	12.00	15720.14	1564.38	1677.15	-112.77	7.21
85	51.00	12.24	14900.60	2322.01	2153.91	168.10	7.24
86	53.00	12.25	12209.80	2214.33	2050.78	163.56	7.39
87	54.00	12.50	12803.00	2182.83	2015.30	167.53	7.67
88	55.00	12.62	14048.00	2303.94	2124.64	179.30	7.78
89	40.00	10.50	12557.00	1471.79	1590.75	-118.97	8.08
90	52.00	10.50	18375.20	1856.36	2007.19	-150.83	8.13
91	55.00	12.75	14048.00	2327.68	2133.93	193.75	8.32
92	52.00	12.50	18263.50	2296.76	2094.51	202.25	8.81
93	52.00	12.43	18255.00	1958.60	2138.87	-180.27	9.20
94	40.00	10.50	14839.39	1635.46	1481.67	153.79	9.40
95	40.00	0.75	15103.29	1419.00	1552.45	-133.45	9.40
96	30.00	12.00	15726.47	1536.00	1680.53	-144.53	9.41
97	54.00	12.00	15255.00	2332.03	2107.74	224.29	9.62
98	55.00	12.40	18255.00	2289.91	2056.19	233.71	10.21
99	40.00	11.20	15720.14	1328.74	1465.06	-136.32	10.26
100	44.00	9.13	14213.20	1541.75	1700.01	-158.26	10.26
101	39.00	12.12	15096.20	1523.89	1686.25	-162.35	10.65
102	42.00	11.75	16839.68	1729.09	1914.05	-184.96	10.70
103	45.00	10.50	14213.20	1635.62	1813.30	-177.68	10.86
104	41.00	11.08	12077.00	1818.94	1618.35	200.59	11.03
105	54.00	11.87	18442.00	2148.75	1910.39	238.37	11.09

No.	engine load	speed	displace ment	Target	Predictio n	Residua l	Differe nce%
106	40.00	11.61	15103.29	1374.78	1528.43	-153.65	11.18
107	40.00	11.80	15103.29	1407.13	1576.63	-169.49	12.05
108	54.00	11.00	18263.50	1415.47	2023.41	-607.94	42.95
109	54.00	12.00	16094.00	1344.99	2012.97	-667.98	49.66

4.3.3 using 3 feature: speed, displacement, and sea condition

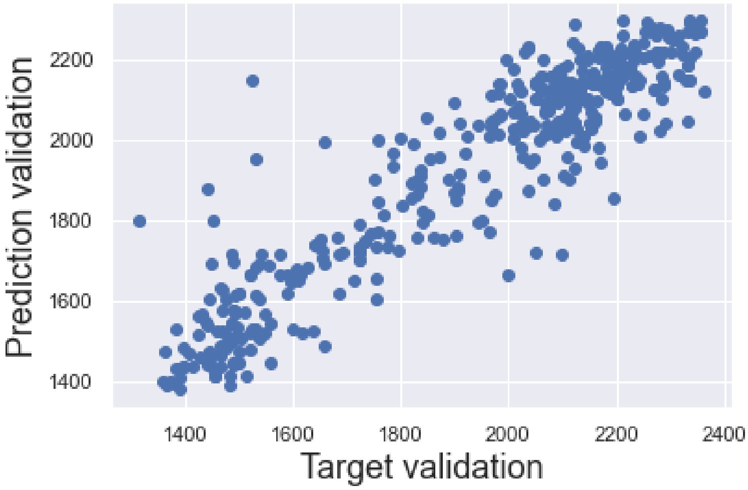


Figure 4. 5 scatter plot of model validation using speed, displacement, and sea condition as a feature

this model is acquired using 3 feature which is speed, displacement, and sea condition. the model made using Kneighbor regressor as its estimator and Gradient boosting regressor as its final estimator. Gradient boosting build an ensemble trees regression in sequence with each tree improving and learning on the previous one. Although regression trees by themselves are prone to overfitting and rather weak predictive models to the data that the model never been seen, they can be boosted to produce a powerful model that, when appropriately tuned, is one of the better algorithms.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1931.6 + 187.89 (speed in knot) + 60.9 (displacement tonnage) + sea condition (39.28 for moderate sea , -12.17 for moderate sea to swell, 1.44 for rippled, 60.4 for slight sea , 28.68 for slight to moderate sea, 6.19 for slight to swell, 14.43 for smooth sea , 7.38 for smooth to slight, 3.13 for smooth to swell, -16.28 for swell sea , -18.26 for very smooth).

with RMSE value of 209.94 and R-value of 0.505. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

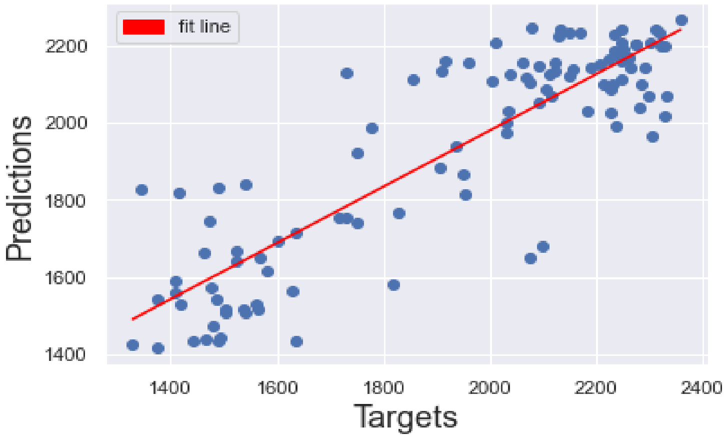


Figure 4. 6 scatter plot of model testing using speed, displacement, and sea condition as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1928.392202	0.652988	6.430103
std	325.243011	271.988141	159.806484	6.360028
min	1328.744275	1415.483976	-482.639523	0.080872
25%	1568.869565	1666.500346	-91.545690	2.208443
50%	2036.642633	2038.493539	18.579003	4.165406
75%	2230.525963	2154.248311	85.774740	9.485268
max	2358.236842	2269.197580	424.228990	35.884282

Table 4. 6 Result analysis of model using speed, engine load, and displacement as a feature

in this model, the difference between the target and prediction ranges between 0.08% as the lowest and 35.88% as the highest. The mean absolute error value is 6.43%.

Table 4. 7 Model Prediction on Testing dataset using 3 features: speed, displacement, and sea condition.

No.	**speed**	**displacement**	**Sea condition**	**Target**	**Prediction**	**Residual**	**Difference %**
1	11.28	18255.00	smooth sea	1937.07	1938.64	-1.57	0.08
2	10.62	14839.39	smooth to slight	1504.71	1506.91	-2.20	0.15
3	12.50	14900.60	slight sea	2233.45	2229.29	4.16	0.19
4	11.75	13725.00	slight sea	2033.90	2029.68	4.22	0.21
5	13.25	15623.00	slight sea	2248.05	2241.83	6.23	0.28
6	10.75	14839.39	smooth sea	1480.52	1473.02	7.50	0.51
7	10.75	15096.20	smooth sea	1443.26	1435.29	7.97	0.55
8	13.50	12232.00	slight sea	2123.64	2135.88	-12.23	0.58
9	12.25	12791.00	swell sea	1750.00	1739.52	10.48	0.60
10	12.50	13725.00	slight sea	2111.27	2125.25	-13.98	0.66
11	11.12	14839.39	smooth sea	1504.10	1514.93	-10.83	0.72
12	12.75	18255.00	smooth sea	2104.63	2086.14	18.49	0.88
13	12.75	16094.00	smooth sea	2156.40	2137.17	19.23	0.89
14	11.00	13725.00	slight sea	1904.08	1885.50	18.58	0.98
15	11.87	18442.00	slight sea	2148.75	2123.39	25.36	1.18
16	12.25	15623.00	slight sea	2073.91	2101.89	-27.97	1.35
17	12.00	15726.47	smooth sea	1536.00	1514.86	21.14	1.38
18	11.50	16335.00	slight sea	1729.81	1754.99	-25.18	1.46
19	11.37	16839.68	slight sea	2030.33	1999.55	30.78	1.52

No.	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
20	12.50	15623.00	smooth to slight	2120.81	2156.13	-35.33	1.67
21	11.75	15257.60	smooth sea	2090.28	2053.77	36.50	1.75
22	13.00	14795.00	smooth sea	2248.16	2205.59	42.57	1.89
23	11.25	15720.14	slight sea	1466.61	1436.90	29.71	2.03
24	11.75	14839.39	smooth sea	1581.98	1614.87	-32.89	2.08
25	12.25	12791.00	slight sea	1717.00	1753.04	-36.04	2.10
26	11.60	15096.20	smooth sea	1560.74	1527.95	32.79	2.10
27	12.50	16767.00	smooth sea	2232.65	2185.20	47.44	2.13
28	12.00	18090.52	slight sea	2191.27	2142.87	48.39	2.21
29	12.00	15255.00	smooth sea	2115.10	2068.30	46.80	2.21
30	0.75	15103.29	slight sea	1542.09	1507.81	34.28	2.22
31	12.25	13725.00	smooth sea	2069.05	2116.32	-47.27	2.28
32	12.75	15255.00	slight sea	2205.33	2149.73	55.59	2.52
33	13.00	18255.00	slight sea	2238.40	2180.90	57.50	2.57
34	12.50	15257.60	smooth sea	2223.70	2166.12	57.58	2.59
35	13.25	16094.00	slight sea	2250.97	2191.48	59.49	2.64
36	12.50	15255.00	smooth sea	2091.98	2148.09	-56.11	2.68
37	11.37	16839.68	moderate sea	2030.33	1974.50	55.82	2.75
38	12.50	16644.60	slight sea	2169.89	2231.76	-61.87	2.85
39	10.75	15726.47	smooth sea	1376.00	1415.48	-39.48	2.87
40	13.00	12557.00	slight sea	2310.89	2241.02	69.88	3.02

No.	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
41	12.30	16644.60	slight sea	2273.47	2203.90	69.56	3.06
42	13.37	18375.20	smooth sea	2274.09	2203.45	70.64	3.11
43	11.97	12791.00	slight sea	1826.42	1769.09	57.33	3.14
44	12.00	15720.14	smooth sea	1564.38	1514.86	49.52	3.17
45	11.00	15720.14	smooth sea	1491.45	1442.84	48.61	3.26
46	12.62	15257.60	smooth sea	2245.93	2165.59	80.35	3.58
47	11.00	14839.39	smooth sea	1487.20	1542.26	-55.06	3.70
48	13.50	16767.00	slight sea	2358.24	2269.20	89.04	3.78
49	12.50	16644.60	slight sea	2150.16	2231.76	-81.60	3.80
50	12.50	16644.60	slight sea	2319.86	2231.76	88.10	3.80
51	11.30	15726.47	smooth sea	1490.02	1433.14	56.88	3.82
52	11.50	14839.39	smooth sea	1628.62	1566.05	62.57	3.84
53	12.75	15255.00	smooth sea	2247.30	2158.84	88.45	3.94
54	12.81	14900.60	slight sea	2300.45	2206.76	93.69	4.07
55	12.75	18090.52	slight sea	2261.83	2167.61	94.21	4.17
56	12.75	13725.00	slight sea	2036.64	2124.91	-88.26	4.33
57	11.50	15623.00	slight sea	1951.14	1865.37	85.77	4.40
58	13.25	18090.52	smooth sea	2129.56	2223.89	-94.33	4.43
59	13.00	13725.00	slight sea	2059.78	2156.54	-96.76	4.70
60	10.50	14213.20	smooth sea	1635.62	1714.26	-78.64	4.81

No.	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
61	12.25	12209.80	smooth sea	2214.33	2100.35	113.98	5.15
62	12.25	12557.00	smooth sea	2004.50	2109.25	-104.75	5.23
63	13.00	15623.00	smooth sea	2131.55	2243.87	-112.32	5.27
64	12.12	15103.29	smooth sea	1568.87	1651.65	-82.78	5.28
65	12.24	14900.60	slight sea	2322.01	2199.16	122.85	5.29
66	12.75	14400.80	slight sea	2265.59	2144.54	121.05	5.34
67	13.00	15623.00	slight sea	2327.86	2197.86	130.00	5.58
68	10.00	14213.20	smooth sea	1600.00	1691.55	-91.55	5.72
69	12.25	12209.80	smooth sea	2230.53	2100.35	130.17	5.84
70	12.87	14837.80	smooth sea	2248.61	2114.23	134.38	5.98
71	12.10	18263.50	slight sea	2227.86	2088.78	139.08	6.24
72	12.40	18255.00	smooth sea	2289.91	2143.56	146.35	6.39
73	11.25	12077.00	slight sea	1474.81	1571.94	-97.12	6.59
74	12.50	12803.00	slight sea	2182.83	2030.89	151.94	6.96
75	11.50	16094.00	smooth sea	1953.67	1815.65	138.02	7.06
76	11.20	15720.14	smooth sea	1328.74	1425.37	-96.63	7.27
77	0.75	15103.29	moderate sea	1419.00	1528.66	-109.66	7.73
78	12.12	15096.20	smooth sea	1523.89	1643.43	-119.54	7.84
79	12.30	18375.20	slight sea	2078.49	2247.30	-168.81	8.12
80	11.75	18442.00	slight sea	2284.80	2099.15	185.65	8.13

No.	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
81	12.75	12803.00	slight sea	2226.48	2024.71	201.77	9.06
82	11.25	12557.00	slight sea	1522.12	1666.50	-144.38	9.49
83	12.50	18090.52	slight sea	2009.02	2205.50	-196.48	9.78
84	12.50	18263.50	smooth sea	2296.76	2070.70	226.06	9.84
85	11.60	16335.00	smooth sea	1748.61	1922.23	-173.62	9.93
86	12.43	18255.00	smooth sea	1958.60	2154.25	-195.65	9.99
87	12.62	12209.80	smooth to swell	2282.12	2038.49	243.63	10.68
88	10.87	15103.29	slight sea	1407.13	1559.19	-152.06	10.81
89	11.50	18442.00	slight sea	2236.18	1990.82	245.36	10.97
90	12.00	15255.00	smooth sea	2332.03	2068.30	263.73	11.31
91	12.00	16644.60	slight sea	1909.51	2134.14	-224.64	11.76
92	12.40	12022.00	slight sea	1776.43	1988.48	-212.05	11.94
93	10.50	14839.39	smooth sea	1635.46	1436.17	199.29	12.19
94	11.61	15103.29	smooth sea	1374.78	1544.49	-169.71	12.34
95	12.15	18255.00	smooth sea	1915.55	2158.95	-243.40	12.71
96	11.80	15103.29	slight sea	1407.13	1589.49	-182.36	12.96
97	11.08	12077.00	smooth sea	1818.94	1579.60	239.34	13.16
98	12.75	14048.00	slight sea	2327.68	2015.60	312.07	13.41
99	10.50	18375.20	slight sea	1856.36	2110.69	-254.33	13.70
100	11.12	14130.97	smooth sea	1461.81	1665.58	-203.77	13.94

No.	speed	displacement	Sea condition	Target	Prediction	Residual	Difference %
101	12.62	14048.00	smooth sea	2303.94	1966.48	337.47	14.65
102	10.50	12557.00	slight sea	1471.79	1744.72	-272.93	18.54
103	9.13	14213.20	slight sea	1541.75	1841.51	-299.76	19.44
104	10.75	12077.00	slight to moderate sea	2097.58	1679.01	418.57	19.96
105	10.62	12077.00	slight to moderate sea	2073.19	1648.96	424.23	20.46
106	11.00	12557.00	smooth to slight	1488.30	1830.21	-341.91	22.97
107	11.75	16839.68	smooth to slight	1729.09	2130.80	-401.71	23.23
108	11.00	18263.50	slight sea	1415.47	1820.33	-404.87	28.60
109	12.00	16094.00	moderate sea	1344.99	1827.63	-482.64	35.88

4.3.4 using 3 feature: speed, engine load, and sea condition

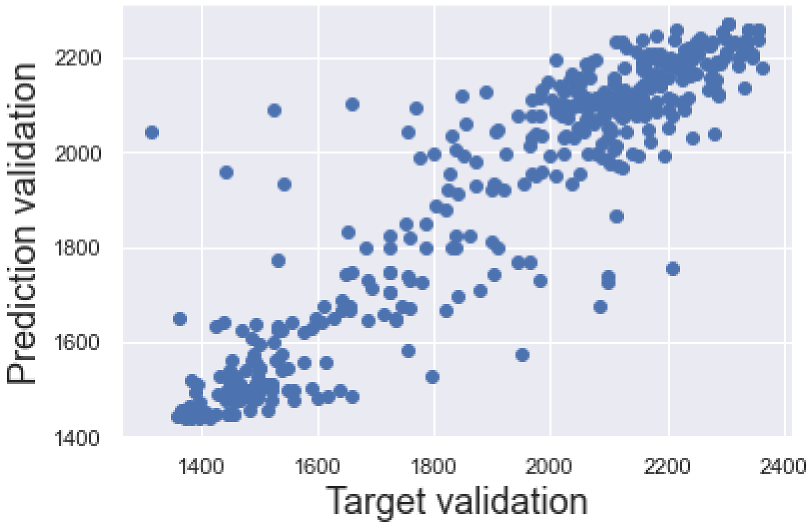


Figure 4. 7 scatter plot of model validation using speed, engine load, and sea condition as a feature

this model is acquired using 3 feature which is speed, engine load, and sea condition. the model made using Elastic net Regressor as its estimator and Random Forest Regressor as its final estimator.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1933.18 + 102.51 (speed in knot) + 197.61 (engine load percentage) + sea condition (22.23 for moderate sea , 3.36 for moderate sea to swell, 11.39 for rippled, 89.63 for slight sea , 23.73 for slight to moderate sea, 8.57 for slight to swell, 78.39 for smooth sea , 32.59 for smooth to slight, 14.16 for smooth to swell, 0.8 for swell sea , -2.19 for very smooth).

with RMSE value of 153.65 and R-value of 0.735. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

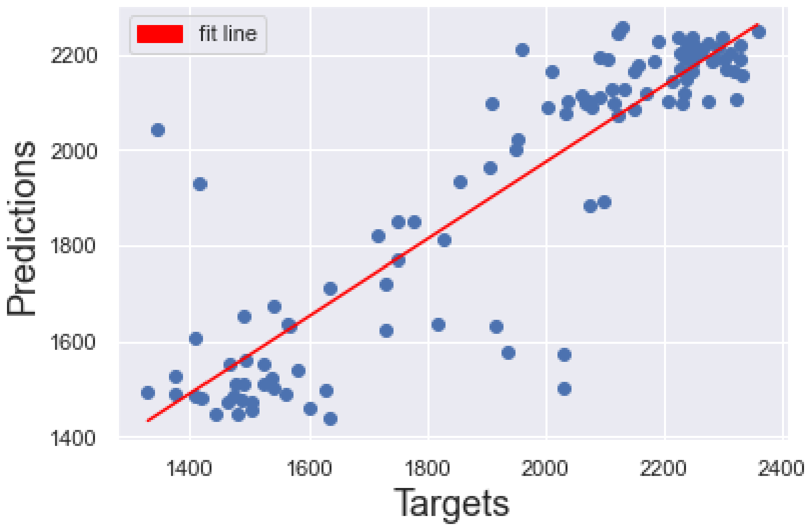


Figure 4. 8 scatter plot of model testing using speed, engine load, and sea condition as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1916.956977	12.088212	5.494328
std	325.243011	295.004390	149.483871	7.034000
min	1328.744275	1438.070719	-698.658082	0.057438
25%	1568.869565	1576.967667	-62.534553	1.714338
50%	2036.642633	2088.578437	12.474179	3.985963
75%	2230.525963	2181.032111	84.113664	5.998135
max	2358.236842	2258.568963	527.979427	51.945276

Table 4. 8 Result analysis of model using speed, engine load, and sea condition as a feature

in this model, the difference between the target and prediction ranges between 0.05% as the lowest and 51.94% as the highest. The mean absolute error value is 5.49%.

Table 4. 9 Model Prediction on Testing dataset using 3 features: engine load, speed, and sea condition.

No.	engine load	speed	sea_condition	Target	Prediction	Residual	Difference %
1	54.00	12.50	slight sea	2182.83	2184.08	-1.25	0.06
2	50.00	13.00	smooth sea	2131.55	2128.27	3.28	0.15
3	39.00	10.75	smooth sea	1443.26	1449.35	-6.09	0.42
4	51.00	12.30	slight sea	2078.49	2088.58	-10.08	0.49
5	52.00	12.50	smooth sea	2223.70	2234.88	-11.18	0.50
6	45.00	11.50	slight sea	1729.81	1720.17	9.63	0.56
7	51.00	13.00	smooth sea	2248.16	2235.47	12.69	0.56
8	53.00	13.00	slight sea	2238.40	2225.71	12.69	0.57
9	40.00	11.00	smooth sea	1487.20	1478.31	8.89	0.60
10	53.00	12.50	slight sea	2150.16	2164.76	-14.59	0.68
11	45.00	11.97	slight sea	1826.42	1812.61	13.80	0.76
12	42.00	11.25	slight sea	1522.12	1510.22	11.90	0.78
13	52.00	12.50	slight sea	2111.27	2128.27	-17.00	0.81
14	30.00	12.00	smooth sea	1536.00	1523.53	12.47	0.81
15	53.00	12.00	smooth sea	2115.10	2097.32	17.78	0.84
16	40.00	11.12	smooth sea	1461.81	1474.66	-12.85	0.88
17	52.00	11.75	smooth sea	2090.28	2109.47	-19.20	0.92
18	51.00	12.75	smooth sea	2156.40	2176.31	-19.91	0.92
19	40.00	10.50	slight sea	1471.79	1486.91	-15.13	1.03
20	53.00	12.75	slight sea	2226.48	2203.01	23.47	1.05

No.	engine load	speed	sea_condition	Target	Prediction	Residual	Difference %
21	45.00	11.60	smooth sea	1748.61	1768.99	-20.38	1.17
22	52.00	12.25	slight sea	2073.91	2101.03	-27.11	1.31
23	53.00	13.25	slight sea	2250.97	2220.91	30.07	1.34
24	52.00	12.25	smooth sea	2069.05	2097.67	-28.62	1.38
25	52.00	12.62	smooth sea	2245.93	2213.00	32.94	1.47
26	40.00	11.30	smooth sea	1490.02	1512.65	-22.63	1.52
27	55.00	12.00	slight sea	2191.27	2227.26	-35.99	1.64
28	54.00	12.50	smooth sea	2232.65	2194.37	38.28	1.71
29	39.00	12.12	smooth sea	1523.89	1553.20	-29.30	1.92
30	40.00	11.12	smooth sea	1504.10	1474.66	29.44	1.96
31	53.00	13.37	smooth sea	2274.09	2224.60	49.49	2.18
32	52.00	11.75	slight sea	2033.90	2078.19	-44.29	2.18
33	50.00	12.50	smooth to slight	2120.81	2072.26	48.54	2.29
34	40.00	10.75	smooth sea	1480.52	1446.23	34.29	2.32
35	51.00	12.50	slight sea	2169.89	2119.36	50.53	2.33
36	42.00	11.25	slight sea	1474.81	1510.22	-35.41	2.40
37	52.00	12.75	slight sea	2265.59	2209.29	56.30	2.49
38	40.00	0.75	slight sea	1542.09	1503.52	38.57	2.50
39	54.00	12.10	slight sea	2227.86	2171.31	56.55	2.54
40	51.00	11.50	slight sea	1951.14	2000.93	-49.79	2.55
41	53.00	12.75	slight sea	2261.83	2203.01	58.81	2.60

No.	engine load	speed	sea_condition	Target	Prediction	Residual	Difference %
42	40.00	11.75	smooth sea	1581.98	1540.06	41.92	2.65
43	50.00	13.00	slight sea	2059.78	2115.01	-55.23	2.68
44	52.00	12.50	smooth sea	2296.76	2234.88	61.88	2.69
45	51.00	13.25	slight sea	2248.05	2187.47	60.59	2.70
46	54.00	11.87	slight sea	2148.75	2087.27	61.48	2.86
47	53.00	12.87	smooth sea	2248.61	2181.03	67.57	3.01
48	51.00	11.00	slight sea	1904.08	1964.44	-60.37	3.17
49	53.00	12.25	smooth sea	2214.33	2144.12	70.22	3.17
50	55.00	12.40	smooth sea	2289.91	2216.95	72.96	3.19
51	39.00	10.62	smooth to slight	1504.71	1456.24	48.47	3.22
52	50.00	12.75	slight sea	2036.64	2103.57	-66.93	3.29
53	53.00	11.50	smooth sea	1953.67	2021.06	-67.39	3.45
54	55.00	12.75	smooth sea	2247.30	2163.18	84.11	3.74
55	42.00	12.12	smooth sea	1568.87	1631.40	-62.53	3.99
56	55.00	11.50	slight sea	2236.18	2146.65	89.53	4.00
57	53.00	12.75	smooth sea	2104.63	2189.76	-85.12	4.04
58	55.00	11.75	slight sea	2284.80	2191.21	93.58	4.10
59	44.00	12.40	slight sea	1776.43	1850.75	-74.32	4.18
60	52.00	12.62	smooth to swell	2282.12	2186.43	95.69	4.19
61	50.00	12.25	smooth sea	2004.50	2089.76	-85.26	4.25
62	52.00	10.50	slight sea	1856.36	1935.83	-79.47	4.28

No.	engine load	speed	sea_condition	Target	Prediction	Residual	Difference %
63	40.00	0.75	moderate sea	1419.00	1480.14	-61.14	4.31
64	40.00	11.60	smooth sea	1560.74	1491.01	69.73	4.47
65	41.00	12.00	smooth sea	1564.38	1634.52	-70.14	4.48
66	45.00	10.50	smooth sea	1635.62	1710.27	-74.65	4.56
67	50.00	12.75	slight sea	2205.33	2103.57	101.76	4.61
68	55.00	13.50	slight sea	2358.24	2247.58	110.65	4.69
69	55.00	12.75	slight sea	2327.68	2218.27	109.41	4.70
70	52.00	13.00	slight sea	2310.89	2201.77	109.12	4.72
71	41.00	11.00	smooth sea	1491.45	1561.88	-70.43	4.72
72	53.00	12.81	slight sea	2300.45	2191.61	108.84	4.73
73	53.00	12.50	smooth sea	2091.98	2195.13	-103.15	4.93
74	51.00	12.50	slight sea	2233.45	2119.36	114.09	5.11
75	40.00	10.87	slight sea	1407.13	1487.28	-80.15	5.70
76	58.00	13.50	slight sea	2123.64	2246.70	-123.06	5.79
77	55.00	12.62	smooth sea	2303.94	2169.99	133.95	5.81
78	45.00	12.25	swell sea	1750.00	1852.25	-102.25	5.84
79	51.00	13.00	slight sea	2327.86	2189.28	138.59	5.95
80	41.00	11.25	slight sea	1466.61	1553.96	-87.35	5.96
81	52.00	12.25	smooth sea	2230.53	2097.67	132.86	5.96
82	42.00	11.75	smooth to slight	1729.09	1625.38	103.71	6.00
83	52.00	13.25	smooth sea	2129.56	2258.57	-129.01	6.06

No.	engine load	speed	sea_condition	Target	Prediction	Residual	Difference %
84	44.00	12.25	slight sea	1717.00	1821.55	-104.55	6.09
85	53.00	12.50	slight sea	2319.86	2164.76	155.11	6.69
86	54.00	12.00	smooth sea	2332.03	2157.46	174.57	7.49
87	52.00	12.30	slight sea	2273.47	2100.96	172.51	7.59
88	53.00	12.50	slight sea	2009.02	2164.76	-155.74	7.75
89	39.00	11.50	smooth sea	1628.62	1496.67	131.95	8.10
90	40.00	11.61	smooth sea	1374.78	1490.59	-115.81	8.42
91	44.00	9.13	slight sea	1541.75	1674.50	-132.75	8.61
92	41.00	10.00	smooth sea	1600.00	1458.40	141.60	8.85
93	49.00	10.62	slight to moderate sea	2073.19	1885.81	187.38	9.04
94	51.00	12.24	slight sea	2322.01	2107.78	214.23	9.23
95	52.00	12.00	slight sea	1909.51	2096.74	-187.23	9.81
96	49.00	10.75	slight to moderate sea	2097.58	1891.17	206.41	9.84
97	41.00	11.08	smooth sea	1818.94	1636.94	181.99	10.01
98	41.00	10.75	smooth sea	1376.00	1526.59	-150.59	10.94
99	42.00	11.00	smooth to slight	1488.30	1654.89	-166.60	11.19
100	40.00	10.50	smooth sea	1635.46	1438.07	197.39	12.07
101	40.00	11.20	smooth sea	1328.74	1495.53	-166.79	12.55
102	52.00	12.43	smooth sea	1958.60	2210.24	-251.65	12.85
103	40.00	11.80	slight sea	1407.13	1607.40	-200.27	14.23

No.	engine load	speed	sea_condition	Target	Prediction	Residual	Difference %
104	42.00	12.15	smooth sea	1915.55	1631.40	284.15	14.83
105	42.00	11.28	smooth sea	1937.07	1576.97	360.11	18.59
106	42.00	11.37	slight sea	2030.33	1573.05	457.28	22.52
107	41.00	11.37	moderate sea	2030.33	1502.35	527.98	26.00
108	54.00	11.00	slight sea	1415.47	1932.24	-516.77	36.51
109	54.00	12.00	moderate sea	1344.99	2043.65	-698.66	51.95

4.3.5 using 3 feature: displacement, engine load, and sea condition

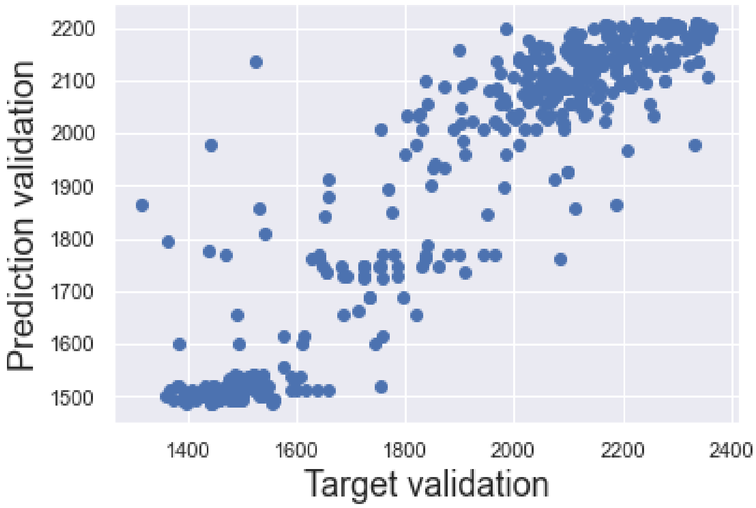


Figure 4. 9 scatter plot of model validation using displacement, engine load, and sea condition as a feature

this model is acquired using 3 feature which is displacement, engine load, and sea condition. the model made using Kneighbors regressor as its estimator and Random Forest Regressor as its final estimator.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1932.63 + 248.42 (engine load percentage) + 5.29 (displacement tonnage) + sea condition (-6.76 for moderate sea , 1.3 for moderate sea to swell, -0.37 for rippled, 58.68 for slight sea , 5.51 for slight to moderate sea, 2.05 for slight to swell, 44.5 for smooth sea ,22.11 for smooth to slight, 3.4 for smooth to swell, -2.41 for swell sea , -2.59 for very smooth).

with RMSE value of 170.32 and R-value of 0.674. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

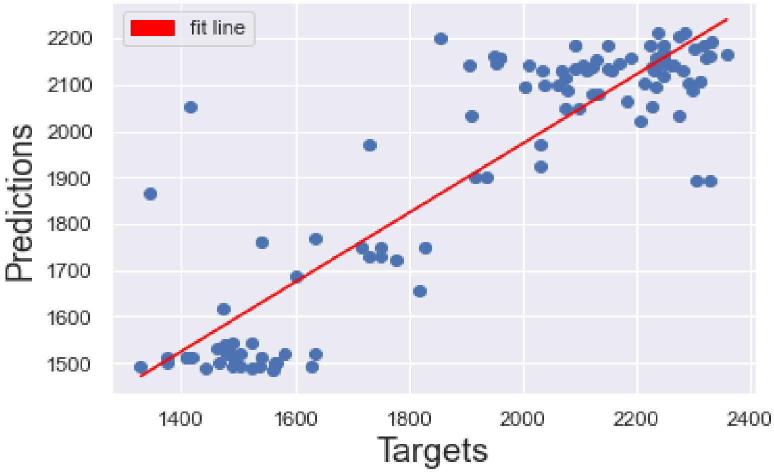


Figure 4. 10 scatter plot of model testing using displacement, engine load, and sea condition as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1919.766313	9.278876	5.675729
std	325.243011	271.931237	147.916269	6.360466
min	1328.744275	1484.804698	-637.840529	0.099590
25%	1568.869565	1616.604722	-53.354767	1.923927
50%	2036.642633	2080.539110	24.937951	4.285357
75%	2230.525963	2142.473851	95.923312	7.126359
max	2358.236842	2210.648236	432.799036	45.062208

Table 4. 10 Result analysis of model using displacement, engine load, and sea condition as a feature

in this model, the difference between the target and prediction ranges between 0.09% as the lowest and 45.06% as the highest. The mean absolute error value is 5.67%.

Table 4. 11 Model Prediction on Testing dataset using 3 features: engine load, displacement, and sea condition.

No.	engine load	displacement	Sea condition	Target	Prediction	Residual	Difference %
1	45.00	16335.00	slight sea	1729.81	1728.09	1.72	0.10
2	45.00	12791.00	swell sea	1750.00	1747.97	2.03	0.12
3	40.00	15726.47	smooth sea	1490.02	1493.92	-3.89	0.26
4	51.00	18375.20	slight sea	2078.49	2087.11	-8.61	0.41
5	54.00	18442.00	slight sea	2148.75	2135.76	12.99	0.60
6	42.00	18255.00	smooth sea	1915.55	1902.68	12.87	0.67
7	41.00	15720.14	smooth sea	1491.45	1501.56	-10.11	0.68
8	58.00	12232.00	slight sea	2123.64	2138.59	-14.95	0.70
9	39.00	14839.39	smooth to slight	1504.71	1492.57	12.14	0.81
10	53.00	15255.00	smooth sea	2115.10	2134.89	-19.79	0.94
11	52.00	13725.00	slight sea	2111.27	2131.89	-20.62	0.98
12	40.00	14839.39	smooth sea	1504.10	1518.91	-14.81	0.98
13	55.00	18442.00	slight sea	2236.18	2210.65	25.53	1.14
14	51.00	16644.60	slight sea	2169.89	2144.96	24.94	1.15
15	49.00	12077.00	slight to moderate sea	2073.19	2049.09	24.10	1.16
16	45.00	16335.00	smooth sea	1748.61	1728.09	20.52	1.17
17	52.00	18090.52	smooth sea	2129.56	2155.27	-25.71	1.21
18	51.00	16094.00	smooth sea	2156.40	2129.03	27.37	1.27

No.	engine load	displacement	Sea condition	Target	Prediction	Residual	Difference %
19	42.00	12557.00	slight sea	1522.12	1541.65	-19.53	1.28
20	55.00	18090.52	slight sea	2191.27	2157.34	33.93	1.55
21	53.00	16644.60	slight sea	2150.16	2184.03	-33.86	1.57
22	52.00	15257.60	smooth sea	2223.70	2186.43	37.27	1.68
23	42.00	18255.00	smooth sea	1937.07	1902.68	34.40	1.78
24	44.00	12791.00	slight sea	1717.00	1747.77	-30.77	1.79
25	53.00	18255.00	smooth sea	2104.63	2142.47	-37.84	1.80
26	50.00	15623.00	smooth to slight	2120.81	2080.54	40.27	1.90
27	50.00	13725.00	slight sea	2059.78	2099.01	-39.23	1.90
28	52.00	15623.00	slight sea	2073.91	2113.81	-39.90	1.92
29	40.00	15103.29	slight sea	1542.09	1511.27	30.83	2.00
30	53.00	15255.00	smooth sea	2091.98	2134.89	-42.91	2.05
31	40.00	14839.39	smooth sea	1487.20	1518.91	-31.71	2.13
32	39.00	15096.20	smooth sea	1523.89	1489.39	34.51	2.26
33	49.00	12077.00	slight to moderate sea	2097.58	2049.09	48.49	2.31
34	41.00	15720.14	slight sea	1466.61	1501.56	-34.95	2.38
35	50.00	15623.00	smooth sea	2131.55	2080.54	51.01	2.39
36	40.00	14839.39	smooth sea	1480.52	1518.91	-38.39	2.59
37	52.00	15257.60	smooth sea	2245.93	2186.43	59.50	2.65
38	30.00	15726.47	smooth sea	1536.00	1493.92	42.08	2.74

No.	engine load	displacement	Sea condition	Target	Prediction	Residual	Difference %
39	44.00	12022.00	slight sea	1776.43	1723.53	52.89	2.98
40	42.00	16839.68	slight sea	2030.33	1969.13	61.20	3.01
41	53.00	18375.20	smooth sea	2274.09	2205.39	68.70	3.02
42	52.00	13725.00	smooth sea	2069.05	2131.89	-62.84	3.04
43	50.00	13725.00	slight sea	2036.64	2099.01	-62.37	3.06
44	39.00	15096.20	smooth sea	1443.26	1489.39	-46.12	3.20
45	55.00	18442.00	slight sea	2284.80	2210.65	74.15	3.25
46	51.00	14900.60	slight sea	2233.45	2156.87	76.58	3.43
47	55.00	15255.00	smooth sea	2247.30	2168.90	78.39	3.49
48	42.00	12557.00	smooth to slight	1488.30	1541.65	-53.35	3.58
49	51.00	15623.00	slight sea	2248.05	2162.86	85.19	3.79
50	53.00	12803.00	slight sea	2226.48	2138.23	88.26	3.96
51	40.00	14839.39	smooth sea	1581.98	1518.91	63.07	3.99
52	53.00	14837.80	smooth sea	2248.61	2158.33	90.28	4.01
53	41.00	15720.14	smooth sea	1564.38	1501.56	62.82	4.02
54	42.00	15103.29	smooth sea	1568.87	1502.60	66.27	4.22
55	53.00	18255.00	slight sea	2238.40	2142.47	95.92	4.29
56	45.00	12791.00	slight sea	1826.42	1747.97	78.44	4.29
57	42.00	12077.00	slight sea	1474.81	1539.53	-64.71	4.39
58	50.00	12557.00	smooth sea	2004.50	2095.79	-91.29	4.55

No.	engine load	displacement	Sea condition	Target	Prediction	Residual	Difference %
59	52.00	12209.80	smooth sea	2230.53	2128.67	101.85	4.57
60	52.00	15257.60	smooth sea	2090.28	2186.43	-96.16	4.60
61	53.00	16094.00	slight sea	2250.97	2146.49	104.48	4.64
62	52.00	13725.00	slight sea	2033.90	2131.89	-97.99	4.82
63	40.00	14130.97	smooth sea	1461.81	1532.45	-70.64	4.83
64	40.00	15096.20	smooth sea	1560.74	1484.80	75.93	4.87
65	53.00	12209.80	smooth sea	2214.33	2103.69	110.64	5.00
66	41.00	16839.68	moderate sea	2030.33	1925.79	104.54	5.15
67	53.00	18090.52	slight sea	2261.83	2143.12	118.71	5.25
68	53.00	14900.60	slight sea	2300.45	2176.94	123.51	5.37
69	41.00	14213.20	smooth sea	1600.00	1687.22	-87.22	5.45
70	54.00	12803.00	slight sea	2182.83	2063.39	119.44	5.47
71	52.00	14400.80	slight sea	2265.59	2140.65	124.94	5.51
72	51.00	14795.00	smooth sea	2248.16	2118.33	129.83	5.78
73	53.00	16644.60	slight sea	2319.86	2184.03	135.84	5.86
74	54.00	15255.00	smooth sea	2332.03	2191.98	140.05	6.01
75	54.00	16767.00	smooth sea	2232.65	2094.98	137.66	6.17
76	40.00	15103.29	moderate sea	1419.00	1511.27	-92.27	6.50
77	52.00	16644.60	slight sea	1909.51	2033.70	-124.19	6.50
78	53.00	18090.52	slight sea	2009.02	2143.12	-134.10	6.67

No.	engine load	displacement	Sea condition	Target	Prediction	Residual	Difference %
79	52.00	12209.80	smooth to swell	2282.12	2128.67	153.45	6.72
80	51.00	15623.00	slight sea	2327.86	2162.86	165.00	7.09
81	51.00	14900.60	slight sea	2322.01	2156.87	165.14	7.11
82	40.00	14839.39	smooth sea	1635.46	1518.91	116.55	7.13
83	40.00	15103.29	slight sea	1407.13	1511.27	-104.14	7.40
84	40.00	15103.29	slight sea	1407.13	1511.27	-104.14	7.40
85	54.00	18263.50	slight sea	2227.86	2053.31	174.55	7.83
86	55.00	16767.00	slight sea	2358.24	2166.60	191.64	8.13
87	55.00	18255.00	smooth sea	2289.91	2101.70	188.20	8.22
88	45.00	14213.20	smooth sea	1635.62	1770.11	-134.49	8.22
89	39.00	14839.39	smooth sea	1628.62	1492.57	136.06	8.35
90	50.00	15255.00	slight sea	2205.33	2019.99	185.34	8.40
91	52.00	12557.00	slight sea	2310.89	2107.04	203.86	8.82
92	41.00	12077.00	smooth sea	1818.94	1654.59	164.34	9.04
93	52.00	18263.50	smooth sea	2296.76	2087.54	209.23	9.11
94	41.00	15726.47	smooth sea	1376.00	1501.56	-125.56	9.12
95	40.00	12557.00	slight sea	1471.79	1616.60	-144.82	9.84
96	53.00	16094.00	smooth sea	1953.67	2146.49	-192.82	9.87
97	40.00	15103.29	smooth sea	1374.78	1511.27	-136.48	9.93
98	52.00	18255.00	smooth sea	1958.60	2159.27	-200.67	10.25

No.	engine load	displacement	Sea condition	Target	Prediction	Residual	Difference %
99	52.00	16644.60	slight sea	2273.47	2033.70	239.77	10.55
100	51.00	15623.00	slight sea	1951.14	2162.86	-211.72	10.85
101	40.00	15720.14	smooth sea	1328.74	1493.92	-165.17	12.43
102	51.00	13725.00	slight sea	1904.08	2141.53	-237.45	12.47
103	42.00	16839.68	smooth to slight	1729.09	1969.13	-240.04	13.88
104	44.00	14213.20	slight sea	1541.75	1760.38	-218.64	14.18
105	55.00	14048.00	smooth sea	2303.94	1894.88	409.07	17.76
106	52.00	18375.20	slight sea	1856.36	2199.81	-343.45	18.50
107	55.00	14048.00	slight sea	2327.68	1894.88	432.80	18.59
108	54.00	16094.00	moderate sea	1344.99	1866.37	-521.38	38.76
109	54.00	18263.50	slight sea	1415.47	2053.31	-637.84	45.06

4.3.6 Using 2 features: speed and engine load

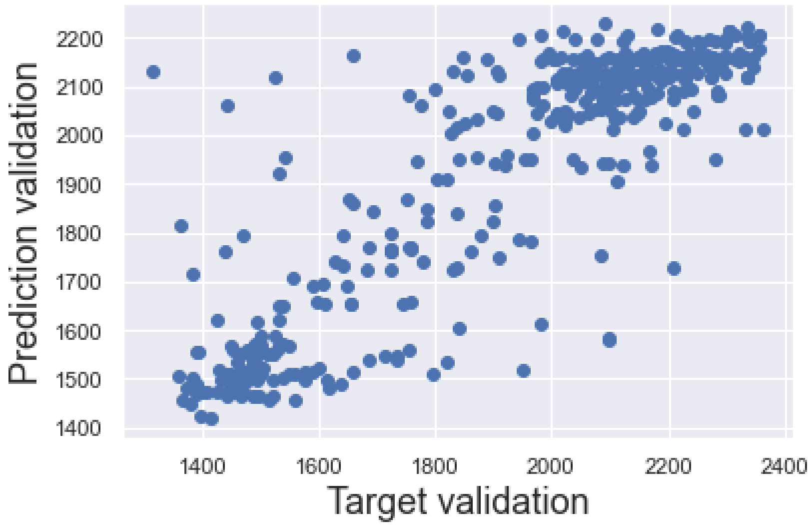


Figure 4. 11 scatter plot of model validation using speed and engine load as a feature

This model is acquired using 2 feature as an input which is speed and engine load value, Ridge regression is the method that is used in this model as its final estimator and extra tree regression as its estimator. This model using ridge regression as its final estimator means that there is high level of multicollinearity means that the predictors feature have high corelation and the information contained in a variable is already present in other variable and one feature can predict the other. This causes overfitting making the model variance large that the prediction can be far from its true value.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1932.45 + 194.61 (engine load percentage) + 104.27 (speed in knot).

with RMSE value of 156.52 and R-value of 0.725. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

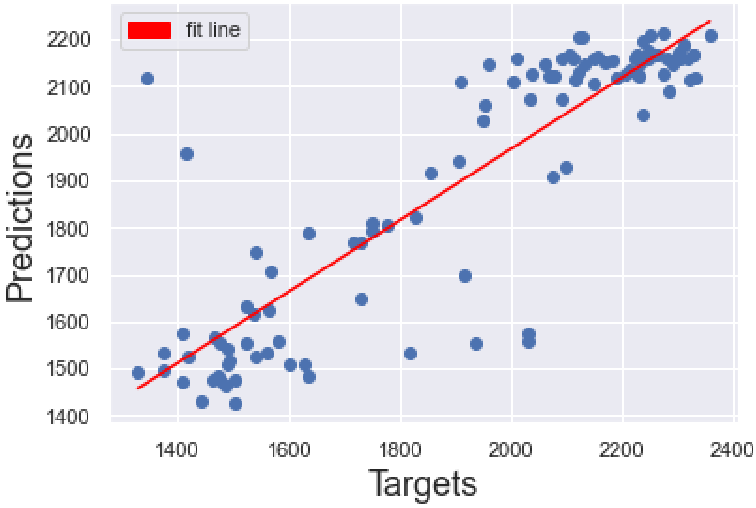


Figure 4. 12 scatter plot of model testing using speed and engine load as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1912.658014	16.387176	5.900825
std	325.243011	280.971597	156.112041	7.291047
min	1328.744275	1424.755263	-773.455534	0.088305
25%	1568.869565	1573.090424	-60.550237	2.112205
50%	2036.642633	2103.366204	17.450360	3.829116
75%	2230.525963	2157.223781	95.960038	6.978642
max	2358.236842	2213.248131	471.877027	57.506472

Table 4. 12 Result analysis of model using engine load and speed as a feature

in this model, the difference between the target and prediction ranges between 0.08% as the lowest and 57.5% with mean absolute error of 5.9%

Table 4. 13 Model Prediction on Testing dataset using 2 features: engine load and speed

No.	**engine load**	**speed**	**Target**	**Prediction**	**Residual**	**Difference%**
1	53.00	12.00	2115.10	2113.23	1.87	0.09
2	51.00	12.75	2156.40	2163.60	-7.20	0.33
3	50.00	12.50	2120.81	2127.91	-7.10	0.33

No.	engine load	speed	Target	Prediction	Residual	Difference%
4	45.00	11.97	1826.42	1819.86	6.56	0.36
5	53.00	12.50	2150.16	2157.97	-7.80	0.36
6	40.00	10.75	1480.52	1472.71	7.81	0.53
7	50.00	13.00	2131.55	2146.58	-15.03	0.71
8	40.00	10.50	1471.79	1482.60	-10.82	0.73
9	52.00	11.75	2090.28	2072.83	17.45	0.83
10	40.00	11.12	1461.81	1474.28	-12.47	0.85
11	39.00	10.75	1443.26	1430.28	12.98	0.90
12	51.00	12.50	2169.89	2149.40	20.49	0.94
13	40.00	11.30	1490.02	1507.18	-17.16	1.15
14	40.00	0.75	1542.09	1523.54	18.56	1.20
15	54.00	12.50	2182.83	2153.30	29.53	1.35
16	40.00	11.75	1581.98	1558.56	23.42	1.48
17	40.00	11.00	1487.20	1465.00	22.20	1.49
18	44.00	12.40	1776.43	1804.93	-28.50	1.60
19	41.00	11.00	1491.45	1515.96	-24.51	1.64
20	40.00	11.60	1560.74	1532.91	27.83	1.78
21	51.00	11.00	1904.08	1940.12	-36.04	1.89
22	52.00	11.75	2033.90	2072.83	-38.93	1.91
23	53.00	13.00	2238.40	2195.51	42.89	1.92
24	53.00	13.25	2250.97	2206.70	44.27	1.97
25	40.00	11.12	1504.10	1474.28	29.82	1.98
26	42.00	11.25	1522.12	1552.53	-30.41	2.00
27	51.00	12.30	2078.49	2121.53	-43.03	2.07
28	54.00	11.87	2148.75	2103.37	45.39	2.11
29	52.00	12.50	2111.27	2157.22	-45.95	2.18
30	45.00	11.50	1729.81	1768.23	-38.42	2.22
31	52.00	12.25	2073.91	2122.94	-49.02	2.36
32	45.00	11.60	1748.61	1793.77	-45.16	2.58
33	52.00	12.25	2069.05	2122.94	-53.89	2.60
34	53.00	13.37	2274.09	2213.25	60.84	2.68
35	53.00	12.75	2226.48	2165.87	60.62	2.72
36	44.00	12.25	1717.00	1766.86	-49.86	2.90

No.	engine load	speed	Target	Prediction	Residual	Difference%
37	53.00	12.75	2104.63	2165.87	-61.24	2.91
38	52.00	12.50	2223.70	2157.22	66.47	2.99
39	53.00	12.50	2091.98	2157.97	-65.99	3.15
40	52.00	10.50	1856.36	1916.91	-60.55	3.26
41	55.00	12.00	2191.27	2118.81	72.46	3.31
42	45.00	12.25	1750.00	1808.58	-58.58	3.35
43	53.00	12.87	2248.61	2173.23	75.38	3.35
44	52.00	13.25	2129.56	2204.14	-74.58	3.50
45	51.00	13.25	2248.05	2168.19	79.86	3.55
46	54.00	12.50	2232.65	2153.30	79.35	3.55
47	42.00	11.00	1488.30	1541.31	-53.02	3.56
48	50.00	12.75	2205.33	2125.68	79.65	3.61
49	55.00	12.75	2247.30	2165.77	81.52	3.63
50	51.00	13.00	2248.16	2166.25	81.91	3.64
51	53.00	12.25	2214.33	2132.31	82.03	3.70
52	41.00	12.00	1564.38	1623.17	-58.79	3.76
53	51.00	12.50	2233.45	2149.40	84.04	3.76
54	58.00	13.50	2123.64	2203.64	-80.00	3.77
55	51.00	11.50	1951.14	2025.85	-74.71	3.83
56	52.00	12.62	2245.93	2157.60	88.34	3.93
57	50.00	13.00	2059.78	2146.58	-86.80	4.21
58	53.00	12.75	2261.83	2165.87	95.96	4.24
59	52.00	12.75	2265.59	2167.05	98.54	4.35
60	50.00	12.75	2036.64	2125.68	-89.04	4.37
61	54.00	12.10	2227.86	2126.53	101.33	4.55
62	42.00	11.75	1729.09	1648.68	80.41	4.65
63	40.00	10.87	1407.13	1472.89	-65.76	4.67
64	52.00	12.25	2230.53	2122.94	107.59	4.82
65	50.00	12.25	2004.50	2108.52	-104.02	5.19
66	42.00	11.25	1474.81	1552.53	-77.72	5.27
67	30.00	12.00	1536.00	1617.46	-81.46	5.30
68	39.00	10.62	1504.71	1424.76	79.95	5.31
69	52.00	13.00	2310.89	2188.04	122.85	5.32
70	52.00	12.62	2282.12	2157.60	124.52	5.46
71	53.00	11.50	1953.67	2060.91	-107.24	5.49
72	53.00	12.81	2300.45	2171.42	129.03	5.61

No.	engine load	speed	Target	Prediction	Residual	Difference%
73	41.00	10.00	1600.00	1509.63	90.37	5.65
74	52.00	12.50	2296.76	2157.22	139.54	6.08
75	55.00	12.62	2303.94	2160.28	143.67	6.24
76	55.00	13.50	2358.24	2209.57	148.67	6.30
77	55.00	12.40	2289.91	2144.89	145.02	6.33
78	52.00	12.30	2273.47	2124.77	148.70	6.54
79	41.00	11.25	1466.61	1566.17	-99.57	6.79
80	51.00	13.00	2327.86	2166.25	161.61	6.94
81	55.00	12.75	2327.68	2165.77	161.90	6.96
82	53.00	12.50	2319.86	2157.97	161.89	6.98
83	39.00	12.12	1523.89	1631.79	-107.89	7.08
84	39.00	11.50	1628.62	1510.39	118.23	7.26
85	40.00	0.75	1419.00	1523.54	-104.54	7.37
86	53.00	12.50	2009.02	2157.97	-148.95	7.41
87	49.00	10.62	2073.19	1907.00	166.19	8.02
88	49.00	10.75	2097.58	1926.53	171.05	8.15
89	55.00	11.75	2284.80	2088.39	196.41	8.60
90	55.00	11.50	2236.18	2041.16	195.02	8.72
91	42.00	12.12	1568.87	1706.96	-138.09	8.80
92	41.00	10.75	1376.00	1497.98	-121.98	8.86
93	51.00	12.24	2322.01	2113.73	208.28	8.97
94	54.00	12.00	2332.03	2118.44	213.58	9.16
95	40.00	10.50	1635.46	1482.60	152.85	9.35
96	45.00	10.50	1635.62	1790.40	-154.78	9.46
97	52.00	12.43	1958.60	2146.27	-187.67	9.58
98	52.00	12.00	1909.51	2108.06	-198.55	10.40
99	42.00	12.15	1915.55	1696.07	219.48	11.46
100	40.00	11.61	1374.78	1533.27	-158.49	11.53
101	40.00	11.80	1407.13	1574.46	-167.33	11.89
102	40.00	11.20	1328.74	1494.31	-165.56	12.46
103	44.00	9.13	1541.75	1748.78	-207.03	13.43
104	41.00	11.08	1818.94	1534.99	283.95	15.61
105	42.00	11.28	1937.07	1555.84	381.23	19.68
106	42.00	11.37	2030.33	1573.09	457.24	22.52
107	41.00	11.37	2030.33	1558.45	471.88	23.24

No.	engine load	speed	Target	Prediction	Residual	Difference%
108	54.00	11.00	1415.47	1955.11	-539.64	38.12
109	54.00	12.00	1344.99	2118.44	-773.46	57.51

4.3.7 Using 2 features: speed and displacement

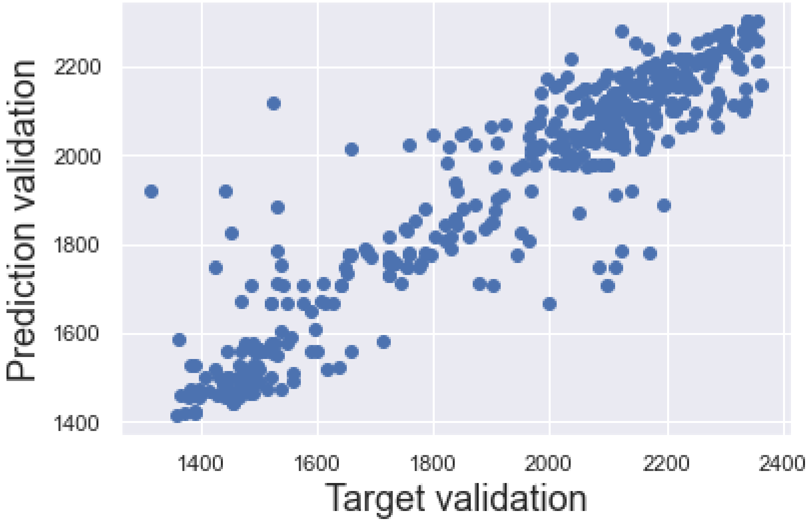


Figure 4. 13 scatter plot of model validation using speed and displacement as a feature

This model is acquired using 2 feature as an input which is speed and displacement. the model made using linear extra trees regressor as its final estimator and linear regression. extra trees work like random forest regression in which it will create a tree-like structure to predict the output this but unlike random forest, the Extra Trees algorithm selects a split point at random.

compared using regular linear regression in python will result with model that generate the following equation::

Fuel consumption = 1933.91 + 192.44 (speed knot) + 56.40 (displacement tonnage).

with RMSE value of 209.46 and R-value of 0.507. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

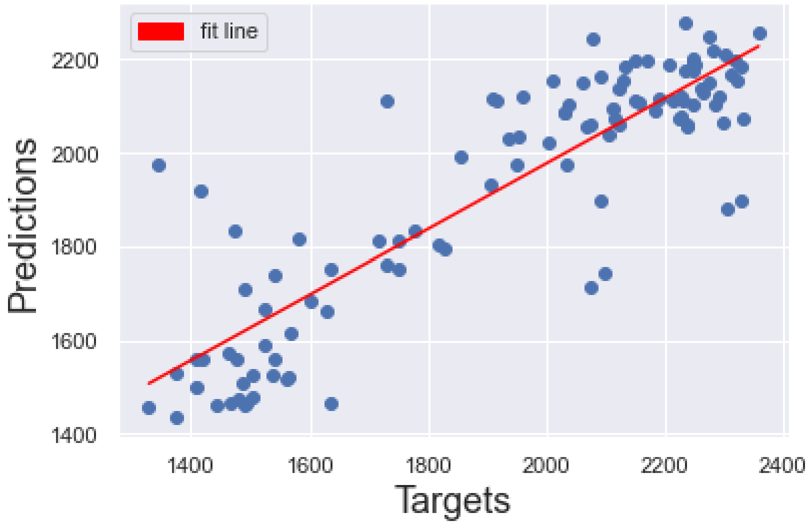


Figure 4. 14 scatter plot of model testing using speed and displacement as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1927.990088	1.055102	6.118030
std	325.243011	259.892167	158.984750	6.875840
min	1328.744275	1434.396941	-632.071025	0.049024
25%	1568.869565	1712.266707	-73.050453	1.997763
50%	2036.642633	2058.606979	9.505847	4.202310
75%	2230.525963	2127.814616	88.192608	7.631382
max	2358.236842	2280.258385	430.503132	46.994524

Table 4. 14 Result analysis of model using speed and displacement as a feature

The RMSE for this model is around 148.73 ton. with the mean error of 6.11%. so on average, the when a data is inputted to the model, the prediction should be within 6.11% difference range. this model has r-squared score of 0.761.

Table 4. 15 Model Prediction on Testing dataset using 2 features: speed and displacement

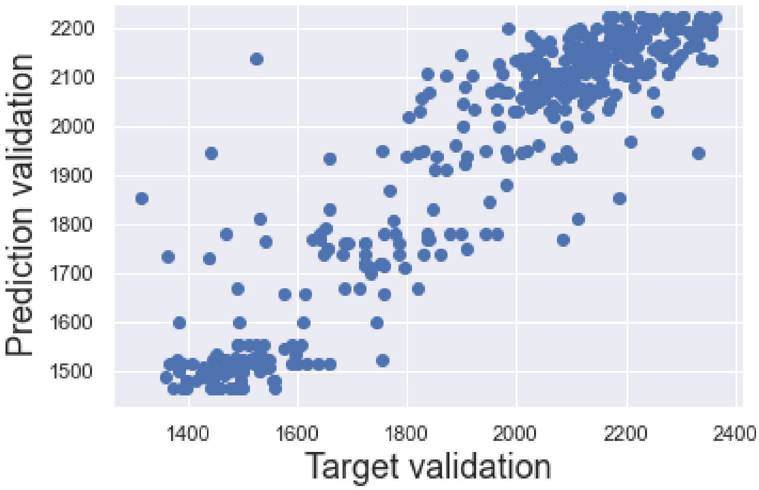
No.	speed	displacement	Target	Prediction	Residual	Difference%
1	11.25	15720.14	1466.61	1465.89	0.72	0.05
2	11.60	16335.00	1748.61	1751.91	-3.30	0.19
3	12.25	13725.00	2069.05	2058.61	10.44	0.50
4	10.75	14839.39	1480.52	1472.77	7.74	0.52
5	12.25	15623.00	2073.91	2062.23	11.68	0.56
6	12.00	15726.47	1536.00	1526.49	9.51	0.62
7	12.75	15255.00	2205.33	2190.70	14.63	0.66
8	11.08	12077.00	1818.94	1805.37	13.57	0.75
9	12.50	13725.00	2111.27	2093.71	17.57	0.83
10	12.50	15623.00	2120.81	2139.29	-18.48	0.87
11	12.25	12557.00	2004.50	2022.74	-18.24	0.91
12	0.75	15103.29	1542.09	1558.74	-16.65	1.08
13	13.25	18090.52	2129.56	2153.79	-24.24	1.14
14	13.37	18375.20	2274.09	2247.55	26.55	1.17
15	12.50	16644.60	2169.89	2197.33	-27.43	1.26
16	11.50	15623.00	1951.14	1976.77	-25.63	1.31
17	11.00	14839.39	1487.20	1507.77	-20.57	1.38
18	10.75	15096.20	1443.26	1463.47	-20.21	1.40
19	11.00	13725.00	1904.08	1933.36	-29.29	1.54
20	11.12	14839.39	1504.10	1528.08	-23.98	1.59
21	10.62	14839.39	1504.71	1479.50	25.21	1.68
22	11.00	15720.14	1491.45	1466.07	25.37	1.70
23	11.87	18442.00	2148.75	2111.60	37.16	1.73
24	11.97	12791.00	1826.42	1794.61	31.81	1.74
25	11.50	16335.00	1729.81	1760.99	-31.18	1.80
26	11.30	15726.47	1490.02	1462.44	27.58	1.85
27	12.00	15255.00	2115.10	2073.77	41.33	1.95
28	13.00	14795.00	2248.16	2203.25	44.91	2.00
29	12.50	16767.00	2232.65	2280.26	-47.61	2.13
30	12.50	16644.60	2150.16	2197.33	-47.16	2.19
31	11.50	14839.39	1628.62	1664.83	-36.20	2.22
32	12.75	16094.00	2156.40	2107.56	48.84	2.27
33	12.87	14837.80	2248.61	2193.78	54.82	2.44

No.	speed	displacement	Target	Prediction	Residual	Difference%
34	13.00	15623.00	2131.55	2184.55	-53.00	2.49
35	12.75	15255.00	2247.30	2190.70	56.60	2.52
36	12.50	14900.60	2233.45	2176.51	56.94	2.55
37	11.60	15096.20	1560.74	1519.07	41.67	2.67
38	12.62	12209.80	2282.12	2220.34	61.78	2.71
39	13.25	16094.00	2250.97	2189.64	61.33	2.72
40	11.37	16839.68	2030.33	2086.83	-56.50	2.78
41	11.37	16839.68	2030.33	2086.83	-56.50	2.78
42	12.00	15720.14	1564.38	1519.75	44.63	2.85
43	11.75	13725.00	2033.90	1975.06	58.84	2.89
44	12.12	15103.29	1568.87	1615.04	-46.17	2.94
45	13.50	12232.00	2123.64	2060.09	63.55	2.99
46	12.75	18255.00	2104.63	2038.75	65.88	3.13
47	13.25	15623.00	2248.05	2177.39	70.67	3.14
48	12.40	12022.00	1776.43	1833.50	-57.07	3.21
49	12.75	13725.00	2036.64	2102.42	-65.77	3.23
50	12.00	18090.52	2191.27	2117.95	73.32	3.35
51	12.50	15255.00	2091.98	2165.03	-73.05	3.49
52	12.25	12791.00	1750.00	1813.91	-63.91	3.65
53	12.81	14900.60	2300.45	2212.26	88.19	3.83
54	12.50	12803.00	2182.83	2091.76	91.07	4.17
55	13.50	16767.00	2358.24	2259.14	99.10	4.20
56	10.75	15726.47	1376.00	1434.40	-58.40	4.24
57	11.50	16094.00	1953.67	2037.36	-83.69	4.28
58	12.12	15096.20	1523.89	1589.66	-65.77	4.32
59	13.00	13725.00	2059.78	2150.49	-90.71	4.40
60	12.25	12209.80	2214.33	2112.51	101.83	4.60
61	11.28	18255.00	1937.07	2030.04	-92.97	4.80
62	12.75	12803.00	2226.48	2118.78	107.70	4.84
63	12.50	16644.60	2319.86	2197.33	122.54	5.28
64	12.25	12209.80	2230.53	2112.51	118.02	5.29
65	10.00	14213.20	1600.00	1685.19	-85.19	5.32
66	12.75	18090.52	2261.83	2139.28	122.55	5.42
67	12.30	16644.60	2273.47	2149.15	124.32	5.47
68	12.25	12791.00	1717.00	1813.91	-96.91	5.64
69	11.25	12077.00	1474.81	1558.39	-83.58	5.67

No.	speed	displacement	Target	Prediction	Residual	Difference%
70	12.75	14400.80	2265.59	2127.81	137.78	6.08
71	13.00	15623.00	2327.86	2184.55	143.31	6.16
72	13.00	12557.00	2310.89	2168.50	142.39	6.16
73	12.62	15257.60	2245.93	2102.75	143.19	6.38
74	10.87	15103.29	1407.13	1498.37	-91.24	6.48
75	12.50	15257.60	2223.70	2075.31	148.39	6.67
76	12.10	18263.50	2227.86	2077.77	150.09	6.74
77	12.24	14900.60	2322.01	2156.89	165.12	7.11
78	10.50	14213.20	1635.62	1752.01	-116.39	7.12
79	10.50	18375.20	1856.36	1991.27	-134.92	7.27
80	12.50	18090.52	2009.02	2155.69	-146.68	7.30
81	12.40	18255.00	2289.91	2121.02	168.89	7.38
82	11.12	14130.97	1461.81	1573.37	-111.56	7.63
83	11.75	18442.00	2284.80	2105.54	179.26	7.85
84	11.50	18442.00	2236.18	2059.94	176.25	7.88
85	12.30	18375.20	2078.49	2244.11	-165.62	7.97
86	13.00	18255.00	2238.40	2058.21	180.18	8.05
87	12.43	18255.00	1958.60	2119.34	-160.74	8.21
88	11.75	15257.60	2090.28	1898.11	192.16	9.19
89	11.25	12557.00	1522.12	1669.13	-147.01	9.66
90	11.20	15720.14	1328.74	1459.13	-130.39	9.81
91	0.75	15103.29	1419.00	1558.74	-139.74	9.85
92	12.50	18263.50	2296.76	2066.44	230.32	10.03
93	10.50	14839.39	1635.46	1466.88	168.58	10.31
94	12.15	18255.00	1915.55	2114.35	-198.80	10.38
95	12.00	16644.60	1909.51	2116.41	-206.90	10.84
96	11.80	15103.29	1407.13	1560.96	-153.83	10.93
97	12.00	15255.00	2332.03	2073.77	258.25	11.07
98	11.61	15103.29	1374.78	1532.24	-157.46	11.45
99	9.13	14213.20	1541.75	1738.51	-196.77	12.76
100	11.00	12557.00	1488.30	1709.21	-220.91	14.84
101	11.75	14839.39	1581.98	1817.90	-235.92	14.91
102	10.75	12077.00	2097.58	1746.31	351.27	16.75
103	10.62	12077.00	2073.19	1712.27	360.93	17.41
104	12.62	14048.00	2303.94	1879.78	424.16	18.41
105	12.75	14048.00	2327.68	1897.17	430.50	18.49

No.	speed	displacement	Target	Prediction	Residual	Difference%
106	11.75	16839.68	1729.09	2112.51	-383.42	22.17
107	10.50	12557.00	1471.79	1832.92	-361.13	24.54
108	11.00	18263.50	1415.47	1920.58	-505.12	35.69
109	12.00	16094.00	1344.99	1977.06	-632.07	46.99

4.3.8 Using 2 Features : engine load and displacement



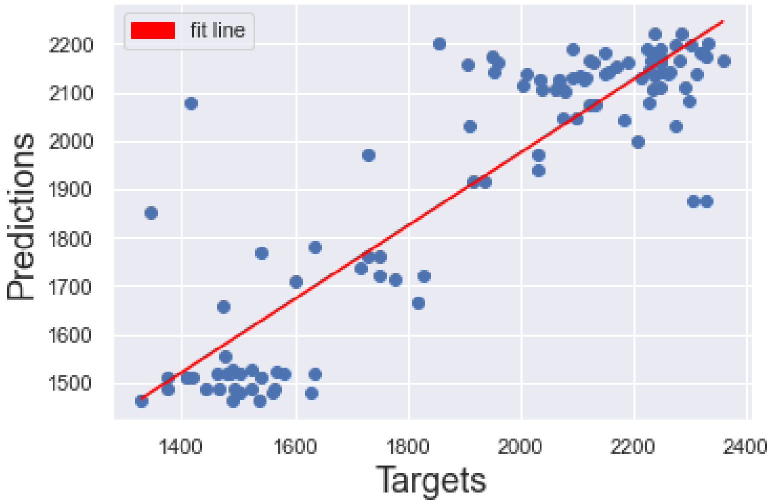
scatter plot of model validation using engine load and displacement as a feature

in this model, it can be seen that the prediction become more 'categorical' form the way the scater plot form more flat spread rather than spread out like any other model before. this is due to data that used to determine the fuel consumption value come from speed and displacement in which both of this feature have a lot of repeated value. for example, displacement only change when the ship load or unload cargo in the port but won't change in the middle of the voyage and for speed, its value is often rounded by the sea crew which make it easier to categorize its consumption. this model use random forest regression as its final estimator and KNeighbor regression as its estimator.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1931.44 + 244.94 (engine load percentage) + 4.35 (displacement tonnage).

with RMSE value of 172.58 and R-value of 0.665. Compared to model created by linear regression, The model generated by the automl library TPOT is better.



scatter plot of model testing using engine load and displacement as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1921.395243	7.649947	5.688194
std	325.243011	276.482421	149.225501	6.466950
min	1328.744275	1462.050495	-661.862285	0.056212
25%	1568.869565	1657.579492	-46.861886	1.894362
50%	2036.642633	2077.328952	25.045657	3.940955
75%	2230.525963	2143.848495	88.616549	6.831703
max	2358.236842	2220.980310	451.391720	46.759299

Table 4. 16 Result analysis of model using engine load and displacement as a feature

The RMSE for this model is around 148.73 ton. with the mean error of 5.6%. so on average, the when a data is inputted to the model, the prediction should be within 5.6% difference range. this model has r-squared score of 0.788.

Table 4. 17 Model Prediction on Testing dataset using 2 features: engine load and displacement

No.	**engine load**	**displacement**	**Target**	**Prediction**	**Residual**	**Difference%**
1	42.00	18255.00	1915.55	1914.47	1.08	0.06
2	42.00	12557.00	1522.12	1525.69	-3.57	0.23

No.	engine load	displacement	Target	Prediction	Residual	Difference%
3	41.00	15720.14	1491.45	1487.25	4.20	0.28
4	54.00	18442.00	2148.75	2137.03	11.72	0.55
5	45.00	16335.00	1748.61	1759.86	-11.25	0.64
6	53.00	15255.00	2115.10	2128.73	-13.63	0.64
7	51.00	16094.00	2156.40	2141.82	14.58	0.68
8	55.00	18442.00	2236.18	2220.98	15.20	0.68
9	52.00	13725.00	2111.27	2126.08	-14.81	0.70
10	51.00	16644.60	2169.89	2152.84	17.05	0.79
11	44.00	12791.00	1717.00	1735.73	-18.73	1.09
12	40.00	14839.39	1504.10	1520.58	-16.48	1.10
13	42.00	18255.00	1937.07	1914.47	22.60	1.17
14	51.00	18375.20	2078.49	2103.93	-25.44	1.22
15	49.00	12077.00	2073.19	2044.91	28.28	1.36
16	41.00	15720.14	1466.61	1487.25	-20.64	1.41
17	55.00	18090.52	2191.27	2160.23	31.04	1.42
18	53.00	18255.00	2104.63	2134.63	-30.00	1.43
19	52.00	18090.52	2129.56	2160.95	-31.39	1.47
20	52.00	15257.60	2223.70	2190.12	33.58	1.51
21	53.00	16644.60	2150.16	2182.64	-32.48	1.51
22	52.00	15623.00	2073.91	2106.66	-32.75	1.58
23	39.00	14839.39	1504.71	1479.66	25.05	1.66
24	45.00	12791.00	1750.00	1719.68	30.32	1.73
25	45.00	16335.00	1729.81	1759.86	-30.05	1.74
26	53.00	15255.00	2091.98	2128.73	-36.75	1.76
27	40.00	15726.47	1490.02	1462.05	27.97	1.88
28	40.00	15103.29	1542.09	1512.88	29.21	1.89
29	58.00	12232.00	2123.64	2164.50	-40.86	1.92
30	50.00	15623.00	2120.81	2075.20	45.60	2.15
31	40.00	14839.39	1487.20	1520.58	-33.38	2.24
32	50.00	13725.00	2059.78	2106.64	-46.86	2.28
33	51.00	14900.60	2233.45	2179.64	53.81	2.41
34	39.00	15096.20	1523.89	1486.80	37.10	2.43
35	52.00	15257.60	2245.93	2190.12	55.82	2.49
36	49.00	12077.00	2097.58	2044.91	52.67	2.51
37	42.00	12557.00	1488.30	1525.69	-37.39	2.51
38	50.00	15623.00	2131.55	2075.20	56.35	2.64

No.	engine load	displacement	Target	Prediction	Residual	Difference%
39	40.00	14839.39	1480.52	1520.58	-40.07	2.71
40	52.00	13725.00	2069.05	2126.08	-57.03	2.76
41	55.00	18442.00	2284.80	2220.98	63.82	2.79
42	52.00	12209.80	2230.53	2165.59	64.94	2.91
43	42.00	15103.29	1568.87	1522.52	46.34	2.95
44	42.00	16839.68	2030.33	1969.34	60.98	3.00
45	39.00	15096.20	1443.26	1486.80	-43.53	3.02
46	51.00	15623.00	2248.05	2175.22	72.83	3.24
47	53.00	18375.20	2274.09	2198.56	75.53	3.32
48	50.00	13725.00	2036.64	2106.64	-70.00	3.44
49	44.00	12022.00	1776.43	1714.72	61.71	3.47
50	53.00	12803.00	2226.48	2143.85	82.64	3.71
51	53.00	12209.80	2214.33	2131.84	82.50	3.73
52	55.00	15255.00	2247.30	2161.18	86.11	3.83
53	40.00	14130.97	1461.81	1518.46	-56.65	3.88
54	40.00	14839.39	1581.98	1520.58	61.39	3.88
55	53.00	14837.80	2248.61	2159.99	88.62	3.94
56	41.00	16839.68	2030.33	1938.46	91.87	4.52
57	52.00	13725.00	2033.90	2126.08	-92.18	4.53
58	53.00	14900.60	2300.45	2195.40	105.05	4.57
59	53.00	18255.00	2238.40	2134.63	103.77	4.64
60	52.00	15257.60	2090.28	2190.12	-99.84	4.78
61	30.00	15726.47	1536.00	1462.05	73.95	4.81
62	53.00	16094.00	2250.97	2142.27	108.70	4.83
63	41.00	15720.14	1564.38	1487.25	77.13	4.93
64	52.00	12209.80	2282.12	2165.59	116.53	5.11
65	40.00	15096.20	1560.74	1478.30	82.44	5.28
66	42.00	12077.00	1474.81	1553.49	-78.68	5.33
67	50.00	12557.00	2004.50	2112.25	-107.75	5.38
68	52.00	14400.80	2265.59	2143.46	122.13	5.39
69	53.00	18090.52	2261.83	2136.75	125.08	5.53
70	54.00	15255.00	2332.03	2199.84	132.18	5.67
71	54.00	16767.00	2232.65	2104.67	127.97	5.73
72	45.00	12791.00	1826.42	1719.68	106.74	5.84
73	53.00	16644.60	2319.86	2182.64	137.22	5.91
74	51.00	14795.00	2248.16	2110.86	137.30	6.11

No.	engine load	displacement	Target	Prediction	Residual	Difference%
75	51.00	14900.60	2322.01	2179.64	142.37	6.13
76	52.00	16644.60	1909.51	2029.81	-120.30	6.30
77	53.00	18090.52	2009.02	2136.75	-127.73	6.36
78	54.00	12803.00	2182.83	2043.87	138.96	6.37
79	51.00	15623.00	2327.86	2175.22	152.64	6.56
80	40.00	15103.29	1419.00	1512.88	-93.88	6.62
81	54.00	18263.50	2227.86	2077.33	150.53	6.76
82	41.00	14213.20	1600.00	1709.31	-109.31	6.83
83	40.00	14839.39	1635.46	1520.58	114.87	7.02
84	40.00	15103.29	1407.13	1512.88	-105.75	7.52
85	40.00	15103.29	1407.13	1512.88	-105.75	7.52
86	52.00	12557.00	2310.89	2136.13	174.77	7.56
87	55.00	18255.00	2289.91	2109.62	180.28	7.87
88	41.00	15726.47	1376.00	1487.25	-111.25	8.08
89	55.00	16767.00	2358.24	2163.72	194.51	8.25
90	41.00	12077.00	1818.94	1666.98	151.96	8.35
91	45.00	14213.20	1635.62	1781.19	-145.57	8.90
92	39.00	14839.39	1628.62	1479.66	148.96	9.15
93	52.00	18263.50	2296.76	2082.17	214.59	9.34
94	50.00	15255.00	2205.33	1998.00	207.33	9.40
95	53.00	16094.00	1953.67	2142.27	-188.60	9.65
96	40.00	15103.29	1374.78	1512.88	-138.10	10.05
97	40.00	15720.14	1328.74	1463.25	-134.51	10.12
98	52.00	18255.00	1958.60	2161.90	-203.30	10.38
99	52.00	16644.60	2273.47	2029.81	243.65	10.72
100	51.00	15623.00	1951.14	2175.22	-224.08	11.48
101	40.00	12557.00	1471.79	1657.58	-185.79	12.62
102	51.00	13725.00	1904.08	2156.78	-252.71	13.27
103	42.00	16839.68	1729.09	1969.34	-240.26	13.89
104	44.00	14213.20	1541.75	1768.08	-226.33	14.68
105	52.00	18375.20	1856.36	2200.65	-344.30	18.55
106	55.00	14048.00	2303.94	1876.29	427.66	18.56
107	55.00	14048.00	2327.68	1876.29	451.39	19.39
108	54.00	16094.00	1344.99	1852.76	-507.77	37.75
109	54.00	18263.50	1415.47	2077.33	-661.86	46.76

4.3.9 Using 2 Features : speed and sea condition

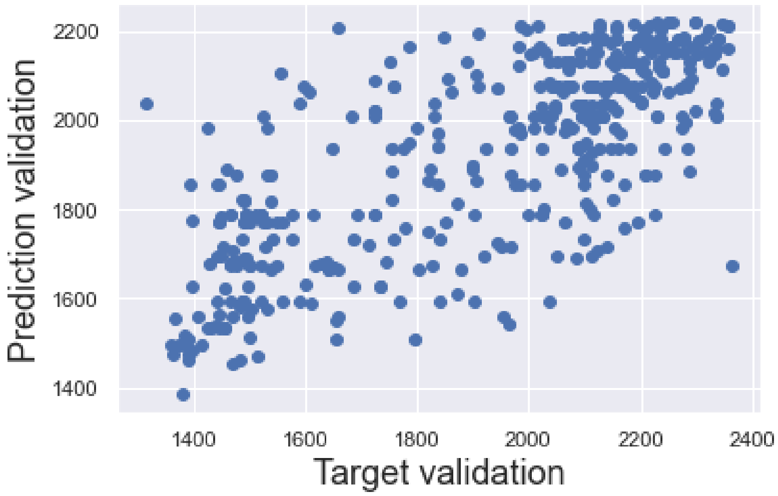


Figure 4. 15 scatter plot of model validation using speed and sea condition as a feature

this model is acquired using 2 feature which is speed and sea condition. the model made using Elastic Net Regressoras its estimator.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1929.55 + 197.61 (speed knot) + sea condition (50.21 for moderate sea , -9.99 for moderate sea to swell, 3.35 for rippled, 70.12 for slight sea, 27.27 for slight to moderate sea, 2.77 for slight to swell, 31.95 for smooth sea, 11.88 for smooth to slight, -2.01 for smooth to swell, -14.4 for swell sea , -17.03 for very smooth).

with RMSE value of 214.5 and R-value of 0.483. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

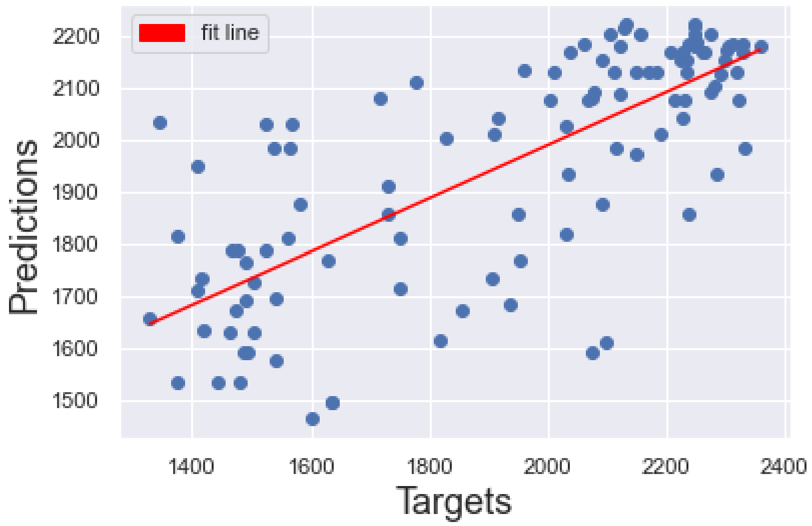


Figure 4. 16 scatter plot of model testing using speed and sea condition as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1952.448012	-23.402823	9.870299
std	325.243011	222.987685	218.067958	8.967497
min	1328.744275	1463.545701	-689.334022	0.196331
25%	1568.869565	1769.986788	-155.643186	3.617259
50%	2036.642633	2029.783750	19.394299	7.172159
75%	2230.525963	2153.069931	136.903001	13.065829
max	2358.236842	2222.377326	487.697691	51.252032

Table 4. 18 Result analysis of model using speed and sea condition as a feature

in this model, the difference between the target and prediction ranges between 0.19% as the lowest and 51.25% as the highest. The mean absolute error value is 9.8%.

Table 4. 19Model Prediction on Testing dataset using 2 features: speed and sea condition

no.	speed	Sea condition	Target	Prediction	Residual	Difference%
1	12.25	slight sea	2073.91	2077.98	-4.07	0.20
2	11.37	moderate sea	2030.33	2025.67	4.66	0.23

no.	speed	Sea condition	Target	Prediction	Residual	Difference%
3	12.25	smooth sea	2069.05	2077.43	-8.38	0.41
4	12.30	slight sea	2078.49	2089.83	-11.33	0.55
5	12.50	slight sea	2150.16	2130.77	19.39	0.90
6	12.50	slight sea	2111.27	2130.77	-19.50	0.92
7	13.00	smooth sea	2248.16	2222.38	25.78	1.15
8	12.87	smooth sea	2248.61	2215.70	32.91	1.46
9	12.50	smooth to slight	2120.81	2086.87	33.94	1.60
10	12.75	slight sea	2205.33	2166.38	38.95	1.77
11	12.50	slight sea	2169.89	2130.77	39.12	1.80
12	12.75	smooth sea	2247.30	2202.41	44.88	2.00
13	12.25	swell sea	1750.00	1712.91	37.09	2.12
14	12.75	smooth sea	2156.40	2202.41	-46.01	2.13
15	0.75	slight sea	1542.09	1578.03	-35.93	2.33
16	12.50	slight sea	2182.83	2130.77	52.06	2.38
17	13.00	slight sea	2238.40	2184.78	53.62	2.40
18	13.50	slight sea	2123.64	2178.71	-55.07	2.59
19	13.25	slight sea	2248.05	2187.90	60.15	2.68
20	12.75	slight sea	2226.48	2166.38	60.11	2.70
21	13.25	slight sea	2250.97	2187.90	63.07	2.80
22	12.50	smooth sea	2091.98	2153.07	-61.09	2.92
23	12.62	smooth sea	2245.93	2180.32	65.62	2.92
24	12.50	smooth sea	2223.70	2153.07	70.63	3.18
25	13.37	smooth sea	2274.09	2200.98	73.11	3.22
26	12.50	smooth sea	2232.65	2153.07	79.58	3.56
27	10.75	smooth sea	1480.52	1533.95	-53.43	3.61
28	11.60	smooth sea	1748.61	1811.86	-63.25	3.62
29	12.25	smooth sea	2004.50	2077.43	-72.93	3.64
30	13.25	smooth sea	2129.56	2213.89	-84.34	3.96

no.	speed	Sea condition	Target	Prediction	Residual	Difference%
31	12.75	slight sea	2261.83	2166.38	95.45	4.22
32	13.00	smooth sea	2131.55	2222.38	-90.82	4.26
33	12.75	slight sea	2265.59	2166.38	99.22	4.38
34	12.50	slight sea	2233.45	2130.77	102.68	4.60
35	12.75	smooth sea	2104.63	2202.41	-97.78	4.65
36	11.50	slight sea	1951.14	1857.81	93.33	4.78
37	11.75	slight sea	2033.90	1934.82	99.07	4.87
38	12.00	slight sea	1909.51	2010.79	-101.28	5.30
39	12.62	smooth sea	2303.94	2180.32	123.63	5.37
40	13.00	slight sea	2310.89	2184.78	126.12	5.46
41	12.81	slight sea	2300.45	2172.31	128.13	5.57
42	12.50	slight sea	2009.02	2130.77	-121.75	6.06
43	13.00	slight sea	2059.78	2184.78	-124.99	6.07
44	13.00	slight sea	2327.86	2184.78	143.09	6.15
45	12.25	smooth sea	2214.33	2077.43	136.90	6.18
46	12.50	smooth sea	2296.76	2153.07	143.69	6.26
47	10.75	smooth sea	1443.26	1533.95	-90.69	6.28
48	12.00	smooth sea	2115.10	1982.10	133.00	6.29
49	12.75	slight sea	2036.64	2166.38	-129.73	6.37
50	12.15	smooth sea	1915.55	2041.19	-125.64	6.56
51	11.00	smooth sea	1491.45	1593.13	-101.68	6.82
52	12.25	smooth sea	2230.53	2077.43	153.10	6.86
53	12.75	slight sea	2327.68	2166.38	161.30	6.93
54	11.00	smooth sea	1487.20	1593.13	-105.93	7.12
55	12.40	smooth sea	2289.91	2125.67	164.24	7.17
56	11.50	slight sea	1729.81	1857.81	-128.01	7.40
57	13.50	slight sea	2358.24	2178.71	179.52	7.61

no.	speed	Sea condition	Target	Prediction	Residual	Difference%
58	12.62	smooth to swell	2282.12	2103.57	178.55	7.82
59	12.30	slight sea	2273.47	2089.83	183.64	8.08
60	12.50	slight sea	2319.86	2130.77	189.09	8.15
61	11.87	slight sea	2148.75	1971.93	176.82	8.23
62	12.00	slight sea	2191.27	2010.79	180.48	8.24
63	11.12	smooth sea	1504.10	1629.08	-124.98	8.31
64	12.10	slight sea	2227.86	2039.10	188.76	8.47
65	10.00	smooth sea	1600.00	1463.55	136.45	8.53
66	10.50	smooth sea	1635.46	1495.48	139.98	8.56
67	10.50	smooth sea	1635.62	1495.48	140.14	8.57
68	11.50	smooth sea	1628.62	1769.99	-141.36	8.68
69	12.43	smooth sea	1958.60	2134.32	-175.72	8.97
70	11.00	slight sea	1904.08	1731.99	172.08	9.04
71	11.50	smooth sea	1953.67	1769.99	183.69	9.40
72	11.97	slight sea	1826.42	2002.00	-175.58	9.61
73	10.50	slight sea	1856.36	1672.30	184.05	9.91
74	9.13	slight sea	1541.75	1697.39	-155.64	10.10
75	11.75	smooth sea	2090.28	1876.21	214.07	10.24
76	11.37	slight sea	2030.33	1820.12	210.21	10.35
77	11.75	smooth to slight	1729.09	1911.28	-182.19	10.54
78	12.24	slight sea	2322.01	2075.55	246.46	10.61
79	11.08	smooth sea	1818.94	1616.57	202.37	11.13
80	11.12	smooth sea	1461.81	1629.08	-167.27	11.44
81	10.75	smooth sea	1376.00	1533.95	-157.95	11.48
82	11.28	smooth sea	1937.07	1683.98	253.09	13.07
83	11.30	smooth sea	1490.02	1691.35	-201.32	13.51

no.	speed	Sea condition	Target	Prediction	Residual	Difference%
84	10.50	slight sea	1471.79	1672.30	-200.52	13.62
85	10.62	smooth to slight	1504.71	1724.97	-220.26	14.64
86	12.00	smooth sea	2332.03	1982.10	349.92	15.01
87	0.75	moderate sea	1419.00	1632.36	-213.36	15.04
88	11.75	slight sea	2284.80	1934.82	349.97	15.32
89	11.60	smooth sea	1560.74	1811.86	-251.12	16.09
90	11.50	slight sea	2236.18	1857.81	378.37	16.92
91	11.25	slight sea	1522.12	1787.97	-265.84	17.47
92	11.00	smooth to slight	1488.30	1763.16	-274.86	18.47
93	11.75	smooth sea	1581.98	1876.21	-294.23	18.60
94	12.40	slight sea	1776.43	2111.63	-335.20	18.87
95	12.25	slight sea	1717.00	2077.98	-360.99	21.02
96	11.25	slight sea	1474.81	1787.97	-313.15	21.23
97	10.87	slight sea	1407.13	1709.71	-302.58	21.50
98	11.25	slight sea	1466.61	1787.97	-321.36	21.91
99	11.00	slight sea	1415.47	1731.99	-316.52	22.36
100	10.75	slight to moderate sea	2097.58	1609.88	487.70	23.25
101	10.62	slight to moderate sea	2073.19	1590.10	483.09	23.30
102	11.20	smooth sea	1328.74	1655.59	-326.85	24.60
103	12.00	smooth sea	1564.38	1982.10	-417.72	26.70
104	12.00	smooth sea	1536.00	1982.10	-446.10	29.04
105	12.12	smooth sea	1568.87	2029.78	-460.91	29.38
106	11.61	smooth sea	1374.78	1816.11	-441.33	32.10
107	12.12	smooth sea	1523.89	2029.78	-505.89	33.20
108	11.80	slight sea	1407.13	1950.37	-543.24	38.61

no.	speed	Sea condition	Target	Prediction	Residual	Difference%
109	12.00	moderate sea	1344.99	2034.32	-689.33	51.25

4.3.10 Using 2 Features : engine load and sea condition

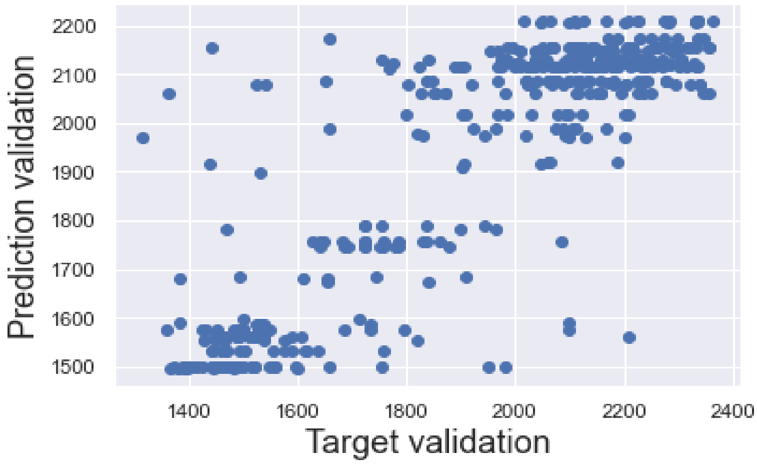


Figure 4. 17 scatter plot of model validation using engine load and sea condition as a feature

this model is acquired using 2 feature which is engine load and sea condition. the model made using Decision Tree Regressor as its estimator and Random Forest Regressor as its final estimator.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1932.49 + 250.33 (engine load percentage) + sea condition (-6.06 for moderate sea , 1.63 for moderate sea to swell, -0.117 for rippled, 59.75 for slight sea ,5.37 for slight to moderate sea, 1.81 for slight to swell, 46.51 for smooth sea, 22.71 for smooth to slight, 3.12 for smooth to swell, -2.1 for swell sea , -2.33 for very smooth).

with RMSE value of 169.87 and R-value of 0.676. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

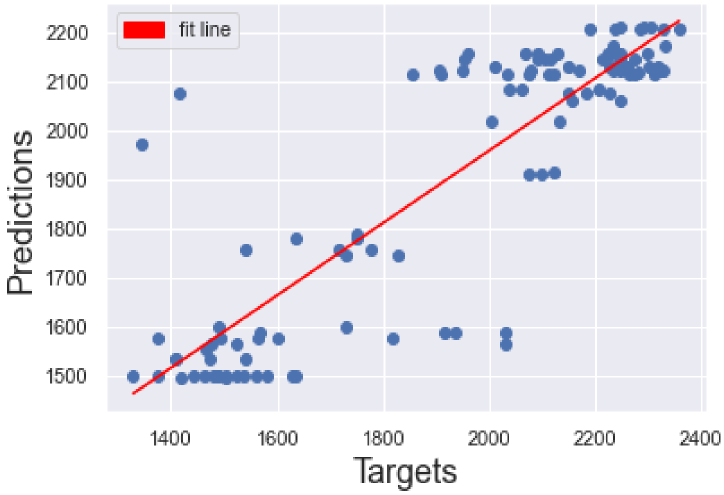


Figure 4. 18 scatter plot of model testing using engine load and sea condition as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1906.246531	22.798658	6.327959
std	325.243011	276.778939	161.358312	7.099683
min	1328.744275	1495.125962	-662.311898	0.112048
25%	1568.869565	1576.662072	-48.025538	2.161600
50%	2036.642633	2077.778565	23.337928	4.812551
75%	2230.525963	2131.149016	120.661499	8.134704
max	2358.236842	2209.170829	466.981655	46.791063

Table 4. 20 Result analysis of model using engine load and sea condition as a feature

in this model, the difference between the target and prediction ranges between 0.11% as the lowest and 46.79% as the highest. The mean absolute error value is 6.32%.

Table 4. 21 Model Prediction on Testing dataset using 2 features: engine load and sea condition

no.	**engine load**	**Sea condition**	**Target**	**Prediction**	**Residual**	**Difference%**
1	52.00	slight sea	2111.27	2113.64	-2.37	0.11
2	40.00	smooth sea	1504.10	1498.88	5.22	0.35
3	58.00	slight sea	2123.64	2113.27	10.38	0.49
4	40.00	slight sea	1542.09	1533.17	8.92	0.58
5	40.00	smooth sea	1490.02	1498.88	-8.86	0.59
6	39.00	smooth to slight	1504.71	1495.13	9.58	0.64
7	50.00	smooth sea	2004.50	2017.36	-12.86	0.64
8	41.00	smooth sea	1564.38	1576.66	-12.28	0.79
9	40.00	smooth sea	1487.20	1498.88	-11.68	0.79
10	55.00	slight sea	2191.27	2208.79	-17.52	0.80
11	45.00	slight sea	1729.81	1744.55	-14.74	0.85
12	53.00	slight sea	2150.16	2131.15	19.01	0.88
13	44.00	slight sea	1776.43	1757.41	19.02	1.07
14	42.00	smooth sea	1568.87	1587.19	-18.32	1.17
15	50.00	slight sea	2059.78	2084.67	-24.89	1.21
16	52.00	smooth sea	2129.56	2155.48	-25.93	1.22
17	55.00	slight sea	2236.18	2208.79	27.39	1.23
18	40.00	smooth sea	1480.52	1498.88	-18.36	1.24
19	41.00	smooth sea	1600.00	1576.66	23.34	1.46
20	53.00	smooth sea	2115.10	2146.37	-31.26	1.48
21	39.00	smooth sea	1523.89	1498.88	25.01	1.64
22	55.00	smooth sea	2247.30	2209.17	38.13	1.70
23	45.00	smooth sea	1748.61	1780.67	-32.06	1.83
24	52.00	slight sea	2073.91	2113.64	-39.73	1.92

no.	engine load	Sea condition	Target	Prediction	Residual	Difference%
25	53.00	smooth sea	2104.63	2146.37	-41.73	1.98
26	51.00	slight sea	2169.89	2123.42	46.47	2.14
27	51.00	slight sea	2078.49	2123.42	-44.93	2.16
28	45.00	swell sea	1750.00	1787.83	-37.83	2.16
29	44.00	slight sea	1717.00	1757.41	-40.41	2.35
30	50.00	slight sea	2036.64	2084.67	-48.03	2.36
31	30.00	smooth sea	1536.00	1498.88	37.12	2.42
32	40.00	smooth sea	1461.81	1498.88	-37.07	2.54
33	53.00	smooth sea	2091.98	2146.37	-54.39	2.60
34	42.00	slight sea	1522.12	1563.35	-41.22	2.71
35	54.00	smooth sea	2232.65	2171.14	61.50	2.75
36	52.00	smooth sea	2223.70	2155.48	68.21	3.07
37	53.00	smooth sea	2214.33	2146.37	67.97	3.07
38	52.00	smooth sea	2090.28	2155.48	-65.21	3.12
39	54.00	slight sea	2148.75	2077.78	70.97	3.30
40	55.00	slight sea	2284.80	2208.79	76.01	3.33
41	52.00	smooth sea	2230.53	2155.48	75.04	3.36
42	55.00	smooth sea	2289.91	2209.17	80.73	3.53
43	39.00	smooth sea	1443.26	1498.88	-55.62	3.85
44	52.00	slight sea	2033.90	2113.64	-79.74	3.92
45	40.00	smooth sea	1560.74	1498.88	61.86	3.96
46	52.00	smooth sea	2245.93	2155.48	90.45	4.03
47	55.00	smooth sea	2303.94	2209.17	94.77	4.11
48	40.00	slight sea	1471.79	1533.17	-61.38	4.17
49	52.00	smooth sea	2069.05	2155.48	-86.43	4.18
50	53.00	slight sea	2226.48	2131.15	95.34	4.28

no.	engine load	sea_condition	Target	Prediction	Residual	Difference%
51	45.00	slight sea	1826.42	1744.55	81.87	4.48
52	51.00	smooth sea	2156.40	2059.30	97.10	4.50
53	53.00	smooth sea	2248.61	2146.37	102.24	4.55
54	53.00	slight sea	2238.40	2131.15	107.25	4.79
55	54.00	slight sea	2182.83	2077.78	105.05	4.81
56	51.00	slight sea	2233.45	2123.42	110.02	4.93
57	55.00	slight sea	2327.68	2208.79	118.89	5.11
58	40.00	smooth sea	1581.98	1498.88	83.09	5.25
59	53.00	slight sea	2250.97	2131.15	119.82	5.32
60	50.00	smooth sea	2131.55	2017.36	114.20	5.36
61	40.00	moderate sea	1419.00	1495.13	-76.13	5.36
62	50.00	slight sea	2205.33	2084.67	120.66	5.47
63	51.00	slight sea	2248.05	2123.42	124.63	5.54
64	53.00	smooth sea	2274.09	2146.37	127.73	5.62
65	41.00	smooth sea	1491.45	1576.66	-85.21	5.71
66	53.00	slight sea	2261.83	2131.15	130.68	5.78
67	41.00	slight sea	1466.61	1554.00	-87.40	5.96
68	42.00	slight sea	1474.81	1563.35	-88.53	6.00
69	53.00	slight sea	2009.02	2131.15	-122.13	6.08
70	52.00	smooth sea	2296.76	2155.48	141.28	6.15
71	55.00	slight sea	2358.24	2208.79	149.45	6.34
72	52.00	slight sea	2265.59	2113.64	151.95	6.71
73	54.00	slight sea	2227.86	2077.78	150.08	6.74
74	54.00	smooth sea	2332.03	2171.14	160.88	6.90
75	52.00	slight sea	2273.47	2113.64	159.83	7.03
76	52.00	smooth to swell	2282.12	2117.02	165.10	7.23
77	53.00	slight sea	2300.45	2131.15	169.30	7.36
78	42.00	smooth to slight	1488.30	1598.77	-110.47	7.42
79	42.00	smooth to slight	1729.09	1598.77	130.32	7.54

no.	**engine load**	**sea_condition**	**Target**	**Prediction**	**Residual**	**Difference%**
80	49.00	slight to moderate sea	2073.19	1912.15	161.04	7.77
81	39.00	smooth sea	1628.62	1498.88	129.74	7.97
82	53.00	slight sea	2319.86	2131.15	188.71	8.13
83	40.00	smooth sea	1635.46	1498.88	136.57	8.35
84	51.00	smooth sea	2248.16	2059.30	188.86	8.40
85	52.00	slight sea	2310.89	2113.64	197.25	8.54
86	51.00	slight sea	2322.01	2123.42	198.59	8.55
87	51.00	slight sea	2327.86	2123.42	204.44	8.78
88	51.00	slight sea	1951.14	2123.42	-172.28	8.83
89	49.00	slight to moderate sea	2097.58	1912.15	185.43	8.84
90	45.00	smooth sea	1635.62	1780.67	-145.05	8.87
91	40.00	slight sea	1407.13	1533.17	-126.04	8.96
92	40.00	slight sea	1407.13	1533.17	-126.04	8.96
93	40.00	smooth sea	1374.78	1498.88	-124.10	9.03
94	50.00	smooth to slight	2120.81	1915.64	205.16	9.67
95	53.00	smooth sea	1953.67	2146.37	-192.69	9.86
96	52.00	smooth sea	1958.60	2155.48	-196.89	10.05
97	52.00	slight sea	1909.51	2113.64	-204.13	10.69
98	51.00	slight sea	1904.08	2123.42	-219.35	11.52
99	40.00	smooth sea	1328.74	1498.88	-170.14	12.80
100	41.00	smooth sea	1818.94	1576.66	242.28	13.32
101	52.00	slight sea	1856.36	2113.64	-257.28	13.86
102	44.00	slight sea	1541.75	1757.41	-215.66	13.99
103	41.00	smooth sea	1376.00	1576.66	-200.66	14.58
104	42.00	smooth sea	1915.55	1587.19	328.36	17.14

no.	**engine load**	**sea_condition**	**Target**	**Prediction**	**Residual**	**Difference%**
105	42.00	smooth sea	1937.07	1587.19	349.88	18.06
106	41.00	moderate sea	2030.33	1589.21	441.12	21.73
107	42.00	slight sea	2030.33	1563.35	466.98	23.00
108	54.00	moderate sea	1344.99	1970.89	-625.90	46.54
109	54.00	slight sea	1415.47	2077.78	-662.31	46.79

4.3.11 Using 2 Features : displacement and sea condition

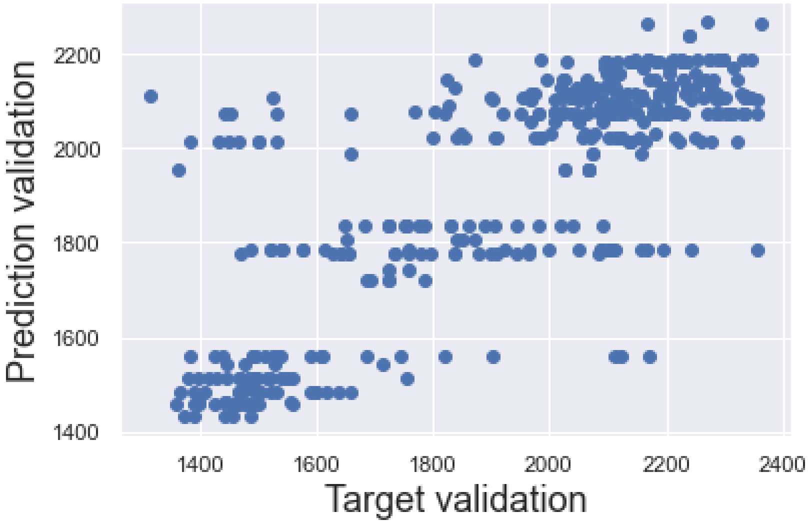


Figure 4. 19 scatter plot of model validation using displacement and sea condition as a feature

this model is acquired using 2 feature which is displacement and sea condition. the model made using Kneighbor regressor as its estimator.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1928.70 + 91.84 (displacement tonnage) + sea condition (-15.68 for moderate sea , -25.86 for moderate sea to swell, -31.91 for rippled, -27.75 for slight sea , -11.88 for slight to moderate sea, -11.75 for slight to swell, -99.44 for smooth sea ,-31.42 for smooth to slight, -30.66 for smooth to swell, --33.75 for swell sea , -28.62 for very smooth).

with RMSE value of 293.23 and R-value of 0.352. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

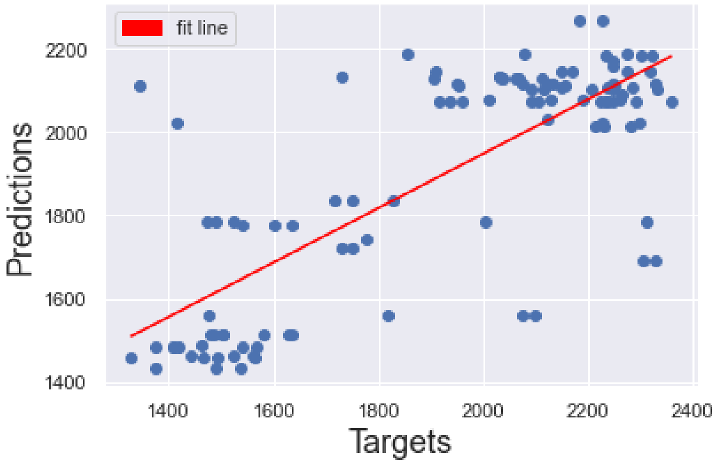


Figure 4. 20 scatter plot of model validation using displacement and sea condition as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1901.752712	27.292477	7.793336
std	325.243011	274.219533	206.484439	8.450532
min	1328.744275	1430.672072	-767.856069	0.169796
25%	1568.869565	1560.893867	-84.953610	2.835599
50%	2036.642633	2073.718993	26.450561	5.664620
75%	2230.525963	2115.647522	132.406169	9.116272
max	2358.236842	2270.141414	635.311421	57.090151

Table 4. 22 Result analysis of model using displacement and sea condition as a feature

in this model, the difference between the target and prediction ranges between 0.16% as the lowest and 57.09% as the highest. The mean absolute error value is 7.79%.

Table 4. 23 Model Prediction on Testing dataset using 2 features: displacement and sea condition

no.	**displacement**	**sea condition**	**Target**	**Prediction**	**Residual**	**Difference%**
1	16644.60	slight sea	2150.16	2146.51	3.65	0.17
2	15623.00	smooth to slight	2120.81	2115.65	5.16	0.24
3	16335.00	slight sea	1729.81	1722.16	7.65	0.44
4	15255.00	smooth sea	2115.10	2105.49	9.61	0.45
5	12791.00	slight sea	1826.42	1834.95	-8.54	0.47
6	15720.14	slight sea	1466.61	1459.40	7.20	0.49
7	15255.00	smooth sea	2091.98	2105.49	-13.51	0.65
8	14839.39	smooth to slight	1504.71	1515.04	-10.33	0.69
9	14839.39	smooth sea	1504.10	1515.04	-10.94	0.73
10	15623.00	smooth sea	2131.55	2115.65	15.91	0.75
11	13725.00	slight sea	2111.27	2127.72	-16.44	0.78
12	15257.60	smooth sea	2090.28	2071.86	18.42	0.88
13	16644.60	slight sea	2169.89	2146.51	23.38	1.08
14	15096.20	smooth sea	1443.26	1460.53	-17.27	1.20
15	18255.00	smooth sea	2104.63	2073.91	30.72	1.46
16	16335.00	smooth sea	1748.61	1722.16	26.45	1.51
17	14130.97	smooth sea	1461.81	1487.73	-25.92	1.77
18	18442.00	slight sea	2148.75	2109.51	39.24	1.83
19	14839.39	smooth sea	1487.20	1515.04	-27.84	1.87
20	12803.00	slight sea	2226.48	2270.14	-43.66	1.96
21	15623.00	slight sea	2073.91	2115.65	-41.73	2.01
22	16094.00	smooth sea	2156.40	2112.84	43.56	2.02
23	12022.00	slight sea	1776.43	1740.54	35.89	2.02
24	15720.14	smooth sea	1491.45	1459.40	32.04	2.15
25	14900.60	slight sea	2233.45	2183.75	49.70	2.23

no.	displacement	sea condition	Target	Prediction	Residual	Difference%
26	14839.39	smooth sea	1480.52	1515.04	-34.52	2.33
27	18090.52	smooth sea	2129.56	2077.24	52.31	2.46
28	13725.00	smooth sea	2069.05	2127.72	-58.67	2.84
29	13725.00	slight sea	2059.78	2127.72	-67.94	3.30
30	14837.80	smooth sea	2248.61	2173.29	75.32	3.35
31	18090.52	slight sea	2009.02	2077.24	-68.23	3.40
32	18375.20	smooth sea	2274.09	2190.22	83.87	3.69
33	15103.29	slight sea	1542.09	1481.37	60.72	3.94
34	15726.47	smooth sea	1376.00	1430.67	-54.67	3.97
35	15726.47	smooth sea	1490.02	1430.67	59.35	3.98
36	12803.00	slight sea	2182.83	2270.14	-87.31	4.00
37	14795.00	smooth sea	2248.16	2157.37	90.79	4.04
38	15096.20	smooth sea	1523.89	1460.53	63.36	4.16
39	14839.39	smooth sea	1581.98	1515.04	66.94	4.23
40	12232.00	slight sea	2123.64	2032.80	90.84	4.28
41	15103.29	moderate sea	1419.00	1481.37	-62.37	4.40
42	13725.00	slight sea	2036.64	2127.72	-91.08	4.47
43	15255.00	slight sea	2205.33	2105.49	99.84	4.53
44	13725.00	slight sea	2033.90	2127.72	-93.82	4.61
45	12791.00	swell sea	1750.00	1834.95	-84.95	4.85
46	14900.60	slight sea	2300.45	2183.75	116.70	5.07
47	16839.68	slight sea	2030.33	2134.45	-104.12	5.13
48	16839.68	moderate sea	2030.33	2134.45	-104.12	5.13
49	18090.52	slight sea	2191.27	2077.24	114.02	5.20
50	15103.29	slight sea	1407.13	1481.37	-74.24	5.28
51	15103.29	slight sea	1407.13	1481.37	-74.24	5.28
52	18375.20	slight sea	2078.49	2190.22	-111.73	5.38
53	15103.29	smooth sea	1568.87	1481.37	87.50	5.58

no.	displacement	sea condition	Target	Prediction	Residual	Difference%
54	16644.60	slight sea	2273.47	2146.51	126.95	5.58
55	18442.00	slight sea	2236.18	2109.51	126.67	5.66
56	12077.00	slight sea	1474.81	1560.89	-86.08	5.84
57	18255.00	smooth sea	1958.60	2073.91	-115.31	5.89
58	15623.00	slight sea	2248.05	2115.65	132.41	5.89
59	14900.60	slight sea	2322.01	2183.75	138.26	5.95
60	16094.00	slight sea	2250.97	2112.84	138.13	6.14
61	15255.00	smooth sea	2247.30	2105.49	141.80	6.31
62	15096.20	smooth sea	1560.74	1460.53	100.21	6.42
63	15720.14	smooth sea	1564.38	1459.40	104.98	6.71
64	15257.60	smooth sea	2223.70	2071.86	151.84	6.83
65	15726.47	smooth sea	1536.00	1430.67	105.33	6.86
66	12791.00	slight sea	1717.00	1834.95	-117.95	6.87
67	14839.39	smooth sea	1628.62	1515.04	113.59	6.97
68	18255.00	smooth sea	1937.07	2073.91	-136.84	7.06
69	16767.00	smooth sea	2232.65	2073.72	158.93	7.12
70	18255.00	slight sea	2238.40	2073.91	164.49	7.35
71	14839.39	smooth sea	1635.46	1515.04	120.42	7.36
72	16644.60	slight sea	2319.86	2146.51	173.35	7.47
73	14400.80	slight sea	2265.59	2092.21	173.38	7.65
74	18442.00	slight sea	2284.80	2109.51	175.28	7.67
75	15257.60	smooth sea	2245.93	2071.86	174.08	7.75
76	15103.29	smooth sea	1374.78	1481.37	-106.59	7.75
77	16094.00	smooth sea	1953.67	2112.84	-159.17	8.15
78	18090.52	slight sea	2261.83	2077.24	184.59	8.16
79	18255.00	smooth sea	1915.55	2073.91	-158.36	8.27
80	15623.00	slight sea	1951.14	2115.65	-164.51	8.43

no.	displacement	sea condition	Target	Prediction	Residual	Difference%
81	14213.20	smooth sea	1635.62	1775.02	-139.40	8.52
82	15623.00	slight sea	2327.86	2115.65	212.21	9.12
83	12209.80	smooth sea	2214.33	2012.20	202.14	9.13
84	18263.50	slight sea	2227.86	2020.74	207.12	9.30
85	18255.00	smooth sea	2289.91	2073.91	216.00	9.43
86	15255.00	smooth sea	2332.03	2105.49	226.53	9.71
87	12209.80	smooth sea	2230.53	2012.20	218.33	9.79
88	15720.14	smooth sea	1328.74	1459.40	-130.66	9.83
89	14213.20	smooth sea	1600.00	1775.02	-175.02	10.94
90	12557.00	smooth sea	2004.50	1783.98	220.52	11.00
91	13725.00	slight sea	1904.08	2127.72	-223.64	11.75
92	12209.80	smooth to swell	2282.12	2012.20	269.92	11.83
93	18263.50	smooth sea	2296.76	2020.74	276.02	12.02
94	16767.00	slight sea	2358.24	2073.72	284.52	12.06
95	16644.60	slight sea	1909.51	2146.51	-237.01	12.41
96	12077.00	smooth sea	1818.94	1560.89	258.04	14.19
97	14213.20	slight sea	1541.75	1775.02	-233.28	15.13
98	12557.00	slight sea	1522.12	1783.98	-261.85	17.20
99	18375.20	slight sea	1856.36	2190.22	-333.86	17.98
100	12557.00	smooth to slight	1488.30	1783.98	-295.68	19.87
101	12557.00	slight sea	1471.79	1783.98	-312.19	21.21
102	12557.00	slight sea	2310.89	1783.98	526.92	22.80
103	16839.68	smooth to slight	1729.09	2134.45	-405.36	23.44
104	12077.00	slight to moderate sea	2073.19	1560.89	512.30	24.71
105	12077.00	slight to moderate sea	2097.58	1560.89	536.69	25.59

no.	**displacement**	**sea condition**	**Target**	**Prediction**	**Residual**	**Difference%**
106	14048.00	smooth sea	2303.94	1692.37	611.58	26.54
107	14048.00	slight sea	2327.68	1692.37	635.31	27.29
108	18263.50	slight sea	1415.47	2020.74	-605.28	42.76
109	16094.00	moderate sea	1344.99	2112.84	-767.86	57.09

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4.3.12 using one feature: engine load

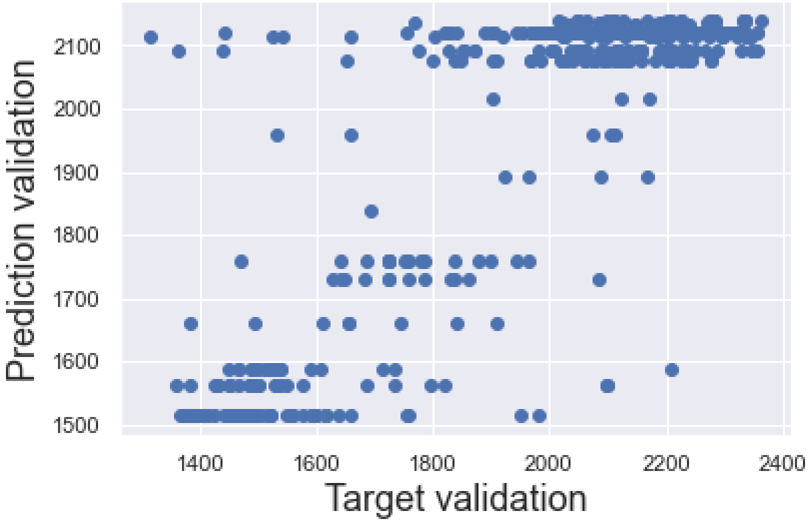

Figure 4. 21 scatter plot of model validation using engine load as a feature

this model is acquired using only one feature which is engine load and made using Extra trees regressor as its estimator and Lasso Regression as its final regressor. lasso regression work in same way as ridge regression but the key difference located in its penalty. this penalty added is in the form of λ(lambda) x |slope|. This model goal is to minimize its absolute error value.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1931.31 + 246.35 (engine load percentage).

with RMSE value of 172.46 and R-value of 0.666. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

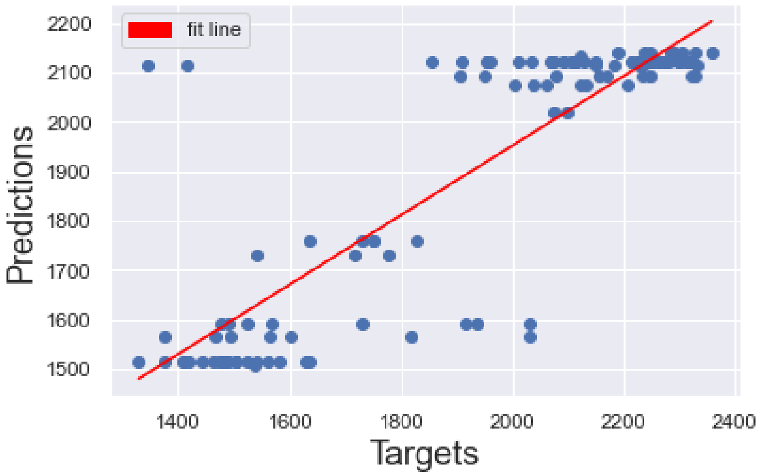

Figure 4. 22 scatter plot of model testing using engine load as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1901.394227	27.650963	6.478672
std	325.243011	267.325931	169.047310	7.813977
min	1328.744275	1508.445948	-770.351767	0.045799
25%	1568.869565	1589.232510	-46.606030	2.262990
50%	2036.642633	2093.540731	33.411822	5.050555
75%	2230.525963	2120.351815	130.612953	7.596438
max	2358.236842	2140.429491	466.665261	57.275707

Table 4. 24 Result analysis of model using engine load as a feature

The RMSE for this model is around 170.52 ton. with the mean error around 6.47%. so on average, the when a data is inputted to the model, the prediction should be within 6.47% difference range. this model has r-squared score of 0.722.

Table 4. 25 Model Prediction on Testing dataset using 1 feature: engine load

no.	**engine load**	**Target**	**Prediction**	**Residual**	**Difference%**
1	41.00	1564.38	1563.66	0.72	0.05
2	53.00	2115.10	2120.35	-5.25	0.25

no.	engine load	Target	Prediction	Residual	Difference%
3	52.00	2129.56	2120.52	9.04	0.42
4	52.00	2111.27	2120.52	-9.24	0.44
5	58.00	2123.64	2133.10	-9.46	0.45
6	45.00	1750.00	1758.48	-8.48	0.48
7	45.00	1748.61	1758.48	-9.87	0.56
8	39.00	1504.71	1513.46	-8.76	0.58
9	40.00	1504.10	1514.02	-9.92	0.66
10	39.00	1523.89	1513.46	10.43	0.68
11	51.00	2078.49	2093.54	-15.05	0.72
12	50.00	2059.78	2074.72	-14.93	0.73
13	53.00	2104.63	2120.35	-15.72	0.75
14	44.00	1717.00	1730.36	-13.36	0.78
15	42.00	1568.87	1589.23	-20.36	1.30
16	53.00	2091.98	2120.35	-28.37	1.36
17	53.00	2150.16	2120.35	29.81	1.39
18	52.00	2090.28	2120.52	-30.24	1.45
19	54.00	2148.75	2115.34	33.41	1.55
20	40.00	1490.02	1514.02	-24.00	1.61
21	45.00	1729.81	1758.48	-28.67	1.66
22	30.00	1536.00	1508.45	27.55	1.79
23	40.00	1487.20	1514.02	-26.82	1.80
24	40.00	1542.09	1514.02	28.07	1.82
25	50.00	2036.64	2074.72	-38.07	1.87
26	50.00	2120.81	2074.72	46.09	2.17
27	52.00	2073.91	2120.52	-46.61	2.25
28	40.00	1480.52	1514.02	-33.50	2.26

no.	engine load	Target	Prediction	Residual	Difference%
29	41.00	1600.00	1563.66	36.34	2.27
30	55.00	2191.27	2140.43	50.84	2.32
31	52.00	2069.05	2120.52	-51.47	2.49
32	44.00	1776.43	1730.36	46.07	2.59
33	50.00	2131.55	2074.72	56.84	2.67
34	49.00	2073.19	2017.31	55.89	2.70
35	40.00	1471.79	1514.02	-42.23	2.87
36	51.00	2156.40	2093.54	62.86	2.92
37	40.00	1560.74	1514.02	46.72	2.99
38	54.00	2182.83	2115.34	67.49	3.09
39	50.00	2004.50	2074.72	-70.22	3.50
40	51.00	2169.89	2093.54	76.35	3.52
41	40.00	1461.81	1514.02	-52.21	3.57
42	45.00	1826.42	1758.48	67.94	3.72
43	49.00	2097.58	2017.31	80.28	3.83
44	53.00	2214.33	2120.35	93.98	4.24
45	52.00	2033.90	2120.52	-86.62	4.26
46	55.00	2236.18	2140.43	95.75	4.28
47	40.00	1581.98	1514.02	67.96	4.30
48	42.00	1522.12	1589.23	-67.11	4.41
49	52.00	2223.70	2120.52	103.18	4.64
50	55.00	2247.30	2140.43	106.87	4.76
51	53.00	2226.48	2120.35	106.13	4.77
52	41.00	1491.45	1563.66	-72.21	4.84
53	39.00	1443.26	1513.46	-70.20	4.86
54	52.00	2230.53	2120.52	110.01	4.93
55	54.00	2227.86	2115.34	112.52	5.05
56	54.00	2232.65	2115.34	117.31	5.25
57	53.00	2238.40	2120.35	118.05	5.27
58	53.00	2009.02	2120.35	-111.34	5.54

no.	**engine load**	**Target**	**Prediction**	**Residual**	**Difference%**
59	52.00	2245.93	2120.52	125.42	5.58
60	53.00	2248.61	2120.35	128.25	5.70
61	53.00	2250.97	2120.35	130.62	5.80
62	50.00	2205.33	2074.72	130.61	5.92
63	53.00	2261.83	2120.35	141.48	6.26
64	51.00	2233.45	2093.54	139.90	6.26
65	55.00	2284.80	2140.43	144.37	6.32
66	52.00	2265.59	2120.52	145.07	6.40
67	55.00	2289.91	2140.43	149.48	6.53
68	41.00	1466.61	1563.66	-97.06	6.62
69	40.00	1419.00	1514.02	-95.02	6.70
70	52.00	2273.47	2120.52	152.95	6.73
71	53.00	2274.09	2120.35	153.74	6.76
72	42.00	1488.30	1589.23	-100.93	6.78
73	51.00	2248.05	2093.54	154.51	6.87
74	51.00	2248.16	2093.54	154.62	6.88
75	39.00	1628.62	1513.46	115.16	7.07
76	52.00	2282.12	2120.52	161.60	7.08
77	55.00	2303.94	2140.43	163.52	7.10
78	51.00	1951.14	2093.54	-142.40	7.30
79	40.00	1635.46	1514.02	121.43	7.43
80	45.00	1635.62	1758.48	-122.86	7.51
81	40.00	1407.13	1514.02	-106.89	7.60
82	40.00	1407.13	1514.02	-106.89	7.60
83	52.00	2296.76	2120.52	176.24	7.67
84	42.00	1474.81	1589.23	-114.42	7.76
85	53.00	2300.45	2120.35	180.10	7.83

no.	engine load	Target	Prediction	Residual	Difference%
86	55.00	2327.68	2140.43	187.25	8.04
87	42.00	1729.09	1589.23	139.86	8.09
88	52.00	2310.89	2120.52	190.37	8.24
89	52.00	1958.60	2120.52	-161.92	8.27
90	53.00	1953.67	2120.35	-166.68	8.53
91	53.00	2319.86	2120.35	199.51	8.60
92	55.00	2358.24	2140.43	217.81	9.24
93	54.00	2332.03	2115.34	216.69	9.29
94	51.00	2322.01	2093.54	228.47	9.84
95	51.00	1904.08	2093.54	-189.47	9.95
96	51.00	2327.86	2093.54	234.32	10.07
97	40.00	1374.78	1514.02	-139.24	10.13
98	52.00	1909.51	2120.52	-211.01	11.05
99	44.00	1541.75	1730.36	-188.61	12.23
100	41.00	1376.00	1563.66	-187.66	13.64
101	40.00	1328.74	1514.02	-185.28	13.94
102	41.00	1818.94	1563.66	255.27	14.03
103	52.00	1856.36	2120.52	-264.16	14.23
104	42.00	1915.55	1589.23	326.32	17.04
105	42.00	1937.07	1589.23	347.84	17.96
106	42.00	2030.33	1589.23	441.10	21.73
107	41.00	2030.33	1563.66	466.67	22.98
108	54.00	1415.47	2115.34	-699.87	49.44
109	54.00	1344.99	2115.34	-770.35	57.28

4.3.13 using one feature: speed

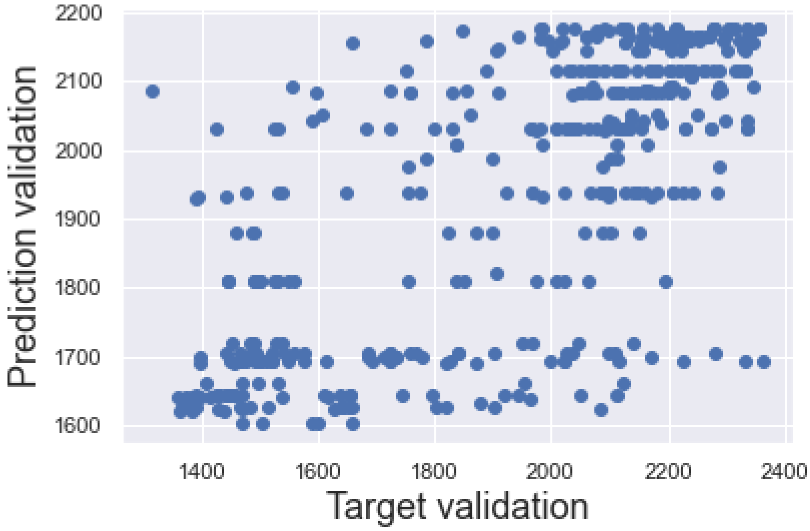

Figure 4. 23 scatter plot of model validation using speed as a feature

like the other model that using one feature, this model use KNeighbor regression as its final estimator means that the prediction is made by looking for the nearest neighbors or the nearest value of oil consumption that correspondent to speed as an input in the training dataset and then take the average of the said value. hence why there is multiple prediction that has almost the same results. this way some of the speed value will have almost the same result.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1932.1 + 201.16 (speed in knot).

with RMSE value of 212.89 and R-value of 0.491. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

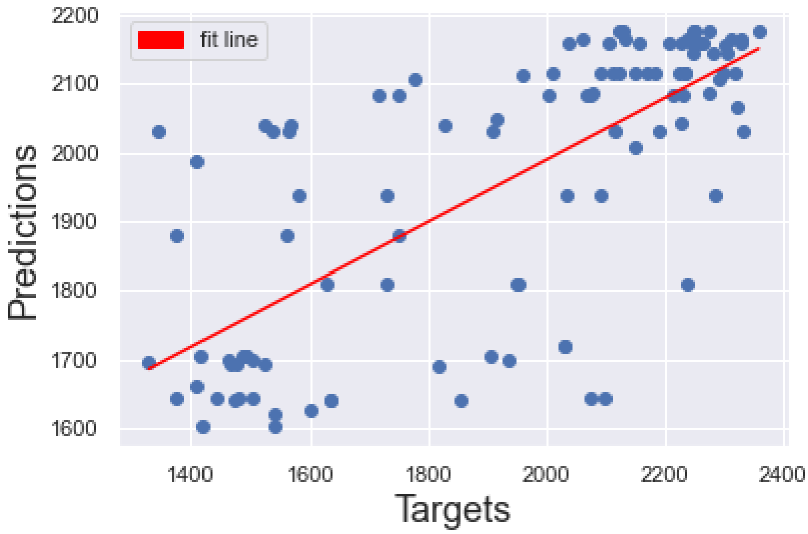

Figure 4. 24 scatter plot of model testing using speed as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1957.370669	-28.325479	10.331698
std	325.243011	202.652197	226.330170	9.281873
min	1328.744275	1601.529729	-685.346707	0.174263
25%	1568.869565	1704.781530	-182.529729	4.121517
50%	2036.642633	2038.809770	-4.417385	7.259865
75%	2230.525963	2116.465781	140.795726	14.413673
max	2358.236842	2177.904755	453.036068	50.955575

Table 4. 26 Result analysis of model using speed as a feature

The RMSE for this model is around 226.87 ton. with the mean error around 10.33%. so on average, the when a data is inputted to the model, the prediction should be within 10.33% difference range. this model has r-squared score of 0.508. this model has the worst performance with the lowest R-squared value and the highest value of RMSE.

Table 4. 27 Model Prediction on Testing dataset using 1 feature: speed

no.	**speed**	**Target**	**Prediction**	**Residual**	**Difference%**
1	12.75	2156.40	2160.16	-3.76	0.17

no.	speed	Target	Prediction	Residual	Difference%
2	12.50	2120.81	2116.47	4.34	0.20
3	12.50	2111.27	2116.47	-5.19	0.25
4	10.50	1635.62	1639.87	-4.25	0.26
5	10.50	1635.46	1639.87	-4.42	0.27
6	12.30	2078.49	2086.27	-7.78	0.37
7	12.25	2073.91	2083.78	-9.86	0.48
8	12.25	2069.05	2083.78	-14.73	0.71
9	12.50	2091.98	2116.47	-24.49	1.17
10	13.00	2131.55	2164.32	-32.76	1.54
11	12.50	2150.16	2116.47	33.70	1.57
12	10.00	1600.00	1626.49	-26.49	1.66
13	12.75	2205.33	2160.16	45.17	2.05
14	13.25	2129.56	2175.93	-46.37	2.18
15	12.50	2169.89	2116.47	53.43	2.46
16	13.50	2123.64	2176.28	-52.63	2.48
17	12.75	2104.63	2160.16	-55.52	2.64
18	12.75	2226.48	2160.16	66.33	2.98
19	12.50	2182.83	2116.47	66.36	3.04
20	13.25	2248.05	2175.93	72.12	3.21
21	13.00	2238.40	2164.32	74.08	3.31
22	13.25	2250.97	2175.93	75.04	3.33
23	13.00	2248.16	2164.32	83.84	3.73
24	0.75	1542.09	1601.53	-59.44	3.85
25	12.75	2247.30	2160.16	87.14	3.88
26	12.25	2004.50	2083.78	-79.28	3.95
27	12.00	2115.10	2030.34	84.77	4.01

no.	speed	Target	Prediction	Residual	Difference%
28	12.87	2248.61	2155.93	92.68	4.12
29	13.37	2274.09	2177.90	96.19	4.23
30	12.62	2245.93	2145.46	100.47	4.47
31	12.75	2261.83	2160.16	101.67	4.50
32	11.50	1729.81	1809.49	-79.68	4.61
33	11.75	2033.90	1939.46	94.44	4.64
34	12.75	2265.59	2160.16	105.44	4.65
35	12.50	2223.70	2116.47	107.23	4.82
36	9.13	1541.75	1619.82	-78.07	5.06
37	13.00	2059.78	2164.32	-104.53	5.08
38	12.50	2232.65	2116.47	116.18	5.20
39	12.50	2233.45	2116.47	116.98	5.24
40	12.50	2009.02	2116.47	-107.45	5.35
41	12.25	2214.33	2083.78	130.56	5.90
42	12.62	2282.12	2145.46	136.66	5.99
43	12.75	2036.64	2160.16	-123.52	6.06
44	12.81	2300.45	2156.45	144.00	6.26
45	12.00	1909.51	2030.34	-120.83	6.33
46	13.00	2310.89	2164.32	146.58	6.34
47	11.87	2148.75	2007.96	140.80	6.55
48	12.25	2230.53	2083.78	146.75	6.58
49	12.62	2303.94	2145.46	158.48	6.88
50	12.15	1915.55	2048.43	-132.88	6.94
51	13.00	2327.86	2164.32	163.54	7.03
52	11.08	1818.94	1690.93	128.01	7.04
53	12.75	2327.68	2160.16	167.52	7.20
54	11.75	2090.28	1939.46	150.82	7.22
55	11.50	1951.14	1809.49	141.65	7.26
56	12.00	2191.27	2030.34	160.93	7.34

no.	speed	Target	Prediction	Residual	Difference%
57	11.50	1953.67	1809.49	144.18	7.38
58	11.60	1748.61	1879.41	-130.80	7.48
59	13.50	2358.24	2176.28	181.96	7.72
60	12.50	2296.76	2116.47	180.30	7.85
61	12.43	1958.60	2113.23	-154.64	7.90
62	12.40	2289.91	2107.90	182.01	7.95
63	12.30	2273.47	2086.27	187.19	8.23
64	12.10	2227.86	2043.87	183.99	8.26
65	12.50	2319.86	2116.47	203.40	8.77
66	10.62	1504.71	1644.96	-140.25	9.32
67	11.00	1904.08	1704.78	199.29	10.47
68	12.24	2322.01	2065.82	256.18	11.03
69	10.75	1480.52	1644.55	-164.03	11.08
70	11.50	1628.62	1809.49	-180.87	11.11
71	11.25	1522.12	1693.70	-171.58	11.27
72	10.50	1471.79	1639.87	-168.09	11.42
73	10.50	1856.36	1639.87	216.48	11.66
74	11.97	1826.42	2039.50	-213.08	11.67
75	11.75	1729.09	1939.46	-210.37	12.17
76	11.28	1937.07	1699.81	237.26	12.25
77	0.75	1419.00	1601.53	-182.53	12.86
78	11.12	1504.10	1697.99	-193.89	12.89
79	12.00	2332.03	2030.34	301.69	12.94
80	10.75	1443.26	1644.55	-201.28	13.95
81	11.00	1491.45	1704.78	-213.33	14.30
82	11.30	1490.02	1704.79	-214.77	14.41
83	11.00	1488.30	1704.78	-216.48	14.55

no.	speed	Target	Prediction	Residual	Difference%
84	11.00	1487.20	1704.78	-217.58	14.63
85	11.25	1474.81	1693.70	-218.89	14.84
86	11.75	2284.80	1939.46	345.34	15.11
87	11.37	2030.33	1718.43	311.90	15.36
88	11.37	2030.33	1718.43	311.90	15.36
89	11.25	1466.61	1693.70	-227.10	15.48
90	11.12	1461.81	1697.99	-236.18	16.16
91	10.87	1407.13	1661.64	-254.51	18.09
92	12.40	1776.43	2107.90	-331.47	18.66
93	12.25	1750.00	2083.78	-333.78	19.07
94	11.50	2236.18	1809.49	426.69	19.08
95	10.75	1376.00	1644.55	-268.55	19.52
96	11.60	1560.74	1879.41	-318.67	20.42
97	11.00	1415.47	1704.78	-289.31	20.44
98	10.62	2073.19	1644.96	428.23	20.66
99	12.25	1717.00	2083.78	-366.78	21.36
100	10.75	2097.58	1644.55	453.04	21.60
101	11.75	1581.98	1939.46	-357.48	22.60
102	11.20	1328.74	1696.47	-367.72	27.67
103	12.00	1564.38	2030.34	-465.96	29.79
104	12.12	1568.87	2038.81	-469.94	29.95
105	12.00	1536.00	2030.34	-494.34	32.18
106	12.12	1523.89	2038.81	-514.92	33.79
107	11.61	1374.78	1879.41	-504.63	36.71
108	11.80	1407.13	1986.46	-579.33	41.17
109	12.00	1344.99	2030.34	-685.35	50.96

4.3.14 using one feature: displacement

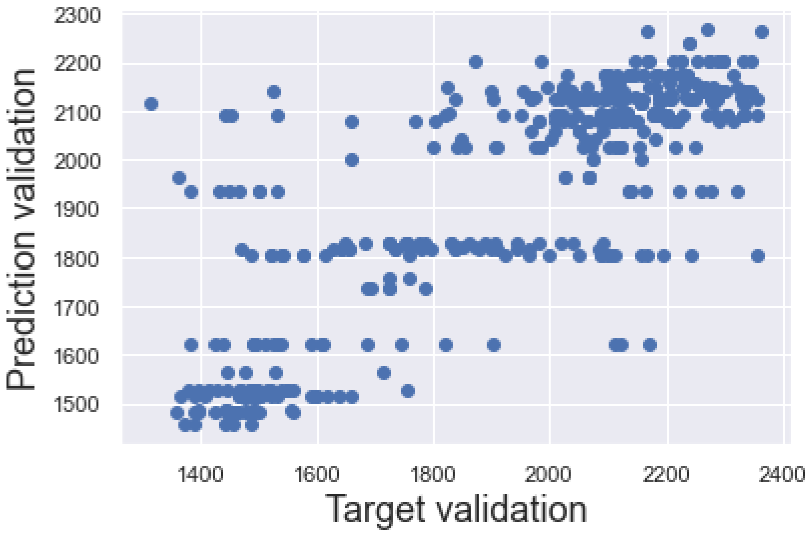

Figure 4. 25 scatter plot of model validation using displacement as a feature

this model used displacement as its only input. it use Kneighbor regression as estimator and extra trees regressor as final estimator. elastic net regressor combine the two penalty of lasso regressor and ridge regressor. this penalty become:

$$\lambda 1(\text{lambda}) \text{ x } (\text{slope}^\wedge 2) \ + \ \lambda 2(\text{lambda}) \text{ x } |\text{slope}|$$

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1931.95 + 87.26 (displacement tonnage).

with RMSE value of 282.74 and R-value of 0.103. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

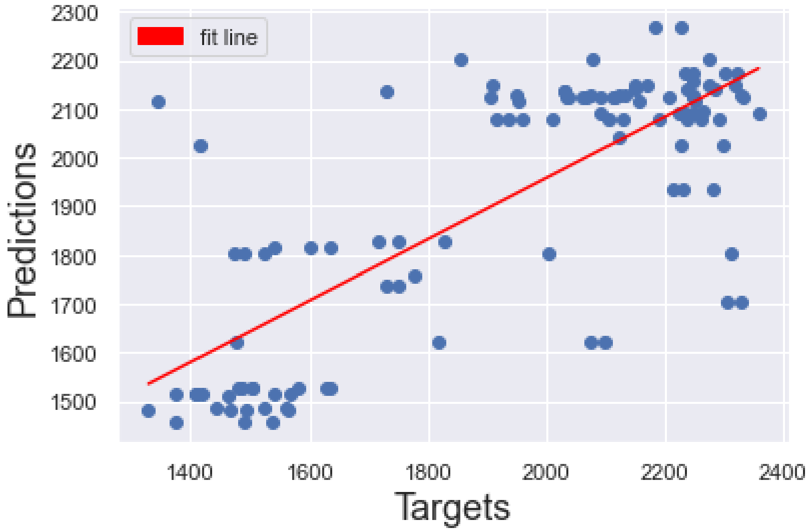

Figure 4. 26 scatter plot of model testing using displacement as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1913.128766	15.916424	7.834069
std	325.243011	264.762758	206.846403	8.507559
min	1328.744275	1455.271590	-770.174931	0.056722
25%	1568.869565	1623.525017	-89.816475	2.697611
50%	2036.642633	2079.484456	10.037769	5.561840
75%	2230.525963	2123.714971	125.643898	9.148086
max	2358.236842	2269.208851	623.672815	57.262559

Table 4. 28 Result analysis of model using displacement as a feature

The RMSE for this model is around 206.5 ton. with the mean error around 7.83%. so on average, the when a data is inputted to the model, the prediction should be within 7.83% difference range. this model has r-squared score of 0.593.

Table 4. 29 Model Prediction on Testing dataset using 1 feature: displacement

no.	**displacement**	**Target**	**Prediction**	**Residual**	**Difference%**
1	15257.60	2090.28	2089.09	1.19	0.06
2	12791.00	1826.42	1828.27	-1.85	0.10

no.	displacement	Target	Prediction	Residual	Difference%
3	16644.60	2150.16	2147.02	3.14	0.15
4	15623.00	2131.55	2128.00	3.55	0.17
5	18442.00	2148.75	2141.88	6.87	0.32
6	15623.00	2120.81	2128.00	-7.20	0.34
7	15255.00	2115.10	2122.76	-7.66	0.36
8	16335.00	1729.81	1736.99	-7.18	0.41
9	13725.00	2111.27	2123.71	-12.44	0.59
10	16335.00	1748.61	1736.99	11.62	0.66
11	15720.14	1491.45	1481.41	10.04	0.67
12	15720.14	1466.61	1481.41	-14.80	1.01
13	16644.60	2169.89	2147.02	22.88	1.05
14	12022.00	1776.43	1757.18	19.25	1.08
15	18255.00	2104.63	2080.42	24.21	1.15
16	15255.00	2091.98	2122.76	-30.78	1.47
17	14839.39	1504.71	1527.32	-22.61	1.50
18	14839.39	1504.10	1527.32	-23.22	1.54
19	15103.29	1542.09	1514.26	27.84	1.81
20	16094.00	2156.40	2115.16	41.24	1.91
21	12803.00	2226.48	2269.21	-42.72	1.92
22	15726.47	1490.02	1455.27	34.75	2.33
23	18090.52	2129.56	2079.48	50.07	2.35
24	15096.20	1523.89	1484.52	39.38	2.58
25	15623.00	2073.91	2128.00	-54.09	2.61
26	14900.60	2233.45	2174.80	58.64	2.63
27	13725.00	2069.05	2123.71	-54.67	2.64
28	14839.39	1487.20	1527.32	-40.12	2.70
29	15096.20	1443.26	1484.52	-41.25	2.86
30	13725.00	2059.78	2123.71	-63.93	3.10
31	14839.39	1480.52	1527.32	-46.80	3.16
32	18375.20	2274.09	2202.03	72.07	3.17
33	14837.80	2248.61	2174.35	74.25	3.30
34	14130.97	1461.81	1511.37	-49.56	3.39
35	14839.39	1581.98	1527.32	54.66	3.46
36	15103.29	1568.87	1514.26	54.61	3.48
37	18090.52	2009.02	2079.48	-70.47	3.51
38	15255.00	2205.33	2122.76	82.57	3.74

no.	displacement	Target	Prediction	Residual	Difference%
39	12232.00	2123.64	2039.87	83.77	3.94
40	12803.00	2182.83	2269.21	-86.38	3.96
41	14795.00	2248.16	2158.97	89.19	3.97
42	18442.00	2236.18	2141.88	94.31	4.22
43	13725.00	2036.64	2123.71	-87.07	4.28
44	13725.00	2033.90	2123.71	-89.82	4.42
45	12791.00	1750.00	1828.27	-78.27	4.47
46	15096.20	1560.74	1484.52	76.22	4.88
47	18090.52	2191.27	2079.48	111.78	5.10
48	16839.68	2030.33	2135.65	-105.32	5.19
49	16839.68	2030.33	2135.65	-105.32	5.19
50	15726.47	1536.00	1455.27	80.73	5.26
51	15720.14	1564.38	1481.41	82.97	5.30
52	15623.00	2248.05	2128.00	120.05	5.34
53	14900.60	2300.45	2174.80	125.64	5.46
54	15255.00	2247.30	2122.76	124.54	5.54
55	16644.60	2273.47	2147.02	126.45	5.56
56	15726.47	1376.00	1455.27	-79.27	5.76
57	18375.20	2078.49	2202.03	-123.53	5.94
58	16094.00	2250.97	2115.16	135.81	6.03
59	15257.60	2223.70	2089.09	134.61	6.05
60	18255.00	1958.60	2080.42	-121.83	6.22
61	14839.39	1628.62	1527.32	101.31	6.22
62	18442.00	2284.80	2141.88	142.92	6.26
63	16767.00	2232.65	2091.31	141.34	6.33
64	14900.60	2322.01	2174.80	147.20	6.34
65	12791.00	1717.00	1828.27	-111.27	6.48
66	14839.39	1635.46	1527.32	108.14	6.61
67	15103.29	1419.00	1514.26	-95.26	6.71
68	15257.60	2245.93	2089.09	156.84	6.98
69	18255.00	2238.40	2080.42	157.97	7.06
70	18255.00	1937.07	2080.42	-143.35	7.40
71	16644.60	2319.86	2147.02	172.84	7.45
72	14400.80	2265.59	2096.15	169.45	7.48
73	15103.29	1407.13	1514.26	-107.13	7.61
74	15103.29	1407.13	1514.26	-107.13	7.61

no.	displacement	Target	Prediction	Residual	Difference%
75	18090.52	2261.83	2079.48	182.34	8.06
76	16094.00	1953.67	2115.16	-161.49	8.27
77	15623.00	2327.86	2128.00	199.86	8.59
78	18255.00	1915.55	2080.42	-164.87	8.61
79	15255.00	2332.03	2122.76	209.27	8.97
80	15623.00	1951.14	2128.00	-176.86	9.06
81	18263.50	2227.86	2024.13	203.73	9.14
82	18255.00	2289.91	2080.42	209.48	9.15
83	12557.00	2004.50	1803.19	201.31	10.04
84	12077.00	1474.81	1623.53	-148.71	10.08
85	15103.29	1374.78	1514.26	-139.48	10.15
86	12077.00	1818.94	1623.53	195.41	10.74
87	14213.20	1635.62	1813.91	-178.28	10.90
88	16767.00	2358.24	2091.31	266.93	11.32
89	15720.14	1328.74	1481.41	-152.67	11.49
90	13725.00	1904.08	2123.71	-219.64	11.54
91	18263.50	2296.76	2024.13	272.63	11.87
92	16644.60	1909.51	2147.02	-237.51	12.44
93	12209.80	2214.33	1936.23	278.10	12.56
94	12209.80	2230.53	1936.23	294.29	13.19
95	14213.20	1600.00	1813.91	-213.91	13.37
96	12209.80	2282.12	1936.23	345.88	15.16
97	14213.20	1541.75	1813.91	-272.16	17.65
98	12557.00	1522.12	1803.19	-281.06	18.47
99	18375.20	1856.36	2202.03	-345.67	18.62
100	12557.00	1488.30	1803.19	-314.89	21.16
101	12077.00	2073.19	1623.53	449.67	21.69
102	12557.00	2310.89	1803.19	507.71	21.97
103	12557.00	1471.79	1803.19	-331.40	22.52
104	12077.00	2097.58	1623.53	474.06	22.60
105	16839.68	1729.09	2135.65	-406.56	23.51
106	14048.00	2303.94	1704.01	599.94	26.04
107	14048.00	2327.68	1704.01	623.67	26.79
108	18263.50	1415.47	2024.13	-608.66	43.00
109	16094.00	1344.99	2115.16	-770.17	57.26

4.3.15 using one feature: sea condition

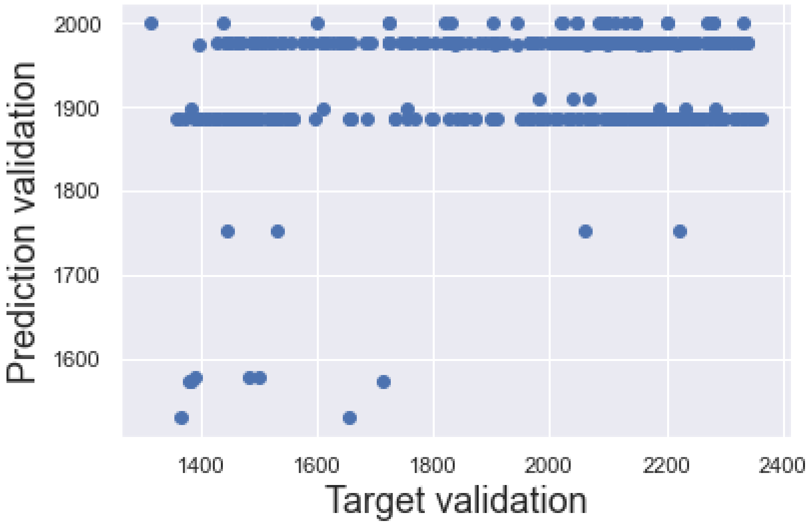

Figure 4. 27 scatter plot of model validation using sea conditiont as a feature

this model used displacement as its sea condition. it use Kneighbor regression as estimator. This model is the worst performing model to predict fuel oil consumption. Its has negative value of R which indicate that a horizontal line of mean have better performance than this model and as it can be seen in scatter plot below the fit line of this model is located abovee mean value.

compared using regular linear regression in python will result with model that generate the following equation:

Fuel consumption = 1925.3 + sea condition (-3.16 for moderate sea , -23.58 for moderate sea to swell, -31.63 for rippled, -19.76 for slight sea ,-17.33 for slight to moderate sea, -18.49 for slight to swell, -81.43 for smooth sea, -27.57 for smooth to slight, -41.36 for smooth to swell, -32.24 for swell sea , 27.55 for very smooth).

with RMSE value of 310.80 and R-value of -0.083. Compared to model created by linear regression, The model generated by the automl library TPOT is better.

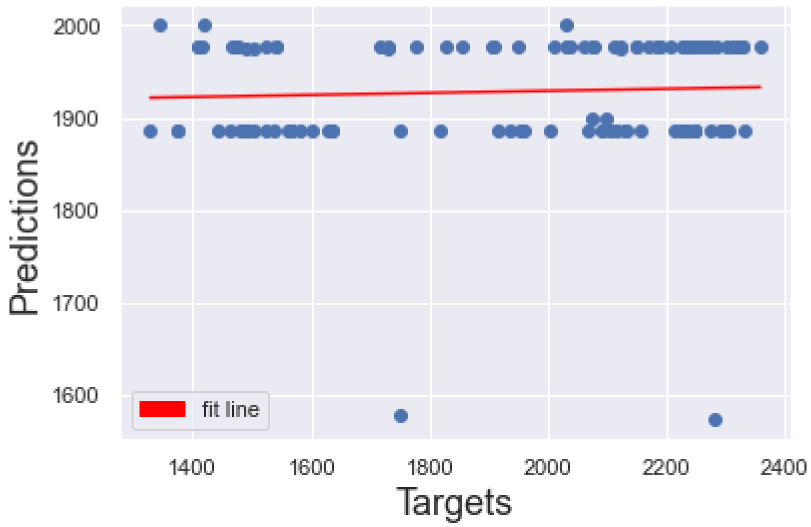

Figure 4. 28 scatter plot of model testing using sea condition as a feature

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1928.409908	0.635281	16.220258
std	325.243011	66.543026	328.440154	10.783913
min	1328.744275	1573.327548	-656.604033	1.299998
25%	1568.869565	1885.703018	-316.833453	8.912352
50%	2036.642633	1975.678512	97.407451	14.261495
75%	2230.525963	1976.505732	270.696982	20.539993
max	2358.236842	2001.592704	708.791500	48.818555

Table 4. 30 Result analysis of model using sea condition a feature

in this model, the difference between the target and prediction ranges between 1.29% as the lowest and 48.81% as the highest. The mean absolute squared error value is 16.2%%.

Table 4. 31 Result analysis of model using sea conditiont as a feature

no.	**Sea condition**	**Target**	**Prediction**	**Residual**	**Difference%**
1	slight sea	1951.14	1976.51	-25.36	1.30
2	moderate sea	2030.33	2001.59	28.74	1.42

no.	Sea condition	Target	Prediction	Residual	Difference%
3	smooth sea	1915.55	1885.70	29.85	1.56
4	slight sea	2009.02	1976.51	32.51	1.62
5	slight sea	2030.33	1976.51	53.82	2.65
6	smooth sea	1937.07	1885.70	51.37	2.65
7	slight sea	2033.90	1976.51	57.39	2.82
8	slight sea	2036.64	1976.51	60.14	2.95
9	smooth sea	1953.67	1885.70	67.97	3.48
10	slight sea	1909.51	1976.51	-67.00	3.51
11	smooth sea	1818.94	1885.70	-66.77	3.67
12	smooth sea	1958.60	1885.70	72.89	3.72
13	slight sea	1904.08	1976.51	-72.43	3.80
14	slight sea	2059.78	1976.51	83.28	4.04
15	slight sea	2073.91	1976.51	97.41	4.70
16	slight sea	2078.49	1976.51	101.99	4.91
17	smooth sea	2004.50	1885.70	118.80	5.93
18	slight sea	2111.27	1976.51	134.77	6.38
19	slight sea	1856.36	1976.51	-120.15	6.47
20	smooth to slight	2120.81	1975.68	145.13	6.84
21	slight sea	2123.64	1976.51	147.14	6.93
22	smooth sea	1748.61	1885.70	-137.09	7.84
23	slight sea	2148.75	1976.51	172.25	8.02
24	slight sea	2150.16	1976.51	173.66	8.08
25	slight sea	1826.42	1976.51	-150.09	8.22
26	slight to moderate sea	2073.19	1898.99	174.20	8.40
27	smooth sea	2069.05	1885.70	183.35	8.86
28	slight sea	2169.89	1976.51	193.39	8.91
29	slight sea	2182.83	1976.51	206.32	9.45
30	slight to moderate sea	2097.58	1898.99	198.59	9.47
31	swell sea	1750.00	1578.84	171.16	9.78
32	smooth sea	2090.28	1885.70	204.57	9.79
33	slight sea	2191.27	1976.51	214.76	9.80
34	smooth sea	2091.98	1885.70	206.28	9.86
35	slight sea	2205.33	1976.51	228.82	10.38
36	smooth sea	2104.63	1885.70	218.93	10.40
37	smooth sea	2115.10	1885.70	229.40	10.85

no.	Sea condition	Target	Prediction	Residual	Difference%
38	slight sea	2226.48	1976.51	249.98	11.23
39	slight sea	1776.43	1976.51	-200.08	11.26
40	slight sea	2227.86	1976.51	251.35	11.28
41	smooth sea	2129.56	1885.70	243.85	11.45
42	slight sea	2233.45	1976.51	256.94	11.50
43	smooth sea	2131.55	1885.70	245.85	11.53
44	slight sea	2236.18	1976.51	259.68	11.61
45	slight sea	2238.40	1976.51	261.89	11.70
46	slight sea	2248.05	1976.51	271.55	12.08
47	slight sea	2250.97	1976.51	274.47	12.19
48	smooth sea	2156.40	1885.70	270.70	12.55
49	slight sea	2261.83	1976.51	285.32	12.61
50	slight sea	2265.59	1976.51	289.09	12.76
51	slight sea	2273.47	1976.51	296.96	13.06
52	slight sea	2284.80	1976.51	308.29	13.49
53	slight sea	2300.45	1976.51	323.94	14.08
54	smooth to slight	1729.09	1975.68	-246.59	14.26
55	slight sea	1729.81	1976.51	-246.70	14.26
56	slight sea	2310.89	1976.51	334.39	14.47
57	slight sea	2319.86	1976.51	343.36	14.80
58	smooth sea	2214.33	1885.70	328.63	14.84
59	slight sea	2322.01	1976.51	345.50	14.88
60	slight sea	2327.68	1976.51	351.17	15.09
61	slight sea	2327.86	1976.51	351.36	15.09
62	slight sea	1717.00	1976.51	-259.51	15.11
63	smooth sea	2223.70	1885.70	337.99	15.20
64	smooth sea	1635.62	1885.70	-250.08	15.29
65	smooth sea	1635.46	1885.70	-250.25	15.30
66	smooth sea	2230.53	1885.70	344.82	15.46
67	smooth sea	2232.65	1885.70	346.94	15.54
68	smooth sea	1628.62	1885.70	-257.08	15.79
69	smooth sea	2245.93	1885.70	360.23	16.04
70	smooth sea	2247.30	1885.70	361.59	16.09
71	smooth sea	2248.16	1885.70	362.46	16.12
72	smooth sea	2248.61	1885.70	362.90	16.14
73	slight sea	2358.24	1976.51	381.73	16.19

no.	Sea condition	Target	Prediction	Residual	Difference%
74	smooth sea	2274.09	1885.70	388.39	17.08
75	smooth sea	2289.91	1885.70	404.20	17.65
76	smooth sea	1600.00	1885.70	-285.70	17.86
77	smooth sea	2296.76	1885.70	411.06	17.90
78	smooth sea	2303.94	1885.70	418.24	18.15
79	smooth sea	2332.03	1885.70	446.32	19.14
80	smooth sea	1581.98	1885.70	-303.73	19.20
81	smooth sea	1568.87	1885.70	-316.83	20.20
82	smooth sea	1564.38	1885.70	-321.32	20.54
83	smooth sea	1560.74	1885.70	-324.96	20.82
84	smooth sea	1536.00	1885.70	-349.70	22.77
85	smooth sea	1523.89	1885.70	-361.81	23.74
86	smooth sea	1504.10	1885.70	-381.60	25.37
87	smooth sea	1491.45	1885.70	-394.25	26.43
88	smooth sea	1490.02	1885.70	-395.68	26.56
89	smooth sea	1487.20	1885.70	-398.50	26.80
90	smooth sea	1480.52	1885.70	-405.18	27.37
91	slight sea	1542.09	1976.51	-434.41	28.17
92	slight sea	1541.75	1976.51	-434.76	28.20
93	smooth sea	1461.81	1885.70	-423.89	29.00
94	slight sea	1522.12	1976.51	-454.38	29.85
95	smooth sea	1443.26	1885.70	-442.44	30.66
96	smooth to swell	2282.12	1573.33	708.79	31.06
97	smooth to slight	1504.71	1975.68	-470.97	31.30
98	smooth to slight	1488.30	1975.68	-487.38	32.75
99	slight sea	1474.81	1976.51	-501.69	34.02
100	slight sea	1471.79	1976.51	-504.72	34.29
101	slight sea	1466.61	1976.51	-509.90	34.77
102	smooth sea	1376.00	1885.70	-509.70	37.04
103	smooth sea	1374.78	1885.70	-510.92	37.16
104	slight sea	1415.47	1976.51	-561.04	39.64
105	slight sea	1407.13	1976.51	-569.38	40.46
106	slight sea	1407.13	1976.51	-569.38	40.46
107	moderate sea	1419.00	2001.59	-582.59	41.06
108	smooth sea	1328.74	1885.70	-556.96	41.92
109	moderate sea	1344.99	2001.59	-656.60	48.82

CHAPTER V
CONCLUSION

5.1 Conclusion

In this study, a regression model using automated machine learning library TPOT was proposed to predict the fuel consumption of the vessel's main engine of M/V waingapu. The conclusions from this research are:

1. based on the model that automl create to predict shil fuel consumption, the regression (r-squared) value and root mean square error (RMSE) is as follows:
   four feature
   - Speed, Engine Load, Displacement, and Sea Condition
     RMSE : 127.05
     R-Squared : 0.845

   three feature
   - Engine load, speed and displacement
     RMSE: 129.97
     R-Squared: 0.838
   - Speed, Engine load, and Sea condition
     RMSE : 149.28
     R-Squared : 0.787
   - Speed, Displacement, Sea condition
     RMSE : 159.07
     R-Squared : 0.758
   - Engine Load, Displacement, Sea condition
     RMSE : 147.52
     R-Squared : 0.792

   two feature
   - engine and displacement
     RMSE: 148.73
     R-Squared: 0.788
   - displacement and speed
     RMSE: 158.25
     R-Squared: 0.761
   - speed and engine load
     RMSE :156.25
     R-Squared : 0.767
   - Speed and Sea condition
     RMSE : 218.32
     R-Squared : 0.545
   - Engine load and Sea condition
     RMSE : 162.22
     R-Squared : 0.748
   - Displacement and Sea condition
     RMSE : 207.33

R-Squared : 0.589

one feature

- Speed
  RMSE : 226.87
  R-Squared : 0.508
- Engine Load
  RMSE :170.52
  R-Squared : 0.722
- Displacement
  RMSE : 206.5
  R-Squared : 0.593
- Sea Condition
  RMSE: 326.93
  R-Squared : -0.019

2. From the model that using one feature, it can be seen which feature is more significant than the others. Engine load model which has the highest R-Squared among all feature sugest that this feature importance is rank highest than any other feature. Not only that This model RMSE value is 170.52 means the standard deviation value of this model is 170.52 ton of fuel consumption. The more insignificant feature would be sea condition with negative R-Squared value means that a horizontal line of mean value is much more accurate to predict fuel consumption rather than this model.
3. the model that yield the least error is model with 4 feature : speed, engine load, displacement and sea condition with R-Squared value of 0.845 and RMSE value of 127.05 means that the standard deviation value of this model is 127.05 ton. That mean 68.2% of errors are within 127.05 ton value. The method that is used to get this value is Extra Tree Regressor as its estimator and K-Neighbor Regressor as its final estimator.

5.2 Suggestion

Based on this research, some suggestion is given by the author to support future research, as follow:

1. To increase the accuracy of fuel consumption, author suggest that the data collected to be automated and to have fewer time interval between data. the data that is collected also should not be rounded to get better model.
2. for the model itself, author suggest to use more than on automated library to make model prediction and author hope that instead of imput the data manually to the python a sort of app can be made to make data entry easier and more readable.

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APPENDIX

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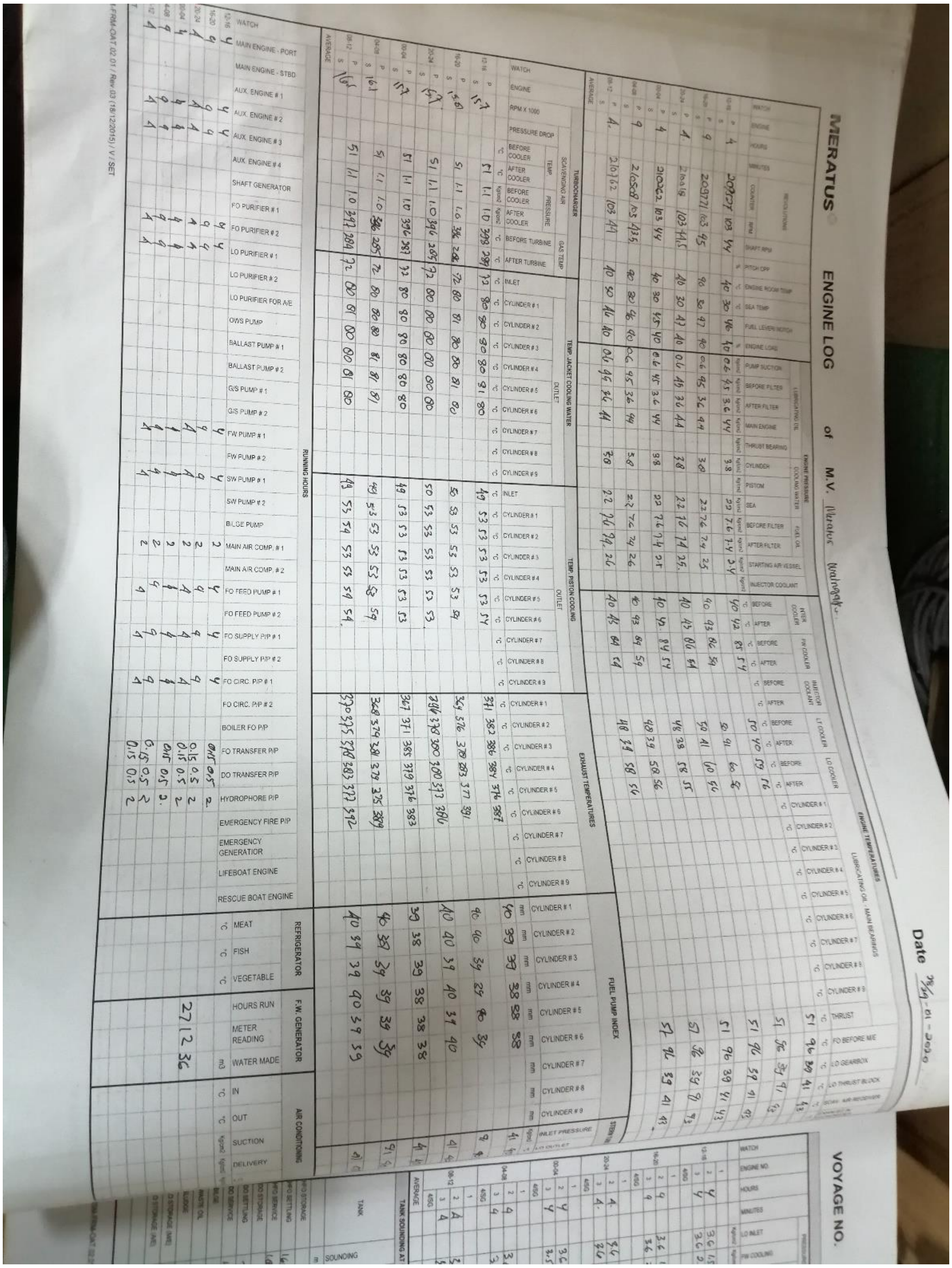
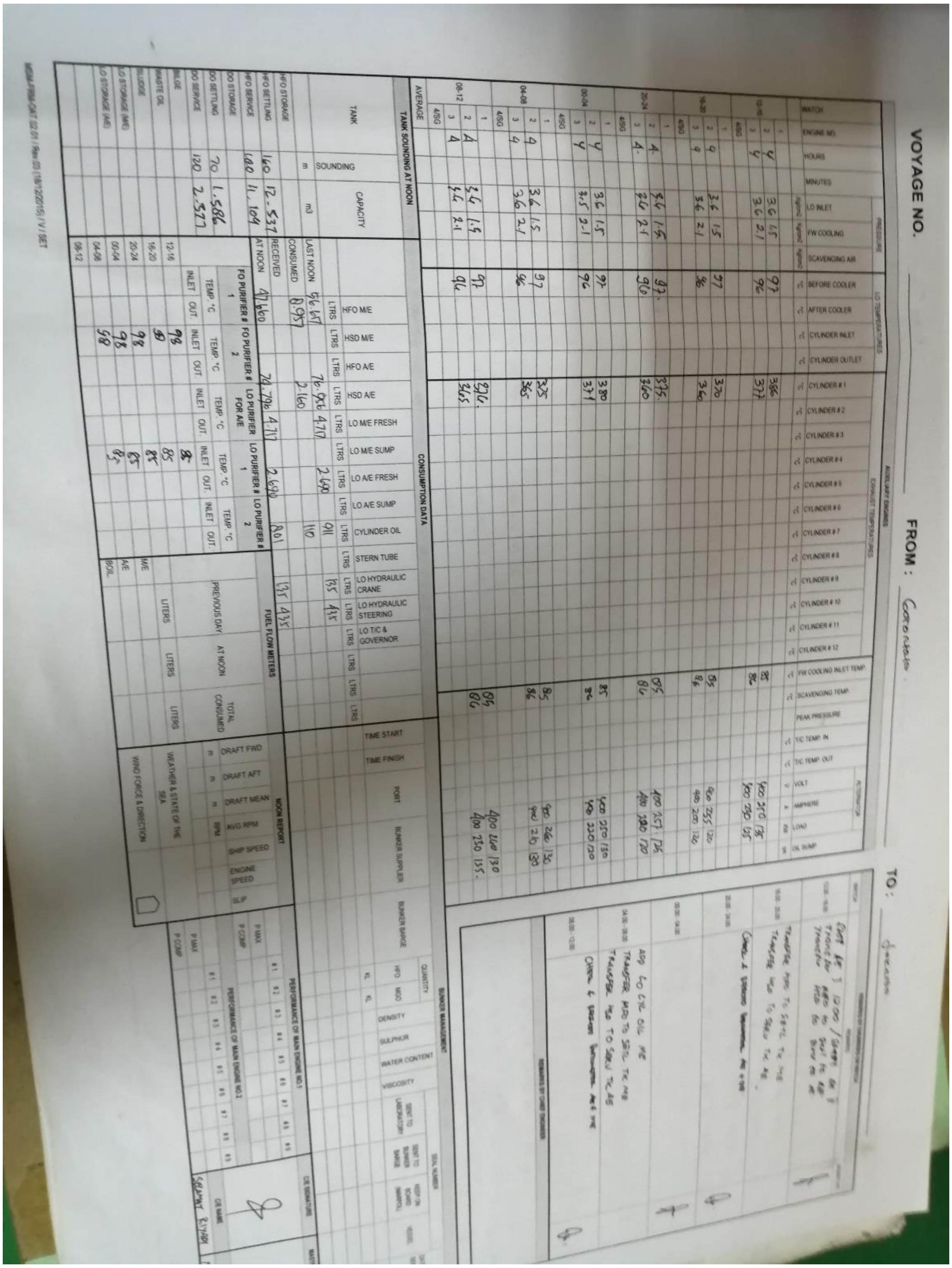
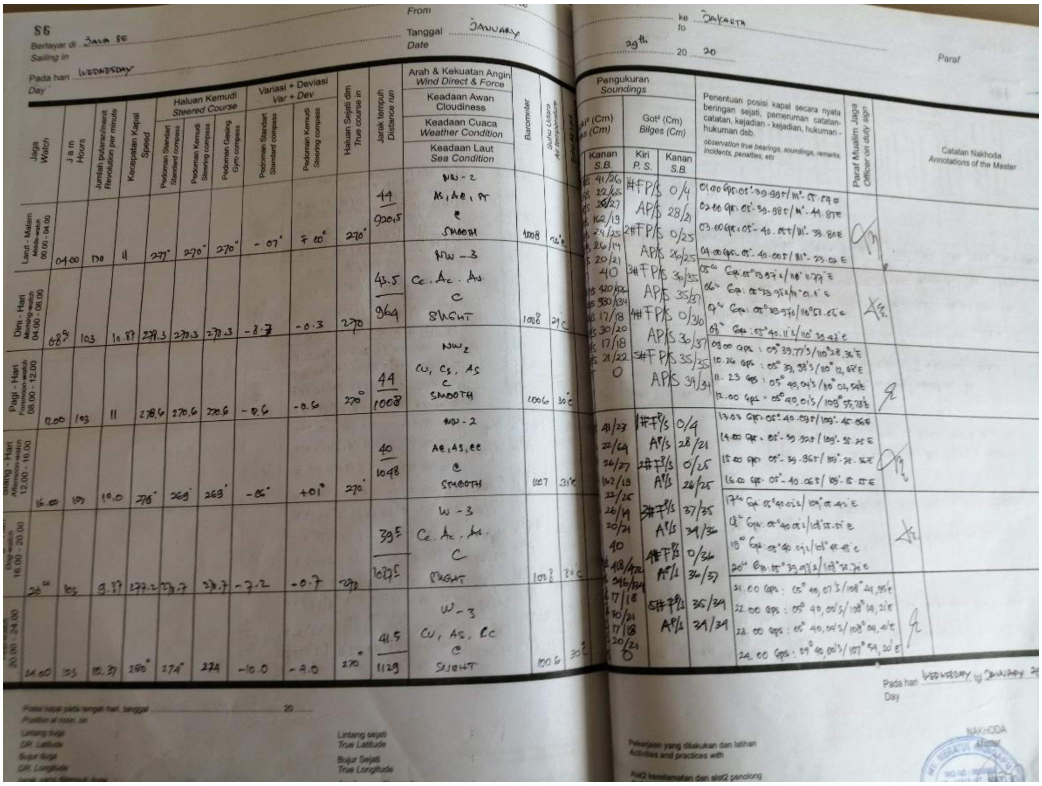
ATTACHMENT 1

Ship log book and noon report example



MERATUS
ENGINE LOG of M.V. Meratus Waingapu
Date 28/29-01-2020
VOYAGE NO.
WATCH	ENGINE	HOURS	COUNTER	RPM	ENGINE ROOM TEMP	SEA TEMP	FUEL LEVER/NOTCH	ENGINE LOAD	LO PUMP SUCTION	LO BEFORE FILTER	LO AFTER FILTER	LO MAIN ENGINE	CW CYLINDER	FO BEFORE FILTER	FO AFTER FILTER	STARTING AIR VESSEL	INTER COOLER BEFORE	INTER COOLER AFTER	FW COOLER BEFORE	FW COOLER AFTER	LT COOLER BEFORE	LT COOLER AFTER	LO COOLER BEFORE	LO COOLER AFTER
12-16	P	4	209527	103	44	40 30	46	40	0.6	45	3.6	4.4	3.8	2.2	7.6	7.4 2.4	40	42	85	54	50	40	59	56
16-20	P	9	209771	103	45	40 30	47	40	0.6	45	3.6	4.4	3.8	2.2	7.6	7.4 2.5	40	43	86	59	50	41	60	58
20-24	P	4	210018	103	44.5	40 30	47	40	0.6	45	3.6	4.4	3.8	2.2	7.6	7.4 2.5	40	43	86	54	50	41	60	56
00-04	P	4	210262	103	44	40 30	45	40	0.6	45	3.6	4.4	3.8	2.2	7.6	7.4 2.5	40	42	84	54	48	38	58	55
04-08	P	9	210508	103	43.5	40 30	46	40	0.6	45	3.6	4.4	3.8	2.2	7.6	7.4 2.6	40	43	84	59	48	39	58	56
08-12	P	4	210762	103	44	40 30	46	40	0.6	45	3.6	4.4	3.8	2.2	7.6	7.4 2.6	40	43	84	54	48	39	58	56
ENGINE TEMPERATURES – LUBRICATING OIL - MAIN BEARINGS
THRUST	FO BEFORE M/E	LO GEARBOX	LO THRUST BLOCK	SCAV. AIR RECEIVER
51	96	39	41	43
51	96	39	91	43
51	96	39	91	43
51	96	39	41	43
57	96	39	91	93
57	96	39	41	43
WATCH	RPM X 1000	SCAV. AIR TEMP BEFORE COOLER	PRESSURE BEFORE COOLER	PRESSURE AFTER COOLER	GAS TEMP BEFORE TURBINE	GAS TEMP AFTER TURBINE	JACKET INLET	JACKET OUTLET CYL #1–#6	PISTON INLET	PISTON OUTLET CYL #1–#6	EXHAUST CYL #1–#6	FUEL PUMP INDEX CYL #1–#6	STERN TUBE INLET PRESSURE
---	---	---	---	---	---	---	---	---	---	---	---	---	---
12-16	157	51	1.1	1.0	393	289	72	80 80 80 80 81 80	49	53 53 53 53 53 54	371 382 386 384 376 387	40 39 39 38 38 38	41
16-20	150	51	1.1	1.0	396	286	72	80 81 80 80 81 80	50	53 53 53 53 53 54	364 376 378 383 377 391	40 40 39 29 40 39	41
20-24	157	51	1.1	1.0	396	285	72	80 80 80 80 80 80	50	53 53 53 53 53 53	396 378 380 380 373 386	40 40 39 40 39 40	41
00-04	157	51	1.1	1.0	396	287	72	80 80 80 80 80 80	49	53 53 53 53 53 53	367 371 385 379 376 383	39 38 39 38 38 38	41
04-08	161	51	1.1	1.0	396	285	72	80 80 80 81 81 81	49	53 53 53 53 53 59	368 379 381 379 375 389	40 39 39 39 39 39	41
08-12	165	51	1.1	1.0	397	284	72	80 81 80 80 81 80	49	55 54 53 53 59 54	370 375 378 383 377 392	40 39 39 40 39 39	41
RUNNING HOURS
WATCH	MAIN ENGINE - PORT	AUX. ENGINE #2	AUX. ENGINE #3	FO PURIFIER #2	LO PURIFIER #1	FW PUMP #1	SW PUMP #1	MAIN AIR COMP. #1	FO FEED PUMP #1	FO SUPPLY P/P #1	FO CIRC. P/P #1	FO TRANSFER P/P	DO TRANSFER P/P	HYDROPHORE P/P
12-16	4	4	4	4	4	4	4	2	4	4	4			
16-20	4	4	4	4	4	4	4	2	4	4	4	0.15	0.5	2
20-24	4	4	4	4	4	4	4	2	4	4	4	0.15	0.5	2
00-04	4	4	4	4	4	4	4	2	4	4	4	0.15	0.5	2
04-08	4	4	4	4	4	4	4	2	4	4	4	0.15	0.5	2
08-12	4	4	4	4	4	4	4	2	4	4	4	0.15	0.5	2
												0.15	0.5	2
REFRIGERATOR: MEAT, FISH, VEGETABLE
F.W. GENERATOR: HOURS RUN, METER READING 271236, WATER MADE
AIR CONDITIONING: IN, OUT, SUCTION, DELIVERY
TANK SOUNDING AT
...-FRM-OAT.02.01 / Rev.03 (18/12/2015) / V / SET





Jaga / Watch	Jam / Hours	Jumlah putaran/menit / Revolution per minute	Kecepatan Kapal / Speed	Pedoman Standart / Standard compass	Pedoman Kemudi / Steering compass	Pedoman Gasing / Gyro compass	Variasi + Deviasi (Standard compass)	Variasi + Deviasi (Steering compass)	Haluan Sejati / True course	Jarak tempuh / Distance run	Arah & Kekuatan Angin / Keadaan Awan / Keadaan Cuaca / Keadaan Laut	Barometer	Suhu Udara / Air temperature
Larut - Malam 00.00 - 04.00	04.00	130	11	271°	270°	270°	-07°	+00°	270°	44 / 920.5	NW-2 / Ac, Ac, St / c / SMOOTH	1008	26°
Dini - Hari 04.00 - 08.00	08	103	10.87	271.3	270.3	270.3	-8.7	-0.3	270	43.5 / 964	NW-3 / Cc, Ac, As / c / SLIGHT	1008	29°C
Pagi - Hari 08.00 - 12.00	12.00	103	11	278.6	270.6	270.6	-8.6	-0.6	270°	44 / 1008	NW 2 / Cu, Cs, As / c / SMOOTH	1006	30°C
Siang - Hari 12.00 - 16.00	16.00	103	10.0	275°	269°	269°	-06°	+01°	270°	40 / 1048	NW-2 / Ac, As, Ce / c / SMOOTH	1007	31°C
Dog-watch 16.00 - 20.00	20	103	9.37	277.2	279.7	279.7	-7.2	-0.7	270	39.5 / 1087.5	W-3 / Cc, Ac, As / c / SLIGHT	1008	30°C
20.00 - 24.00	24.00	103	10.37	280°	274°	274	-10.0	-4.0	270	41.5 / 1129	W-3 / Cu, As, Cc / c / SLIGHT	1006	30°C

Departure GORONTALO /25.01.2020

WPU/424/VOY.2001S/ GORONTALO - JAKARTA

1. Comm.disch : 24.01.2020 – 09.12 Lt
2. Compl.disch : 24.01.2020 – 17.00 Lt
3. Cargo. Disch : SUB - GTO : 10FF+82TF : 92 BOXES/ 102 TEUS

: JKT - GTO : 43 20GP + 7 40HC : 50 BOXES/ 57 TEUS

: BIT – GTO : -

:

TOTAL DISCH : 142 BOXES /159 TEUS

ATTACHMENT 2

Ship Particular

SHIP PARTICULARS ON THE BRIDGE

hip's Name	: Huang Hai 6 (TBR MV MERATUS WAINGAPU)
revious Name	:
all Sign	: E5U3579
lag/ Port of Registry	: Cook Islands/Avatiu
Dwner	: Marina Transport Service Limited Inc. Panama
Classification	: Sing-Lloyd
Official Number/ Hull No.	: 2688 / HCY-182
IMO Number	: 9838888
Class Number/ Reg.No.	: 191524
MMSI Number	: 518100665
Inmarsat-C Number	: 451800831
AAIC	: BE02
Built	: 2019
Builder	: Huanghai Shipbuilding Co., Ltd
Kind of Ship	: Open Top - Container Vessel, Great Coastal Service R1, Cargo Hold 1&2 w/ hatch cover for Dangerous Goods Class 4.1, 4.2, 4.3, 5.1 & 5.2
L.O.A.	: 146 M
L.B.P.	: 142.2 M
Length from Bridge to Stern	: 13.4 M
Breadth (Moulded)	: 23.25 M
Depth (Moulded)	: 10.5 M
Summer/ Tropical Draft	: 7 M / 7.135 M
Light Ship Draft	: 1.98 M
Highest point from keel	: 38.5 M
Gross Tonnage	: 11512 Tons
Net Tonnage	: 6447 Tons
Summer/ Tropical Deadweight	: 14798 / 15174 Tons
Light Ship Weight	: 5097 Tons
Main Engine	: Two Stroke, Diesel Engne Mitsubishi 6UEC33LSE-C2, 3990kW, 133.3 RPM, single acting, crosshead type
Auxiliary Engine	: 3 x Volvo Penta D16MG- 420kW; 1x Emergency Genset : Volvo Penta D9MG – 227 kW
Propeller	: FPP, dia. 4.00 m, pitch 3.4 m at 0.7R, Material Cu3 (Ni-Al-Bronze)
Bow Thruster	: 350 Kw
Service Speed	: 11 Knots *(loading condition)
Fuel Oil Consumption	: About 9.0 T/day HFO
Crane/ ~~Derrick~~	: 2x40T
Container Capacity	: 814 TEUS or 392 FEUs or 798 TEUS @14T
Ballast Water Capacity	: 6866 m^3 (100%)
Fresh Water Capacity	: 140 m^3 (100%)
Fuel Oil Capacity	: 512 m^3 (100%)
Diesel Oil Capacity	: 143 m^3 (100%)
Deck Load Capacity	: Tank Top = ____ Tons/m^2 On Hatch Cover = ____ Tons/m^2
Container Stacking Load	: Double Bottom – Closed hatch = 100 LT/Stack (20') , 120 LT/Stack (40') Double Bottom – Open hatch = 150 LT/Stack (20') , 175 LT/Stack (40') Hatch Cover = 30 LT/Stack (20') , 45 LT/Stack (40') Main Deck = 80 LT/Stack (20'), 100 LT/Stack (40')
Reefer Plug	: 54 Plugs 380 V 50 Hz +50 Plugs with Shore genset

ote *) = Being Observed

Note: All figures are believed to be correct but are given without guarantee

ATTACHMENT 3:

Ship Fuel Consumption Data

Date	Hours	engine load (%)	speed (knot)	Wind	displacement (ton)	sea condition	fuel consumption (ton)
17-Jun-19	20:00:00	NaN	9,25	3	NaN	moderate sea	NaN
17-Jun-19	00:00:00	NaN	10	3	NaN	moderate sea	NaN
18-Jun-19	04:00:00	NaN	10,25	3	NaN	slight to moderate sea	NaN
18-Jun-19	08:00:00	NaN	10,25	4	NaN	moderate sea	NaN
18-Jun-19	12:00:00	NaN	9,5	4	NaN	moderate sea	NaN
18-Jun-19	16:00:00	42	9	4	NaN	moderate sea	NaN
18-Jun-19	20:00:00	42	9,25	4	NaN	moderate sea	NaN
18-Jun-19	00:00:00	NaN	10,25	4	NaN	moderate sea	NaN
19-Jun-19	04:00:00	41	10,4	3	NaN	slight sea	NaN
20-Jun-19	00:00:00	NaN	11,25	3	NaN	slight to moderate sea	NaN
21-Jun-19	04:00:00	59	11,75	3	NaN	slight sea	NaN
21-Jun-19	08:00:00	59	NaN	3	NaN	slight sea	NaN
21-Jun-19	12:00:00	59	11	3	NaN	slight sea	NaN

21-Jun-19	16:00:00	49	11,5	3	NaN	slight sea	NaN
21-Jun-19	20:00:00	49	NaN	3	NaN	slight sea	NaN
21-Jun-19	00:00:00	49	12,35	3	NaN	slight sea	NaN
22-Jun-19	04:00:00	49	11,75	3	NaN	slight sea	NaN
22-Jun-19	08:00:00	49	11,25	3	NaN	slight sea	NaN
22-Jun-19	12:00:00	49	10,06	3	NaN	smoth sea	NaN
22-Jun-19	16:00:00	51	11,5	3	NaN	smooth sea	NaN
22-Jun-19	20:00:00	51	12,25	3	NaN	smooth sea	NaN
22-Jun-19	00:00:00	51	13,05	3	NaN	smooth sea	NaN
23-Jun-19	04:00:00	50	11	3	NaN	slight sea	NaN
23-Jun-19	08:00:00	50	10,75	3	NaN	smooth sea	NaN
23-Jun-19	12:00:00	50	12,25	3	NaN	calm sea	NaN
23-Jun-19	16:00:00	50	12,12	2	NaN	calm sea	NaN
23-Jun-19	20:00:00	51	12,2	2	NaN	smooth sea	NaN

23-Jun-19	00:00:00	51	12,5	2	NaN	smooth to slight	NaN
24-Jun-19	04:00:00	53	13	3	NaN	slight sea	NaN
24-Jun-19	08:00:00	50	12	3	NaN	slight sea	NaN
24-Jun-19	12:00:00	51	11	3	NaN	slight sea	NaN
24-Jun-19	16:00:00	NaN	NaN	3	NaN	slight sea	NaN
24-Jun-19	20:00:00	NaN	NaN	3	NaN	slight sea	NaN
27-Jun-19	12:00:00	NaN	NaN	3	NaN	slight sea	NaN
27-Jun-19	16:00:00	NaN	NaN	3	NaN	slight sea	NaN
27-Jun-19	20:00:00	NaN	12,5	3	NaN	slight sea	NaN
27-Jun-19	00:00:00	NaN	10,75	3	NaN	slight sea	NaN
01-Jul-19	04:00:00	NaN	NaN	3	NaN	slight sea	NaN
01-Jul-19	08:00:00	NaN	NaN	3	NaN	slight sea	NaN
01-Jul-19	12:00:00	NaN	8	2	NaN	smooth sea	NaN
01-Jul-19	16:00:00	NaN	10,6	2	NaN	smooth sea	NaN

01-Jul-19	20:00:00	46	10,9	2	NaN	smooth sea	NaN
01-Jul-19	00:00:00	46	11,5	2	NaN	slight sea	NaN
02-Jul-19	04:00:00	46	11,37	3	NaN	slight sea	NaN
02-Jul-19	08:00:00	46	11	3	NaN	slight sea	NaN
02-Jul-19	12:00:00	46	11,75	3	NaN	swell sea	NaN
02-Jul-19	16:00:00	52	12	3	NaN	smooth sea	NaN
02-Jul-19	20:00:00	52	12,75	3	NaN	slight sea	NaN
02-Jul-19	00:00:00	52	13,6	3	NaN	slight sea	NaN
03-Jul-19	04:00:00	52	12,5	3	NaN	slight sea	NaN
03-Jul-19	08:00:00	52	12,2	3	NaN	slight sea	NaN
03-Jul-19	12:00:00	51	12,5	3	NaN	slight sea	NaN
03-Jul-19	16:00:00	52	12	3	NaN	slight sea	NaN
03-Jul-19	20:00:00	52	11,5	3	NaN	slight sea	NaN
03-Jul-19	00:00:00	52	12	3	NaN	slight sea	NaN

04-Jul-19	04:00:00	52	12,37	3	NaN	slight sea	NaN
04-Jul-19	08:00:00	52	12,5	3	NaN	slight sea	NaN
04-Jul-19	12:00:00	52	12,45	3	NaN	slight sea	NaN
04-Jul-19	16:00:00	52	13,1	3	NaN	slight sea	NaN
04-Jul-19	20:00:00	52	13,25	3	NaN	slight sea	NaN
04-Jul-19	00:00:00	52	12,5	3	NaN	slight sea	NaN
05-Jul-19	04:00:00	53	11,75	3	NaN	slight sea	NaN
05-Jul-19	08:00:00	52	12	3	NaN	slight sea	NaN
07-Jul-19	12:00:00	53	11	3	NaN	slight sea	NaN
07-Jul-19	16:00:00	53	11	3	NaN	slight sea	NaN
07-Jul-19	20:00:00	53	10,8	4	NaN	moderate sea	NaN
07-Jul-19	00:00:00	53	11,25	4	NaN	moderate sea	NaN
08-Jul-19	04:00:00	52	11,6	3	NaN	slight sea	NaN
08-Jul-19	08:00:00	52	12	4	NaN	slight sea	NaN

08-Jul-19	12:00:00	52	11,25	4	NaN	slight sea	NaN
08-Jul-19	16:00:00	52	11	4	NaN	slight sea	NaN
10-Jul-19	20:00:00	NaN	NaN	3		NaN	1323,889908
10-Jul-19	00:00:00	52	11,75	3	18090,522	slight sea	2145,614679
11-Jul-19	04:00:00	55	12	4	18090,522	slight sea	2191,266055
11-Jul-19	08:00:00	57	11,75	4	18090,522	moderate sea	2145,614679
11-Jul-19	12:00:00	57	11,75	4	18090,522	moderate sea	2145,614679
11-Jul-19	16:00:00	57	11,5	4	18090,522	moderate sea	2024,16458
11-Jul-19	20:00:00	55	12	4	18090,522	moderate sea	2112,171735
11-Jul-19	00:00:00	55	12,5	4	18090,522	moderate sea	2200,178891
12-Jul-19	04:00:00	56	11,9	4	18090,522	moderate sea	2090,169946
12-Jul-19	08:00:00	54	10,25	3	18090,522	slight sea	1804,146691
12-Jul-19	12:00:00	54	11,75	3	18090,522	calm sea	2068,168157
12-Jul-19	16:00:00	53	12,5	3	18090,522	smooth sea	2009,016393

12-Jul-19	20:00:00	53	13,25	3	18090,522	slight sea	2129,557377
12-Jul-19	00:00:00	53	12,5	3	18090,522	slight sea	2009,016393
13-Jul-19	04:00:00	66	11	2	18090,522	smooth sea	1767,934426
13-Jul-19	08:00:00	52	13,75	2	18090,522	slight sea	2209,918033
13-Jul-19	12:00:00	52	13,25	2	18090,522	smooth sea	2129,557377
13-Jul-19	16:00:00	53	12,5	3	18090,522	smooth to slight	2217,479675
13-Jul-19	20:00:00	53	12,75	3	18090,522	slight sea	2261,829268
13-Jul-19	00:00:00	54	12	3	18090,522	moderate sea	2128,780488
14-Jul-19	04:00:00	53	12,5	3	18090,522	smooth sea	2217,479675
14-Jul-19	08:00:00	56	11,75	3	18090,522	moderate sea	2084,430894
16-Jul-19	16:00:00	43	12,3	3	12022	slight sea	1148,398977
16-Jul-19	20:00:00	44	12,4	3	12022	slight sea	1776,429668
16-Jul-19	00:00:00	44	12,25	3	12022	slight sea	1758,485934
17-Jul-19	04:00:00	44	12	3	12022	slight sea	1722,598465

17-Jul-19	08:00:00	NaN	NaN	NaN	12791	NaN	610,0869565
19-Jul-19	20:00:00	NaN	NaN	NaN	12791	NaN	1416,370293
19-Jul-19	00:00:00	51	11,75	3	12791	slight sea	1775,1841
20-Jul-19	04:00:00	50	12,6	3	12791	smooth to slight	1907,378661
20-Jul-19	08:00:00	52	12,5	3	12791	slight sea	1888,493724
20-Jul-19	12:00:00	52	13,5	3	12791	calm sea	2039,573222
20-Jul-19	16:00:00	53	13,2	3	12791	calm sea	1980,598071
20-Jul-19	20:00:00	53	12,25	4	12791	moderate sea	1831,118971
20-Jul-19	00:00:00	53	13	4	12791	moderate sea	1943,228296
21-Jul-19	04:00:00	53	14	3	12791	moderate sea	2092,707395
21-Jul-19	08:00:00	53	13,5	4	12791	moderate sea	2017,967846
21-Jul-19	12:00:00	53	11,75	3	12791	slight sea	1756,379421
21-Jul-19	16:00:00	45	11,5	3	12791	slight to moderate sea	1754,703287
21-Jul-19	20:00:00	45	11,3	3	12791	moderate sea	1724,186708

21-Jul-19	00:00:00	45	11,3	3	12791	moderate sea	1724,186708
22-Jul-19	04:00:00	45	11,97	3	12791	slight sea	1826,417248
22-Jul-19	08:00:00	44	12,2	3	12791	slight sea	1861,511314
22-Jul-19	12:00:00	44	12	3	12791	slight sea	1830,994735
22-Jul-19	16:00:00	45	12,5	3	12791	slight sea	1752,039429
22-Jul-19	20:00:00	44	12,3	3	12791	slight sea	1724,006798
22-Jul-19	00:00:00	44	12,75	3	12791	slight sea	1787,080218
23-Jul-19	04:00:00	44	12	3	12791	slight sea	1681,957852
23-Jul-19	08:00:00	44	11,75	3	12791	slight sea	1646,917063
23-Jul-19	12:00:00	44	12,25	3	12791	slight sea	1716,99864
23-Jul-19	16:00:00	45	12,25	3	12791	swell sea	1750
27-Jul-19	12:00:00	51	8,3	2	12870	smooth sea	1364
27-Jul-19	16:00:00	52	12,25	3	12870	smooth sea	2068,739726
27-Jul-19	20:00:00	52	12	3	12870	slight sea	2026,520548

27-Jul-19	00:00:00	52	12,25	3	12870	slight sea	2068,739726
28-Jul-19	04:00:00	52	12,25	3	12870	smooth sea	2068,739726
28-Jul-19	08:00:00	54	12,25	3	12870	slight sea	2068,739726
28-Jul-19	12:00:00	54	12	3	12870	slight sea	2026,520548
28-Jul-19	16:00:00	NaN	NaN	3	12870	NaN	1513
28-Jul-19	08:00:00	NaN	NaN	3	12870	NaN	NaN
31-Jul-19	12:00:00	52	11,7	3	16767	smooth sea	1441
31-Jul-19	16:00:00	54	11,62	3	16767	slight sea	2087,63603
31-Jul-19	20:00:00	54	12,25	3	16767	slight sea	2200,821116
31-Jul-19	00:00:00	56	12,17	3	16767	slight sea	2186,448407
01-Aug-19	04:00:00	56	11,25	4	16767	slight sea	2021,16225
01-Aug-19	08:00:00	55	11,4	4	16767	moderate sea	2048,11108
01-Aug-19	12:00:00	54	12,25	4	16767	moderate sea	2200,821116
01-Aug-19	16:00:00	54	11,75	4	16767	moderate sea	2098,687636

01-Aug-19	20:00:00	55	11,75	4	16767	moderate sea	2098,687636
01-Aug-19	00:00:00	52	10,2	4	16767	moderate sea	1821,839479
02-Aug-19	04:00:00	53	12,2	4	16767	slight sea	2179,062907
02-Aug-19	08:00:00	54	10,75	3	16767	slight sea	1920,075922
02-Aug-19	12:00:00	54	12,5	3	16767	smooth sea	2232,646421
02-Aug-19	16:00:00	54	12,75	3	16767	smooth sea	2378,378289
02-Aug-19	20:00:00	53	12,75	3	16767	slight sea	2378,378289
02-Aug-19	00:00:00	52	13,25	3	16767	slight sea	2471,648026
03-Aug-19	04:00:00	52	12,5	3	16767	smooth sea	2331,743421
03-Aug-19	08:00:00	55	12,5	3	16767	smooth sea	2331,743421
03-Aug-19	12:00:00	62	12,25	4	16767	slight to moderate sea	2285,108553
03-Aug-19	16:00:00	62	13	3	16767	moderate sea	2270,894737
03-Aug-19	20:00:00	55	13,5	3	16767	slight sea	2358,236842
03-Aug-19	00:00:00	52	11,5	5	16767	slight sea	2008,868421

04-Aug-19	04:00:00	NaN	NaN	3	16767	NaN	NaN
08-Aug-19	08:00:00	NaN	NaN	3	16767	NaN	1647,386364
08-Aug-19	12:00:00	55	12,5	3	13444	smooth to slight	2167,613636
08-Aug-19	16:00:00	55	11,25	3	13444	smooth sea	2361,818182
08-Aug-19	20:00:00	56	12,5	3	13444	slight sea	2624,242424
11-Aug-19	04:00:00	54	13	3	14048	smooth sea	NaN
11-Aug-19	08:00:00	54	13,5	3	14048	slight sea	NaN
11-Aug-19	12:00:00	55	12,75	2	14048	smooth sea	NaN
11-Aug-19	16:00:00	55	12,62	2	14048	smooth sea	2303,94469
11-Aug-19	20:00:00	55	12,75	3	14048	slight sea	2327,677876
11-Aug-19	00:00:00	55	13,3	3	14048	slight sea	2428,08751
12-Aug-19	04:00:00	NaN	13,25	3	14048	smooth sea	2418,959361
12-Aug-19	08:00:00	NaN	12,6	3	14048	slight sea	2300,29343
12-Aug-19	12:00:00	NaN	12,5	3	14048	slight sea	2282,037133

12-Aug-19	16:00:00	NaN	12,75	3	14048	slight sea	2200,679537
12-Aug-19	20:00:00	NaN	13	3	14048	slight sea	2243,830116
12-Aug-19	00:00:00	NaN	13	3	14048	slight sea	2243,830116
13-Aug-19	04:00:00	NaN	12,75	3	14048	smooth to slight	2200,679537
13-Aug-19	08:00:00	NaN	13,25	3	14048	slight sea	2286,980695
13-Aug-19	12:00:00	NaN	13	3	14048	smooth sea	NaN
14-Aug-19	08:00:00	50	13,3	3	12232	slight sea	1848,356436
14-Aug-19	12:00:00	58	13,5	3	12232	slight sea	2123,643564
14-Aug-19	16:00:00	58	13,75	3	12232	slight sea	2178,95036
14-Aug-19	20:00:00	52	13,1	3	12232	slight sea	2075,945434
14-Aug-19	00:00:00	51	13	3	12232	slight sea	2060,098522
15-Aug-19	04:00:00	51	12,6	2	12232	slight sea	2000,672603
15-Aug-19	08:00:00	50	13,5	3	12232	slight sea	
15-Aug-19	12:00:00	NaN	NaN		12232	slight sea	NaN

16-Aug-19	20:00:00	54	11,25	3	12814	slight sea	NaN
16-Aug-19	00:00:00	54	12	3	12814	slight sea	NaN
17-Aug-19	04:00:00	54	NaN	NaN	12814	slight sea	NaN
17-Aug-19	08:00:00	54	NaN	NaN	12814	slight sea	NaN
17-Aug-19	12:00:00	53	NaN	NaN	12814	slight sea	NaN
17-Aug-19	16:00:00	54	NaN	NaN	12814	slight sea	NaN
17-Aug-19	20:00:00	47	NaN	NaN	12814	slight sea	NaN
17-Aug-19	00:00:00	NaN	NaN	NaN	12814	slight sea	NaN
21-Aug-19	20:00:00	53	NaN	NaN	16094	slight sea	1866,082192
21-Aug-19	00:00:00	55	11,75	3	16094	slight sea	2436,273973
22-Aug-19	04:00:00	55	11,75	3	16094	slight to moderate sea	2436,273973
22-Aug-19	08:00:00	55	11	4	16094	moderate sea	2280,767123
22-Aug-19	12:00:00	55	11,25	4	16094	moderate sea	2332,60274
22-Aug-19	16:00:00	54	11,37	4	16094	moderate sea	1274,937178

22-Aug-19	20:00:00	54	12	4	16094	moderate sea	1344,988671
22-Aug-19	00:00:00	54	12,3	4	16094	moderate sea	1316,968074
23-Aug-19	04:00:00	54	11	4	16094	slight sea	1120,823893
23-Aug-19	08:00:00	57	10,3	3	16094	slight sea	1120,823893
23-Aug-19	12:00:00	52	11,5	3	16094	smooth sea	1288,947477
23-Aug-19	16:00:00	54	12,87	2	16094	smooth sea	2187,265239
23-Aug-19	20:00:00	52	13,75	3	16094	slight sea	2335,914333
23-Aug-19	00:00:00	53	13,25	3	16094	slight sea	2250,971993
24-Aug-19	04:00:00	53	11,5	2	16094	smooth sea	1953,673806
24-Aug-19	08:00:00	50	12	3	16094	slight sea	2038,616145
24-Aug-19	12:00:00	50	12,5	3	16094	smooth sea	2123,558484
24-Aug-19	16:00:00	51	13,25	3	16094	smooth sea	2156,4
24-Aug-19	20:00:00	51	13	3	16094	slight sea	2156,4
24-Aug-19	00:00:00	51	12,75	3	16094	smooth sea	2156,4

25-Aug-19	04:00:00	51	12,75	3	16094	smooth sea	2156,4
25-Aug-19	08:00:00	53	12,6	3	16094	slight sea	2156,4
30-Aug-19	00:00:00	48	10	3	11805	slight sea	1658,75
31-Aug-19	04:00:00	48	12,5	3	11805	slight sea	2073,4375
31-Aug-19	08:00:00	50	13	3	11805	slight sea	2156,375
31-Aug-19	12:00:00	50	12,5	3	11805	slight sea	2073,4375
31-Aug-19	16:00:00	NaN	NaN	3	11805	slight sea	NaN
31-Aug-19	20:00:00	NaN	NaN	NaN	11805	slight sea	NaN
31-Aug-19	00:00:00	NaN	NaN	NaN	11805	slight sea	NaN
02-Sep-19	16:00:00	52	12	3	13725	smooth sea	1038,586466
02-Sep-19	20:00:00	52	11,75	3	13725	slight sea	2033,898496
02-Sep-19	00:00:00	51	11	3	13725	slight sea	1904,075188
03-Sep-19	04:00:00	50	12	3	13725	smooth sea	2077,172932
03-Sep-19	08:00:00	50	12,75	3	13725	smooth sea	2206,996241

03-Sep-19	12:00:00	51	13	3	13725	smooth sea	2250,270677
03-Sep-19	16:00:00	52	12,25	3	13725	smooth sea	2069,04902
03-Sep-19	20:00:00	52	12,5	3	13725	slight sea	2111,27451
03-Sep-19	00:00:00	51	13	3	13725	slight sea	2195,72549
04-Sep-19	04:00:00	51	14,12	3	13725	smooth to slight	2385,740196
04-Sep-19	08:00:00	51	12	4	13725	moderate sea	2047,936275
04-Sep-19	12:00:00	50	12,5	3	13725	slight sea	2111,27451
04-Sep-19	16:00:00	50	11,5	3	13725	slight sea	1836,971787
04-Sep-19	20:00:00	50	12,75	3	13725	slight sea	2036,642633
04-Sep-19	00:00:00	50	13,5	3	13725	slight sea	2276,247649
05-Sep-19	04:00:00	50	13	3	13725	slight sea	2236,31348
05-Sep-19	08:00:00	50	13,2	3	13725	slight sea	2276,247649
05-Sep-19	12:00:00	50	13	3	13725	slight sea	2076,576803
05-Sep-19	16:00:00	50	13	3	13725	slight sea	2059,782537

05-Sep-19	20:00:00	50	13	3	13725	slight sea	2059,782537
05-Sep-19	00:00:00	50	12,75	3	13725	slight sea	2020,171334
06-Sep-19	04:00:00	50	13	3	13725	slight sea	2059,782537
06-Sep-19	08:00:00	50	13,3	3	13725	slight sea	2099,39374
06-Sep-19	12:00:00	NaN	NaN	3	13725	slight sea	1723,087315
08-Sep-19	08:00:00	53	12	3	14400,8	slight sea	831,5801527
08-Sep-19	12:00:00	51	11,25	3	14400,8	smooth sea	1825,419847
08-Sep-19	16:00:00	51	11,75	3	14400,8	slight sea	2087,900172
08-Sep-19	20:00:00	51	12	3	14400,8	slight sea	2132,32358
08-Sep-19	00:00:00	52	12,75	3	14400,8	slight sea	2265,593804
09-Sep-19	04:00:00	52	12	3	14400,8	slight sea	2132,32358
09-Sep-19	08:00:00	52	11,3	3	14400,8	slight sea	2110,111876
09-Sep-19	12:00:00	52	12,25	3	14400,8	smooth sea	2176,746988
09-Sep-19	16:00:00	NaN	NaN	3	14400,8	smooth sea	NaN

11-Sep-19	12:00:00	53	11,3	3	14400,8	smooth sea	729
11-Sep-19	16:00:00	54	11,75	3	14400,8	slight sea	2180,671233
11-Sep-19	20:00:00	54	12	3	16644,6	slight sea	2227,068493
11-Sep-19	00:00:00	53	12,5	3	16644,6	slight sea	2319,863014
12-Sep-19	04:00:00	53	12	3	16644,6	slight sea	2227,068493
12-Sep-19	08:00:00	52	12,3	3	16644,6	slight sea	2273,465753
12-Sep-19	12:00:00	54	12,5	3	16644,6	slight sea	2319,863014
12-Sep-19	16:00:00	53	12,5	3	16644,6	slight sea	2169,894366
12-Sep-19	20:00:00	51	12,5	3	16644,6	slight sea	2169,894366
12-Sep-19	00:00:00	52	11,6	3	16644,6	slight sea	1822,711268
13-Sep-19	04:00:00	52	12,77	2	16644,6	smooth sea	1996,302817
13-Sep-19	08:00:00	52	12	3	16644,6	slight sea	1909,507042
13-Sep-19	12:00:00	52	13	3	16644,6	smooth sea	2256,690141
13-Sep-19	16:00:00	53	12,5	2	16644,6	slight sea	2150,163934

13-Sep-19	20:00:00	50	11,75	4	16644,6	slight sea	2021,154098
13-Sep-19	00:00:00	54	14,5	4	16644,6	slight sea	2494,190164
14-Sep-19	04:00:00	55	12,25	3	16644,6	slight sea	2107,160656
14-Sep-19	08:00:00	55	13,25	4	16644,6	moderate sea	2279,17377
14-Sep-19	12:00:00	51	12	2	16644,6	smooth to slight	2064,157377
14-Sep-19	16:00:00	50	12,5	2	16644,6	slight sea	2179,124579
14-Sep-19	20:00:00	51	13	3	16644,6	slight sea	2266,289562
14-Sep-19	00:00:00	54	11,3	4	16644,6	slight sea	2026,585859
19-Sep-19	16:00:00	48	NaN	2	12305,3	slight sea	1597,943445
19-Sep-19	20:00:00	48	NaN	3	12305,3	slight sea	2097,300771
19-Sep-19	00:00:00	52	NaN	3	12305,3	slight sea	2117,275064
20-Sep-19	04:00:00	52	NaN	2	15623	smooth sea	1957,48072
21-Sep-19	20:00:00	50	NaN	3	15623	slight sea	1270,733906
21-Sep-19	00:00:00	50	13	3	15623	slight sea	2131,553648

22-Sep-19	04:00:00	52	12,5	2	15623	slight sea	2049,570815
22-Sep-19	08:00:00	50	12	3	15623	slight sea	1967,587983
22-Sep-19	12:00:00	50	13	2	15623	smooth sea	2131,553648
22-Sep-19	16:00:00	51	12	2	15623	smooth sea	2035,973154
22-Sep-19	20:00:00	51	11,5	3	15623	slight sea	1951,14094
22-Sep-19	00:00:00	52	12,25	3	15623	slight sea	2078,389262
23-Sep-19	04:00:00	51	13,25	3	15623	slight sea	2248,053691
23-Sep-19	08:00:00	51	13	3	15623	slight sea	2205,637584
23-Sep-19	12:00:00	50	12,5	3	15623	smooth to slight	2120,805369
23-Sep-19	16:00:00	57	12	3	15623	slight sea	2031,588424
23-Sep-19	20:00:00	50	12,5	3	15623	slight sea	2116,237942
23-Sep-19	00:00:00	51	13	2	15623	slight sea	2327,861736
24-Sep-19	04:00:00	51	12,7	3	15623	slight sea	2327,861736
24-Sep-19	08:00:00	51	12,5	3	15623	slight sea	2285,536977

24-Sep-19	12:00:00	52	12,25	3	15623	slight sea	2073,913183
24-Sep-19	16:00:00	51	12,75	3	15623	slight to moderate sea	2188,036913
24-Sep-19	20:00:00	51	12,6	3	15623	slight to swell	2059,328859
24-Sep-19	00:00:00	52	11,5	3	15623	slight sea	1973,52349
25-Sep-19	04:00:00	52	12,5	3	15623	slight sea	2145,134228
25-Sep-19	08:00:00	52	12,75	3	15623	slight sea	2188,036913
25-Sep-19	12:00:00	52	13	3	15623	slight sea	2230,939597
25-Sep-19	16:00:00	50	13,25	3	15623	slight sea	2120
25-Sep-19	20:00:00	NaN	NaN	3	15623	slight sea	160
28-Sep-19	08:00:00	50	NaN	3	15634	slight sea	827,4461538
28-Sep-19	12:00:00	52	11,75	2	15634	slight sea	2160,553846
28-Sep-19	16:00:00	52	11,75	3	15634	slight sea	1967,423208
28-Sep-19	20:00:00	51	12	3	15634	slight sea	2009,283276
28-Sep-19	00:00:00	51	12,25	3	15634	slight sea	2051,143345

29-Sep-19	04:00:00	55	12,25	2	15634	slight sea	2051,143345
29-Sep-19	08:00:00	52	12,5	3	15634	slight sea	2093,003413
29-Sep-19	12:00:00	52	12,15	2	15634	swell	502
29-Sep-19	16:00:00	NaN	NaN	NaN	15634	NaN	226
02-Oct-19	12:00:00	NaN	NaN	2	18263,5	smooth sea	NaN
02-Oct-19	16:00:00	54	11	3	18263,5	slight sea	1415,466667
02-Oct-19	20:00:00	53	11,6	3	18263,5	slight sea	2056,85
02-Oct-19	00:00:00	53	12	3	18263,5	slight sea	2123,2
03-Oct-19	04:00:00	53	11,8	3	18263,5	slight sea	2101,083333
03-Oct-19	08:00:00	53	12	3	18263,5	slight sea	2123,2
03-Oct-19	12:00:00	53	12	4	18263,5	slight sea	2123,2
03-Oct-19	16:00:00	54	12,1	3	18263,5	slight sea	2227,859712
03-Oct-19	20:00:00	53	12,2	3	18263,5	slight sea	2250,827338
03-Oct-19	00:00:00	53	11,9	3	18263,5	slight sea	1975,215827

04-Oct-19	04:00:00	52	11,52	3	18263,5	slight sea	1906,31295
04-Oct-19	08:00:00	52	12,5	2	18263,5	smooth sea	2113,021583
04-Oct-19	12:00:00	52	12,5	2	18263,5	smooth sea	2296,76259
04-Oct-19	16:00:00	52	12,37	2	18263,5	smooth sea	2069,688119
04-Oct-19	20:00:00	53	11,87	3	18263,5	slight sea	1986,064356
04-Oct-19	00:00:00	53	11	3	18263,5	slight sea	1839,722772
05-Oct-19	04:00:00	52	12,8	2	18263,5	smooth to slight	2153,311881
05-Oct-19	08:00:00	53	14,3	2	18263,5	smooth to slight	2404,183168
05-Oct-19	12:00:00	52	13,25	2	18263,5	smooth sea	2216,029703
05-Oct-19	16:00:00	50	13,25	2	18263,5	smooth sea	1985,926941
05-Oct-19	20:00:00	50	12,7	2	18263,5	smooth sea	1910,986301
05-Oct-19	00:00:00	50	12	2	18263,5	smooth sea	1798,575342
06-Oct-19	04:00:00	51	12,3	2	18263,5	smooth sea	1854,780822
06-Oct-19	08:00:00	NaN	12,5	3	18263,5	smooth sea	655,7305936

09-Oct-19	20:00:00	NaN	NaN	3	12557	slight sea	525,6382979
09-Oct-19	00:00:00	54	11	3	12557	slight sea	1541,87234
10-Oct-19	04:00:00	40	11,25	2	12557	slight sea	1576,914894
10-Oct-19	08:00:00	40	10,5	3	12557	slight sea	1471,787234
10-Oct-19	12:00:00	40	10,5	2	12557	smooth sea	NaN
10-Oct-19	16:00:00	NaN	NaN	2	12557	smooth sea	NaN
12-Oct-19	00:00:00	50	11,75	3	12557	slight sea	2242,161111
13-Oct-19	04:00:00	50	11	2	12557	slight sea	2099,044444
13-Oct-19	08:00:00	51	10,75	3	12557	slight sea	2051,338889
13-Oct-19	12:00:00	51	11,5	3	12557	smooth sea	2194,455556
13-Oct-19	16:00:00	51	12,1	2	12557	smooth sea	2155,353242
13-Oct-19	20:00:00	52	13	3	12557	slight sea	2310,894198
13-Oct-19	00:00:00	52	11,25	3	12557	slight sea	1999,812287
14-Oct-19	04:00:00	51	11,8	2	12557	smooth sea	2110,912969

14-Oct-19	08:00:00	52	11,75	3	12557	slight sea	2088,692833
14-Oct-19	12:00:00	52	13,25	3	12557	smooth sea	2355,334471
14-Oct-19	16:00:00	50	12,25	2	12557	smooth sea	2004,500835
14-Oct-19	20:00:00	47	11,75	3	12557	slight sea	1922,684474
14-Oct-19	00:00:00	47	12,3	3	12557	slight sea	2168,133556
15-Oct-19	04:00:00	48	11,97	3	12557	slight sea	2106,771285
15-Oct-19	08:00:00	47	11,77	3	12557	slight sea	2086,317195
15-Oct-19	12:00:00	47	12	3	12557	slight sea	1963,592654
15-Oct-19	16:00:00	42	11,25	3	12557	slight sea	1522,122905
15-Oct-19	20:00:00	42	11	3	12557	slight sea	1488,297952
15-Oct-19	00:00:00	42	11,25	3	12557	slight sea	1522,122905
16-Oct-19	04:00:00	42	11,37	3	12557	slight sea	1539,035382
16-Oct-19	08:00:00	42	11,25	3	12557	slight sea	1522,122905
16-Oct-19	12:00:00	42	11	3	12557	smooth to slight	1488,297952

16-Oct-19	16:00:00	41	11	3	12557	slight sea	1578
16-Oct-19	20:00:00	40	11,25	3	12557	slight sea	1613,863636
16-Oct-19	00:00:00	40	12,25	3	12557	slight sea	1757,318182
17-Oct-19	04:00:00	NaN	NaN	2	12557	smooth sea	573,8181818
18-Oct-19	00:00:00	NaN	12	3	16335	slight sea	459,6164384
19-Oct-19	04:00:00	45	11,25	3	16335	slight sea	1723,561644
19-Oct-19	08:00:00	45	11	3	16335	slight sea	1685,260274
19-Oct-19	12:00:00	45	11,25	3	16335	slight sea	1723,561644
19-Oct-19	16:00:00	45	11,6	2	16335	smooth sea	1748,611364
19-Oct-19	20:00:00	45	11,8	3	16335	slight sea	1786,215909
19-Oct-19	00:00:00	45	11,5	3	16335	slight sea	1729,809091
20-Oct-19	04:00:00	46	11,25	3	16335	slight sea	1692,204545
20-Oct-19	08:00:00	NaN	11,66	3	16335	slight sea	1316,159091
23-Oct-19	08:00:00	NaN	NaN	2	18442	smooth sea	731,4647887

23-Oct-19	12:00:00	54	12	3	18442	slight sea	1526,535211
23-Oct-19	16:00:00	55	11,75	3	18442	slight sea	2284,795775
23-Oct-19	20:00:00	55	12	3	18442	slight sea	2333,408451
23-Oct-19	00:00:00	55	11,5	3	18442	slight sea	2236,183099
24-Oct-19	04:00:00	55	12	3	18442	slight sea	2333,408451
24-Oct-19	08:00:00	55	12,1	3	18442	slight sea	2333,408451
24-Oct-19	12:00:00	55	11,75	3	18442	slight sea	2284,795775
24-Oct-19	16:00:00	54	11,87	3	18442	slight sea	2148,75226
24-Oct-19	20:00:00	52	11,75	3	18442	slight sea	2126,133816
24-Oct-19	00:00:00	52	11,6	3	18442	slight sea	1899,949367
25-Oct-19	04:00:00	53	12,5	3	18442	slight sea	2035,660036
25-Oct-19	08:00:00	52	12,29	3	18442	slight sea	2035,660036
25-Oct-19	12:00:00	52	12,5	3	18442	smooth sea	2261,844485
25-Oct-19	16:00:00	53	10,87	2	18442	smooth sea	1955,22597

25-Oct-19	20:00:00	54	11,25	3	18442	slight sea	2022,647555
25-Oct-19	00:00:00	54	12,75	3	18442	slight sea	2292,333895
26-Oct-19	04:00:00	54	13	3	18442	slight sea	2337,281619
26-Oct-19	08:00:00	54	13	3	18442	slight sea	2337,281619
26-Oct-19	12:00:00	54	13,25	2	18442	smooth sea	2382,229342
26-Oct-19	16:00:00	51	12,87	3	18442	smooth sea	2346,534979
26-Oct-19	20:00:00	52	12,6	3	18442	slight sea	2300,971193
26-Oct-19	00:00:00	NaN	NaN	3	18442	smooth sea	888,4938272
01-Nov-19	08:00:00	50	NaN	3	13085,2	slight sea	805,1515152
01-Nov-19	12:00:00	51	11,5	3	13085,2	smooth sea	1851,848485
01-Nov-19	16:00:00	51	11,6	2	13085,2	smooth sea	1871,977273
01-Nov-19	20:00:00	50	9,87	3	13085,2	slight sea	1652,117424
01-Nov-19	00:00:00	43	11	2	13085,2	smooth sea	1840,333333
02-Nov-19	04:00:00	NaN	NaN	2	13085,2	smooth sea	83,65151515

03-Nov-19	20:00:00	NaN	NaN	3	14900,6	smooth sea	610,9012658
03-Nov-19	00:00:00	52	11,75	2	14900,6	smooth sea	2208,643038
04-Nov-19	04:00:00	52	11,37	2	14900,6	smooth sea	2138,15443
04-Nov-19	08:00:00	53	11,25	3	14900,6	slight sea	2114,658228
04-Nov-19	12:00:00	55	11,75	2	14900,6	smooth sea	2208,643038
04-Nov-19	16:00:00	53	12,81	3	14900,6	slight sea	2300,448739
04-Nov-19	20:00:00	51	12,5	3	14900,6	slight sea	2233,445378
04-Nov-19	00:00:00	52	11,75	2	14900,6	smooth sea	2099,438655
05-Nov-19	04:00:00	53	12,5	3	14900,6	slight sea	2233,445378
05-Nov-19	08:00:00	53	12,25	3	14900,6	slight sea	2188,776471
05-Nov-19	12:00:00	53	12,5	3	14900,6	slight to moderate sea	2233,445378
05-Nov-19	16:00:00	52	12,25	3	14900,6	slight sea	2146,763578
05-Nov-19	20:00:00	51	12,75	3	14900,6	slight sea	2234,386581
05-Nov-19	00:00:00	52	12,4	3	14900,6	slight sea	2365,821086

06-Nov-19	04:00:00	52	12,7	3	14900,6	slight sea	2409,632588
06-Nov-19	08:00:00	51	12,24	3	14900,6	slight sea	2322,009585
06-Nov-19	12:00:00	51	12,75	2	14900,6	smooth sea	2234,386581
06-Nov-19	16:00:00	53	12,5	2	14900,6	smooth sea	2180,704698
06-Nov-19	20:00:00	51	12	3	14900,6	slight sea	2093,47651
06-Nov-19	00:00:00	51	12,25	2	14900,6	smooth sea	2137,090604
07-Nov-19	04:00:00	51	12,25	2	14900,6	smooth sea	2224,318792
07-Nov-19	08:00:00	50	12,25	3	14900,6	slight sea	2137,090604
07-Nov-19	12:00:00	50	12,75	3	14900,6	slight sea	2224,318792
07-Nov-19	16:00:00	50	12,5	2	14900,6	smooth sea	2029,444444
07-Nov-19	20:00:00	NaN	12,5	3	14900,6	slight sea	1623,555556
09-Nov-19	12:00:00	50	12	2	14795	smooth sea	967
09-Nov-19	16:00:00	50	12,1	2	14795	smooth sea	2096,840796
09-Nov-19	20:00:00	51	12,25	3	14795	slight sea	2118,457711

09-Nov-19	00:00:00	51	13	2	14795	smooth sea	2248,159204
10-Nov-19	04:00:00	54	13	2	14795	smooth sea	2248,159204
10-Nov-19	08:00:00	51	12,25	3	14795	slight sea	2118,457711
10-Nov-19	12:00:00	52	12,75	2	14795	smooth sea	2204,925373
10-Nov-19	16:00:00	NaN	NaN	2	14795	smooth sea	1894
13-Nov-19	12:00:00	54	NaN	3	18375,2	slight sea	988
13-Nov-19	16:00:00	55	11,25	3	18375,2	slight sea	2226,135417
13-Nov-19	20:00:00	55	12	3	18375,2	slight sea	2273,5
13-Nov-19	00:00:00	55	11,75	2	18375,2	smooth sea	2226,135417
14-Nov-19	04:00:00	54	12,1	2	18375,2	smooth sea	2297,182292
14-Nov-19	08:00:00	54	12,37	3	18375,2	smooth sea	2344,546875
14-Nov-19	12:00:00	54	12	2	18375,2	smooth sea	2273,5
14-Nov-19	16:00:00	54	11,7	2	18375,2	smooth sea	2170,871143
14-Nov-19	20:00:00	51	12,3	3	18375,2	slight sea	2078,493648

14-Nov-19	00:00:00	51	11,06	2	18375,2	smooth sea	1870,644283
15-Nov-19	04:00:00	52	11,7	2	18375,2	smooth sea	1986,116152
15-Nov-19	08:00:00	52	12,6	3	18375,2	slight sea	2332,53176
15-Nov-19	12:00:00	52	12,37	2	18375,2	smooth sea	2286,343013
15-Nov-19	16:00:00	53	12,25	2	18375,2	smooth sea	2165,751244
15-Nov-19	20:00:00	52	10,5	3	18375,2	slight sea	1856,358209
15-Nov-19	00:00:00	52	13	2	18375,2	smooth sea	2298,348259
16-Nov-19	04:00:00	55	13,8	3	18375,2	smooth sea	2453,044776
16-Nov-19	08:00:00	52	12,75	3	18375,2	slight sea	2254,149254
16-Nov-19	12:00:00	53	13	2	18375,2	smooth sea	2298,348259
16-Nov-19	16:00:00	53	13,37	2	18375,2	smooth sea	2274,092949
16-Nov-19	20:00:00	51	13	3	18375,2	slight sea	2210,333333
16-Nov-19	00:00:00	52	12,6	2	18375,2	smooth sea	2146,573718
17-Nov-19	04:00:00	NaN	NaN	2	18375,2	smooth sea	282

21-Nov-19	20:00:00	53	NaN	3	12803	slight sea	1397,010101
21-Nov-19	00:00:00	54	12,5	3	12803	slight sea	2182,828283
22-Nov-19	04:00:00	53	13	3	12803	slight sea	2270,141414
22-Nov-19	08:00:00	53	12,75	3	12803	slight sea	2226,484848
22-Nov-19	12:00:00	NaN	NaN	2	12803	smooth sea	NaN
24-Nov-19	16:00:00	52	NaN	2	15255	smooth sea	1210,769231
24-Nov-19	20:00:00	50	NaN	3	15255	slight sea	2162,087912
24-Nov-19	00:00:00	50	11	2	15255	smooth sea	1902,637363
25-Nov-19	04:00:00	50	11,37	2	15255	smooth sea	1967,5
25-Nov-19	08:00:00	50	12,75	3	15255	slight sea	2205,32967
25-Nov-19	12:00:00	51	13,62	2	15255	smooth sea	2356,675824
25-Nov-19	16:00:00	51	12	2	15255	smooth sea	2115,102041
25-Nov-19	20:00:00	54	12,5	3	15255	slight sea	2203,231293
25-Nov-19	00:00:00	53	12	2	15255	smooth sea	2115,102041

26-Nov-19	04:00:00	55	12,75	2	15255	smooth sea	2247,295918
26-Nov-19	08:00:00	53	12	3	15255	slight sea	2115,102041
26-Nov-19	12:00:00	53	12,25	2	15255	smooth sea	2159,166667
26-Nov-19	16:00:00	53	12,5	2	15255	smooth sea	2242,333333
26-Nov-19	20:00:00	54	12,24	3	15255	slight sea	2376,873333
26-Nov-19	00:00:00	54	12	2	15255	smooth sea	2332,026667
27-Nov-19	04:00:00	53	11,77	2	15255	smooth sea	2287,18
27-Nov-19	08:00:00	53	12	2	15255	smooth sea	2152,64
27-Nov-19	12:00:00	52	11,5	2	15255	smooth sea	2062,946667
27-Nov-19	16:00:00	53	11,75	2	15255	smooth sea	1966,460751
27-Nov-19	20:00:00	53	12	2	15255	smooth sea	2008,300341
27-Nov-19	00:00:00	53	12,25	2	15255	smooth sea	2050,139932
28-Nov-19	04:00:00	52	12,25	2	15255	smooth sea	2050,139932
28-Nov-19	08:00:00	50	12,5	2	15255	smooth sea	2091,979522

28-Nov-19	12:00:00	53	12,5	2	15255	smooth sea	2091,979522
28-Nov-19	16:00:00	NaN	NaN	2	15255	smooth sea	1827
30-Nov-19	08:00:00	NaN	NaN	2	14837,8	smooth sea	248,6634615
30-Nov-19	12:00:00	52	11,6	2	14837,8	smooth sea	2102,336538
30-Nov-19	16:00:00	53	12,3	2	14837,8	smooth sea	2161,281457
30-Nov-19	20:00:00	52	13,25	3	14837,8	slight sea	2314,099338
30-Nov-19	00:00:00	53	12,87	2	14837,8	smooth sea	2248,60596
01-Dec-19	04:00:00	53	12,3	2	14837,8	smooth sea	2161,281457
01-Dec-19	08:00:00	53	12	3	14837,8	slight sea	2095,788079
01-Dec-19	12:00:00	53	12,62	2	14837,8	smooth sea	2204,943709
01-Dec-19	16:00:00	NaN	NaN	2	14837,8	smooth sea	666
04-Dec-19	12:00:00	54	12,8	2	18255	smooth sea	1660
04-Dec-19	16:00:00	55	12,8	2	18255	smooth sea	2125,267327
04-Dec-19	20:00:00	55	12,5	3	18255	slight sea	2063,366337

04-Dec-19	00:00:00	53	12,75	2	18255	smooth sea	2104,633663
05-Dec-19	04:00:00	52	12,25	2	18255	smooth sea	2104,633663
05-Dec-19	08:00:00	52	12,87	2	18255	smooth sea	2125,267327
05-Dec-19	12:00:00	40	12	2	18255	smooth sea	1980,831683
05-Dec-19	16:00:00	42	11,28	2	18255	smooth sea	1937,074468
05-Dec-19	20:00:00	42	12,15	2	18255	smooth sea	1915,551418
05-Dec-19	00:00:00	51	12,56	2	18255	smooth sea	1980,120567
06-Dec-19	04:00:00	52	12,43	2	18255	smooth sea	1958,597518
06-Dec-19	08:00:00	53	13	3	18255	slight sea	2238,397163
06-Dec-19	12:00:00	53	12,25	2	18255	smooth sea	2109,258865
06-Dec-19	16:00:00	53	11	2	18255	smooth sea	2035,471698
06-Dec-19	20:00:00	55	12,4	2	18255	smooth sea	2289,90566
06-Dec-19	00:00:00	54	13	2	18255	smooth sea	2405,557461
07-Dec-19	04:00:00	51	11,62	2	18255	smooth sea	2151,123499

07-Dec-19	08:00:00	53	12,3	2	18255	smooth sea	2289,90566
07-Dec-19	12:00:00	52	12,5	2	18255	smooth sea	2313,036021
07-Dec-19	16:00:00	51	13	2	18255	smooth sea	2471,575758
07-Dec-19	20:00:00	53	13,5	3	18255	slight sea	2566,636364
07-Dec-19	00:00:00	41	NaN	2	18255	smooth sea	1235,787879
13-Dec-19	04:00:00	52	12,5	3	13313,6	slight sea	1017,222222
13-Dec-19	08:00:00	52	12,4	3	13313,6	slight sea	2237,888889
13-Dec-19	12:00:00	60	12,4	3	13313,6	slight sea	2237,888889
13-Dec-19	16:00:00	51	12	3	13313,6	smooth sea	2717,6
13-Dec-19	20:00:00	NaN	NaN	3	13313,6	smooth sea	679,4
15-Dec-19	20:00:00	52	12,6	3	12209,8	slight to swell	2223,176699
15-Dec-19	00:00:00	52	12,6	3	12209,8	slight to swell	2399,269903
16-Dec-19	04:00:00	52	12,1	2	12209,8	slight sea	2135,130097
16-Dec-19	08:00:00	52	12,2	2	12209,8	slight sea	2135,130097

16-Dec-19	12:00:00	52	13,8	2	12209,8	smooth sea	2443,293204
16-Dec-19	16:00:00	52	12,5	2	12209,8	smooth sea	2276,046901
16-Dec-19	20:00:00	52	12,25	2	12209,8	smooth sea	2230,525963
16-Dec-19	00:00:00	52	12,75	2	12209,8	smooth sea	2321,567839
17-Dec-19	04:00:00	52	13,5	2	12209,8	smooth sea	2458,130653
17-Dec-19	08:00:00	52	11,87	3	12209,8	slight sea	2162,244556
17-Dec-19	12:00:00	53	11,75	2	12209,8	smooth sea	2139,484087
17-Dec-19	16:00:00	53	12,25	2	12209,8	smooth sea	2214,333333
17-Dec-19	20:00:00	53	12,47	3	12209,8	slight sea	2440,285714
17-Dec-19	00:00:00	52	12,7	2	12209,8	smooth sea	2666,238095
18-Dec-19	04:00:00	52	12,12	2	12209,8	smooth sea	2372,5
18-Dec-19	08:00:00	52	12,62	2	12209,8	smooth to swell	2282,119048
18-Dec-19	12:00:00	52	12,5	2	12209,8	smooth sea	2259,52381
18-Dec-19	16:00:00	40	11	2	12209,8	smooth sea	1466,555766

18-Dec-19	20:00:00	41	10,4	2	12209,8	smooth to swell	1383,228733
18-Dec-19	00:00:00	41	10,75	2	12209,8	smooth sea	1433,224953
19-Dec-19	04:00:00	41	11,25	2	12209,8	smooth sea	1499,886578
19-Dec-19	08:00:00	41	11,5	2	12209,8	smooth sea	1533,217391
19-Dec-19	12:00:00	41	11,25	2	12209,8	smooth sea	1499,886578
19-Dec-19	16:00:00	41	10,75	3	12209,8	slight sea	1448,769231
19-Dec-19	20:00:00	NaN	NaN	3	12209,8	slight sea	741,2307692
21-Dec-19	16:00:00	NaN	NaN	2	15726,47	smooth sea	114,6171171
21-Dec-19	20:00:00	40	10,5	2	15726,47	smooth sea	1375,405405
21-Dec-19	00:00:00	40	11,1	2	15726,47	smooth sea	1457,274775
22-Dec-19	04:00:00	40	11	2	15726,47	smooth sea	1440,900901
22-Dec-19	08:00:00	40	10,6	2	15726,47	smooth sea	1391,779279
22-Dec-19	12:00:00	40	11,3	2	15726,47	smooth sea	1490,022523
22-Dec-19	16:00:00	30	12	2	15726,47	smooth sea	1536

22-Dec-19	20:00:00	41	10,75	2	15726,47	smooth sea	1376
22-Dec-19	00:00:00	40	11,62	2	15726,47	smooth sea	1488
23-Dec-19	04:00:00	NaN	NaN	2	15726,47	smooth sea	160
25-Dec-19	16:00:00	NaN	NaN	2	15720,14	smooth sea	188,3898305
25-Dec-19	20:00:00	40	11,5	3	15720,14	slight sea	1444,322034
25-Dec-19	00:00:00	40	11,75	2	15720,14	smooth sea	1475,720339
26-Dec-19	04:00:00	40	11,1	3	15720,14	smooth to slight	1397,224576
26-Dec-19	08:00:00	40	11,6	3	15720,14	slight sea	1460,021186
26-Dec-19	12:00:00	40	11,5	2	15720,14	smooth sea	1444,322034
26-Dec-19	16:00:00	40	11,5	2	15720,14	smooth sea	1490,78626
26-Dec-19	20:00:00	41	12	2	15720,14	smooth sea	1425,969466
26-Dec-19	00:00:00	40	11,2	2	15720,14	smooth sea	1328,744275
27-Dec-19	04:00:00	40	11,7	2	15720,14	smooth sea	1393,561069
27-Dec-19	08:00:00	41	10,5	2	15720,14	smooth sea	1361,152672

27-Dec-19	12:00:00	40	11,5	2	15720,14	smooth sea	1490,78626
27-Dec-19	16:00:00	40	11	2	15720,14	smooth sea	1491,448276
27-Dec-19	20:00:00	41	11	2	15720,14	smooth sea	1491,448276
27-Dec-19	00:00:00	40	10,75	2	15720,14	smooth sea	1457,551724
28-Dec-19	04:00:00	40	10,25	2	15720,14	smooth sea	1389,758621
28-Dec-19	08:00:00	40	10,75	2	15720,14	smooth sea	1457,551724
28-Dec-19	12:00:00	40	11,5	2	15720,14	smooth sea	1559,241379
28-Dec-19	16:00:00	40	11,5	2	15720,14	smooth sea	1499,19708
28-Dec-19	20:00:00	42	11,25	3	15720,14	slight sea	1466,605839
28-Dec-19	00:00:00	41	12	2	15720,14	smooth sea	1564,379562
29-Dec-19	04:00:00	41	11,25	3	15720,14	slight sea	1466,605839
29-Dec-19	08:00:00	42	11,23	3	15720,14	slight sea	1450,310219
29-Dec-19	12:00:00	40	11,4	3	15720,14	moderate sea to swell	1482,90146
29-Dec-19	16:00:00	NaN	NaN	2	15720,14	smooth sea	497

07-Jan-20	08:00:00	NaN	NaN	3	12077	slight to swell	527,9487179
07-Jan-20	12:00:00	48	10,87	2	12077	slight to swell	1531,051282
07-Jan-20	16:00:00	43	11,25	2	12077	slight sea	1493,432282
07-Jan-20	20:00:00	40	11,25	3	12077	slight sea	1493,432282
07-Jan-20	00:00:00	40	10,75	3	12077	smooth sea	1427,057514
08-Jan-20	04:00:00	42	11,25	2	12077	slight sea	1493,432282
08-Jan-20	08:00:00	42	11,25	3	12077	slight sea	1510,025974
08-Jan-20	12:00:00	42	11,5	2	12077	smooth sea	1526,619666
08-Jan-20	16:00:00	41	11,3	2	12077	smooth sea	1491,199643
08-Jan-20	20:00:00	42	12,1	2	12077	slight sea	1589,520499
08-Jan-20	00:00:00	42	12,2	3	12077	slight sea	1605,907308
09-Jan-20	04:00:00	42	11,25	2	12077	slight sea	1474,812834
09-Jan-20	08:00:00	42	11,37	3	12077	slight sea	1491,199643
09-Jan-20	12:00:00	42	11,75	2	12077	smooth sea	1540,360071

09-Jan-20	16:00:00	41	11,12	2	12077	smooth sea	1686,306968
09-Jan-20	20:00:00	41	11,08	3	12077	slight sea	1818,937853
09-Jan-20	00:00:00	41	11,08	3	12077	smooth sea	1818,937853
10-Jan-20	04:00:00	43	10,62	3	12077	slight sea	1743,148776
10-Jan-20	08:00:00	43	10,62	3	12077	slight to moderate sea	1610,517891
10-Jan-20	12:00:00	43	9,1	3	12077	slight to moderate sea	1383,150659
10-Jan-20	16:00:00	51	7,37	3	12077	moderate sea	1439,039256
10-Jan-20	20:00:00	49	9,75	4	12077	moderate sea	1902,458678
10-Jan-20	00:00:00	49	10,62	3	12077	slight to moderate sea	2073,192149
11-Jan-20	04:00:00	49	11,12	2	12077	slight sea	2170,754132
11-Jan-20	08:00:00	49	10,75	4	12077	slight to moderate sea	2097,582645
11-Jan-20	12:00:00	49	10,87	3	12077	slight sea	2121,97314
11-Jan-20	16:00:00	48	10,75	2	12077	slight sea	2113,569444
11-Jan-20	20:00:00	NaN	NaN	3	12077	slight sea	1425,430556

13-Jan-20	00:00:00	NaN	NaN	3	15096,2	slight sea	251,7321429
14-Jan-20	04:00:00	39	10,75	2	15096,2	smooth sea	1443,264286
14-Jan-20	08:00:00	40	10,75	3	15096,2	slight sea	1443,264286
14-Jan-20	12:00:00	40	11,6	3	15096,2	smooth sea	1560,739286
14-Jan-20	16:00:00	39	12,12	2	15096,2	smooth sea	1523,893246
14-Jan-20	20:00:00	40	12,37	3	15096,2	slight sea	1555,313725
14-Jan-20	00:00:00	40	11,5	2	15096,2	smooth sea	1445,342048
15-Jan-20	04:00:00	40	11,12	2	15096,2	smooth sea	1398,211329
15-Jan-20	08:00:00	NaN	11,71	2	15096,2	smooth sea	1288,239651
17-Jan-20	04:00:00	40	NaN	2	15257,6	smooth sea	351,3684211
17-Jan-20	08:00:00	41	12	2	15257,6	smooth sea	1533,244019
17-Jan-20	12:00:00	41	11,37	2	15257,6	smooth sea	1453,38756
17-Jan-20	16:00:00	40	11,37	2	15257,6	smooth sea	1949,888889
17-Jan-20	20:00:00	55	NaN	3	15257,6	smooth sea	1885,606838

17-Jan-20	00:00:00	55	12,85	2	15257,6	smooth sea	2014,17094
18-Jan-20	04:00:00	52	13,552	2	15257,6	smooth sea	2121,307692
18-Jan-20	08:00:00	54	13,6	2	15257,6	smooth sea	2335,581197
18-Jan-20	12:00:00	54	13	2	15257,6	smooth sea	2228,444444
18-Jan-20	16:00:00	50	12,37	2	15257,6	smooth sea	2201,460504
18-Jan-20	20:00:00	52	12,62	2	15257,6	smooth sea	2245,934454
18-Jan-20	00:00:00	52	13,25	2	15257,6	smooth sea	2357,119328
19-Jan-20	04:00:00	52	11,87	2	15257,6	smooth sea	2112,512605
19-Jan-20	08:00:00	52	11,75	2	15257,6	smooth sea	2090,27563
19-Jan-20	12:00:00	52	12,5	2	15257,6	smooth sea	2223,697479
19-Jan-20	16:00:00	52	12,75	2	15257,6	slight sea	2177,724247
19-Jan-20	20:00:00	53	12,75	3	15257,6	slight sea	2177,724247
19-Jan-20	00:00:00	53	13,5	3	15257,6	slight sea	2305,825674
20-Jan-20	04:00:00	53	13,5	3	15257,6	slight sea	2305,825674

20-Jan-20	08:00:00	53	13,5	3	15257,6	slight sea	2305,825674
20-Jan-20	12:00:00	53	12,87	3	15257,6	slight sea	2199,074485
20-Jan-20	16:00:00	NaN	NaN	2	15257,6	smooth sea	1693
22-Jan-20	08:00:00	NaN	10,53	3	11431,1	slight to swell	693,504
22-Jan-20	12:00:00	42	11,12	2	11431,1	smooth to swell	1714,496
22-Jan-20	16:00:00	41	11,37	2	11431,1	smooth sea	1528,8
22-Jan-20	20:00:00	40	10,75	3	11431,1	slight to swell	1444,8
22-Jan-20	00:00:00	40	11,28	2	11431,1	smooth sea	1478,4
25-Jan-20	20:00:00	40	NaN	3	14839,39	slight to swell	1186,063415
25-Jan-20	00:00:00	40	9,75	2	14839,39	smooth to swell	1380,790244
26-Jan-20	04:00:00	39	10,62	2	14839,39	smooth to slight	1504,707317
26-Jan-20	08:00:00	39	11	2	14839,39	smooth sea	1557,814634
26-Jan-20	12:00:00	39	11,5	2	14839,39	smooth sea	1628,62439
26-Jan-20	16:00:00	40	11,5	2	14839,39	smooth sea	1548,318182

26-Jan-20	20:00:00	39	10,5	2	14839,39	smooth sea	1413,681818
26-Jan-20	00:00:00	39	10,37	2	14839,39	smooth sea	1396,852273
27-Jan-20	04:00:00	39	11,12	2	14839,39	smooth sea	1497,829545
27-Jan-20	08:00:00	40	10,75	2	14839,39	smooth sea	1447,340909
27-Jan-20	12:00:00	40	11,75	2	14839,39	smooth sea	1581,977273
27-Jan-20	16:00:00	41	11,25	2	14839,39	smooth sea	1549,379562
27-Jan-20	20:00:00	40	11,77	2	14839,39	smooth sea	1755,963504
27-Jan-20	00:00:00	40	10,5	2	14839,39	smooth sea	1635,456204
28-Jan-20	04:00:00	40	10,16	2	14839,39	smooth sea	1514,948905
28-Jan-20	08:00:00	40	10,75	2	14839,39	smooth sea	1480,518248
28-Jan-20	12:00:00	41	10,87	2	14839,39	smooth sea	1497,733577
28-Jan-20	16:00:00	41	11	2	14839,39	smooth sea	1487,2
28-Jan-20	20:00:00	40	11,25	2	14839,39	smooth sea	1521
28-Jan-20	00:00:00	40	11,12	2	14839,39	smooth sea	1504,1

29-Jan-20	04:00:00	40	11	2	14839,39	smooth sea	1487,2
29-Jan-20	08:00:00	40	10,87	3	14839,39	slight sea	1470,3
29-Jan-20	12:00:00	40	11	2	14839,39	smooth sea	1487,2
29-Jan-20	16:00:00	41	10	2	14839,39	smooth sea	1484,631579
29-Jan-20	20:00:00	41	9,7	3	14839,39	slight sea	1466,073684
29-Jan-20	00:00:00	41	10,37	3	14839,39	slight sea	1540,305263
30-Jan-20	04:00:00	41	9,62	3	14839,39	slight sea	1428,957895
30-Jan-20	08:00:00	NaN	10,16	2	14839,39	slight sea	1132,031579
31-Jan-20	20:00:00	NaN	NaN	3	14130,97	slight sea	903,3651551
31-Jan-20	00:00:00	40	11,3	2	14130,97	smooth sea	1494,658711
01-Feb-20	04:00:00	40	11,25	2	14130,97	smooth sea	1478,23389
01-Feb-20	08:00:00	40	11,12	2	14130,97	smooth sea	1461,809069
01-Feb-20	12:00:00	40	11,75	NaN	14130,97	smooth sea	1543,933174
01-Feb-20	16:00:00	40	11,87	NaN	14130,97	smooth sea	1522,338462

01-Feb-20	20:00:00	40	11,62	2	14130,97	smooth sea	1490,289231
01-Feb-20	00:00:00	40	11,25	NaN	14130,97	smooth sea	1442,215385
02-Feb-20	04:00:00	NaN	NaN	2	14130,97	smooth sea	753,1569231
07-Feb-20	12:00:00	NaN	12,2	3	15103,29	slight to swell	NaN
07-Feb-20	16:00:00	42	11,25	3	15103,29	slight sea	1467,931034
07-Feb-20	20:00:00	40	0,75	3	15103,29	moderate sea	1419
07-Feb-20	00:00:00	42	11,5	3	15103,29	swell sea	1500,551724
08-Feb-20	04:00:00	42	11,75	2	15103,29	smooth sea	1533,172414
08-Feb-20	08:00:00	40	11,25	2	15103,29	smooth sea	1467,931034
08-Feb-20	12:00:00	39	12,25	2	15103,29	smooth sea	1598,413793
08-Feb-20	16:00:00	42	12,12	2	15103,29	smooth sea	1568,869565
08-Feb-20	20:00:00	40	11,8	3	15103,29	slight sea	1407,130435
08-Feb-20	00:00:00	40	11,72	1	15103,29	very smooth	1390,956522
09-Feb-20	04:00:00	40	11,61	2	15103,29	smooth sea	1374,782609

09-Feb-20	08:00:00	40	10,87	2	15103,29	slight sea	1407,130435
09-Feb-20	12:00:00	40	10,87	2	15103,29	smooth sea	1407,130435
09-Feb-20	16:00:00	40	11	2	15103,29	smooth sea	1521,751938
09-Feb-20	20:00:00	40	10,62	3	15103,29	slight sea	1469,874031
09-Feb-20	00:00:00	40	9,87	1	15103,29	rippled	1366,118217
10-Feb-20	04:00:00	40	0,5	2	15103,29	slight sea	1590,922481
10-Feb-20	08:00:00	40	0,75	3	15103,29	slight sea	1504,459302
10-Feb-20	12:00:00	40	0,5	2	15103,29	smooth sea	1469,874031
10-Feb-20	16:00:00	40	0,5	2	15103,29	smooth sea	1657,750557
10-Feb-20	20:00:00	40	0,75	3	15103,29	moderate sea	1599,922049
10-Feb-20	00:00:00	40	0,75	3	15103,29	slight sea	1542,093541
11-Feb-20	04:00:00	40	10,5	3	15103,29	slight sea	1619,198218
11-Feb-20	08:00:00	40	10,62	3	15103,29	slight sea	1638,474388
11-Feb-20	12:00:00	NaN	NaN	1	15103,29	rippled	597,5612472

15-Feb-20	00:00:00	NaN	11,2	2	12335,98	swell sea	1650,021413
16-Feb-20	04:00:00	NaN	11,37	2	12335,98	slight sea	1675,802998
16-Feb-20	08:00:00	NaN	12	3	12335,98	slight sea	1767,880086
16-Feb-20	12:00:00	NaN	12,13	3	12335,98	slight sea	301
16-Feb-20	16:00:00	NaN	NaN	2	12335,98	smooth sea	NaN
17-Feb-20	00:00:00	45	NaN	3	14213,2	smooth sea	1093,927464
18-Feb-20	04:00:00	45	11,87	2	14213,2	smooth to slight	1836,097334
18-Feb-20	08:00:00	44	11,87	3	14213,2	slight sea	1836,097334
18-Feb-20	12:00:00	45	9,5	2	14213,2	smooth sea	1468,877867
18-Feb-20	16:00:00	45	10,5	2	14213,2	smooth sea	1635,622642
18-Feb-20	20:00:00	43	12,25	3	14213,2	slight sea	1908,226415
18-Feb-20	00:00:00	43	10,6	1	14213,2	rippled	1655,09434
19-Feb-20	04:00:00	43	10,6	2	14213,2	smooth sea	1655,09434
19-Feb-20	08:00:00	42	11,12	2	14213,2	smooth sea	1732,981132

19-Feb-20	12:00:00	41	11,12	2	14213,2	smooth sea	1732,981132
19-Feb-20	16:00:00	45	11,8	2	14213,2	smooth sea	1900
19-Feb-20	20:00:00	45	11,12	3	14213,2	slight sea	1780
19-Feb-20	00:00:00	45	11	3	14213,2	slight sea	1760
20-Feb-20	04:00:00	45	10,25	2	14213,2	slight sea	1640
20-Feb-20	08:00:00	44	10,25	3	14213,2	slight sea	1640
20-Feb-20	12:00:00	41	10	2	14213,2	smooth sea	1600
20-Feb-20	16:00:00	41	10,6	2	14213,2	smooth sea	1795,18664
20-Feb-20	20:00:00	45	10,27	3	14213,2	slight sea	1879,666012
20-Feb-20	00:00:00	45	10,8	2	14213,2	smooth sea	1964,145383
21-Feb-20	04:00:00	45	10,6	2	14213,2	smooth to slight	1943,02554
21-Feb-20	08:00:00	44	9,6	3	14213,2	slight sea	1626,227898
21-Feb-20	12:00:00	44	9,13	3	14213,2	slight sea	1541,748527
21-Feb-20	16:00:00	44	9,25	3	14213,2	slight sea	2085,112016

21-Feb-20	20:00:00	59	10,75	4	14213,2	moderate sea	2423,238289
21-Feb-20	00:00:00	58	11,3	4	14213,2	moderate sea	2535,947047
22-Feb-20	04:00:00	58	11,75	2	14213,2	slight sea	2648,655804
22-Feb-20	08:00:00	59	11,75	3	14213,2	slight sea	2648,655804
22-Feb-20	12:00:00	NaN	NaN	3	14213,2	slight sea	1493,391039
24-Feb-20	12:00:00	NaN	NaN	NaN	16839,68	moderate sea	872
24-Feb-20	16:00:00	54	11,6	3	16839,68	moderate sea	NaN
24-Feb-20	20:00:00	41	11,37	4	16839,68	moderate sea	2030,328358
24-Feb-20	00:00:00	41	11,75	2	16839,68	smooth to slight	2097,26226
25-Feb-20	04:00:00	41	11,7	2	16839,68	smooth sea	2097,26226
25-Feb-20	08:00:00	42	11,37	3	16839,68	slight sea	2030,328358
25-Feb-20	12:00:00	42	12,37	3	16839,68	slight sea	2208,818763
25-Feb-20	16:00:00	42	11,75	2	16839,68	smooth to slight	1729,088435
25-Feb-20	20:00:00	NaN	NaN	3	16839,68	slight sea	974,9115646

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ATTACHMENT 4:

Python code example

```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import autoimpute as imp
import sklearn
import seaborn as sea
import statsmodels.api as sm
sea.set()
```

```python
data = pd.read_csv('data kapal ta 6.csv', decimal=',', sep=';')
```

```python
data = data.loc[:, ~data.columns.str.contains('^Unnamed')]
```

```python
new_data = data.dropna(axis = 0)
```

```python
new_data.isnull().sum()
```

```
Date                0
Hours               0
engine load         0
speed               0
Wind                0
displacement        0
seacondition        0
fuel consumption    0
dtype: int64
```

```python
new_data1 = new_data.copy()
```

```python
new_data1 = new_data1[new_data1['fuel consumption']>1300]
```

```python
new_data1 .describe(include='all')
```

	Date	Hours	engine load	speed	Wind	displacement	seacondition	fuel consumption
count	572	572	572.000000	572.000000	572.000000	572.000000	572	572.000000
unique	135	6	NaN	NaN	NaN	NaN	12	NaN
top	13-Sep-19	00:00:00	NaN	NaN	NaN	NaN	slight sea	NaN
freq	6	102	NaN	NaN	NaN	NaN	269	NaN
mean	NaN	NaN	48.823427	11.787469	2.645105	15158.922923	NaN	1958.194779
std	NaN	NaN	5.624123	1.536347	0.604936	2019.414627	NaN	320.135632
min	NaN	NaN	30.000000	0.500000	1.000000	11431.100000	NaN	1316.968074
25%	NaN	NaN	42.750000	11.250000	2.000000	13725.000000	NaN	1654.350111
50%	NaN	NaN	51.000000	12.000000	3.000000	15103.290000	NaN	2063.156502
75%	NaN	NaN	53.000000	12.500000	3.000000	16644.600000	NaN	2205.040199
max	NaN	NaN	66.000000	14.500000	5.000000	18442.000000	NaN	2717.600000

```python
outlier = new_data1['fuel consumption'].quantile(0.95)
data_baru = new_data1[new_data1['fuel consumption']<outlier]
```

```
data_standard = data_baru.drop(['Date','Hours','Wind'], axis=1)
```

```
data_dummy = pd.get_dummies(data_standard, columns= ['seacondition'], drop_first=True)
```

```
data_dummy
```

	engine load	speed	displacement	fuel consumption	seacondition_moderate sea	seacondition_moderate sea to swell	seacondition_rippled	seacondition_slight sea	seacondition_sligh to moderate se
72	52.0	11.75	18090.522	2145.614679	0	0	0	1	
73	55.0	12.00	18090.522	2191.266055	0	0	0	1	
74	57.0	11.75	18090.522	2145.614679	1	0	0	0	
75	57.0	11.75	18090.522	2145.614679	1	0	0	0	
76	57.0	11.50	18090.522	2024.164580	1	0	0	0	
...	...	...	...	...	...	...	...	...	.
749	41.0	11.75	16839.680	2097.262260	0	0	0	0	
750	41.0	11.70	16839.680	2097.262260	0	0	0	0	
751	42.0	11.37	16839.680	2030.328358	0	0	0	1	
752	42.0	12.37	16839.680	2208.818763	0	0	0	1	

```
data_dummy.columns.values
```

In [13]:
```
data_dummy.columns.values
```

Out[13]:
```
array(['engine load', 'speed', 'displacement', 'fuel consumption',
       'seacondition_moderate sea', 'seacondition_moderate sea to swell',
       'seacondition_rippled', 'seacondition_slight sea',
       'seacondition_slight to moderate sea',
       'seacondition_slight to swell', 'seacondition_smooth sea',
       'seacondition_smooth to slight', 'seacondition_smooth to swell',
       'seacondition_swell sea', 'seacondition_very smooth'], dtype=object)
```

In [14]:
```
cols = (['engine load', 'speed', 'displacement',
      'seacondition_moderate sea', 'seacondition_moderate sea to swell',
       'seacondition_rippled', 'seacondition_slight sea',
       'seacondition_slight to moderate sea',
       'seacondition_slight to swell', 'seacondition_smooth sea',
       'seacondition_smooth to slight', 'seacondition_smooth to swell',
       'seacondition_swell sea', 'seacondition_very smooth','fuel consumption'])
```

In [15]:
```
data_dummy = data_dummy[cols]
```

In [16]:
```
data_dummy
```

```
data_dummy = data_dummy[cols]
```

```
data_dummy
```

	engine load	speed	displacement	seacondition_moderate sea	seacondition_moderate sea to swell	seacondition_rippled	seacondition_slight sea	seacondition_slight to moderate sea	seacondition_s to
72	52.0	11.75	18090.522	0	0	0	1	0	
73	55.0	12.00	18090.522	0	0	0	1	0	
74	57.0	11.75	18090.522	1	0	0	0	0	
75	57.0	11.75	18090.522	1	0	0	0	0	
76	57.0	11.50	18090.522	1	0	0	0	0	
...	...	...	...	...	...	...	...	...	
749	41.0	11.75	16839.680	0	0	0	0	0	
750	41.0	11.70	16839.680	0	0	0	0	0	
751	42.0	11.37	16839.680	0	0	0	1	0	
752	42.0	12.37	16839.680	0	0	0	1	0	
753	42.0	11.75	16839.680	0	0	0	0	0	

543 rows × 15 columns

```
Input = data_dummy.drop(['fuel consumption'],axis=1)
Target = data_dummy['fuel consumption']
```

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(Input, Target,test_size = 0.2, random_state = 0)
```

```
from tpot import TPOTRegressor
```

```
tpot = TPOTRegressor(generations=10, population_size=100, verbosity=2, random_state=42)
tpot.fit(X_train, y_train)
print(tpot.score(X_test, y_test))
```

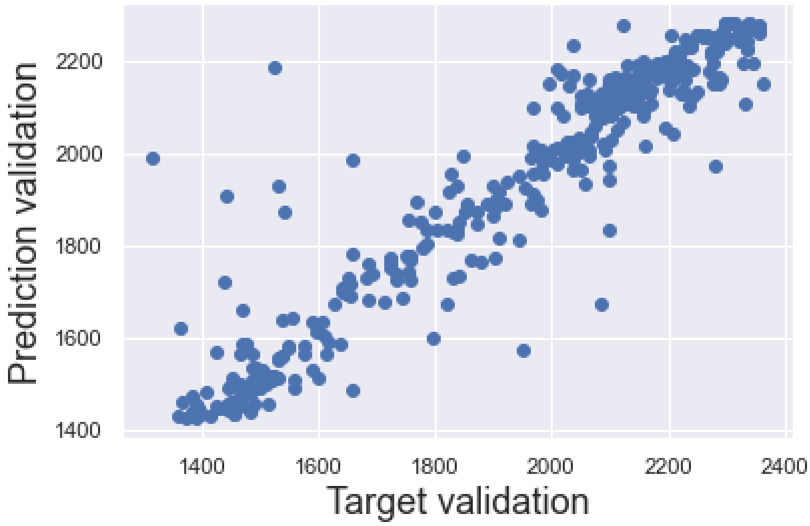
```
Generation 1 - Current best internal CV score: -19968.630757054863
Generation 2 - Current best internal CV score: -19968.630757054863
Generation 3 - Current best internal CV score: -19562.879584894512
Generation 4 - Current best internal CV score: -19503.09770134869
Generation 5 - Current best internal CV score: -19503.09770134869
Generation 6 - Current best internal CV score: -19284.521427028543
Generation 7 - Current best internal CV score: -19169.607858094852
Generation 8 - Current best internal CV score: -19018.974141475173
Generation 9 - Current best internal CV score: -18947.409240018966
Generation 10 - Current best internal CV score: -18875.778883248036

Best pipeline: RandomForestRegressor(GradientBoostingRegressor(input_matrix, alpha=0.85, learning_rate=0.5, loss=lad, max_depth
=9, max_features=0.5, min_samples_leaf=12, min_samples_split=18, n_estimators=100, subsample=0.9000000000000001), bootstrap=Tru
e, max_features=0.5, min_samples_leaf=7, min_samples_split=9, n_estimators=100)
-17333.53114870025
```

```
tpot.score(X_test, y_test)
```

```
-17333.53114870025
```

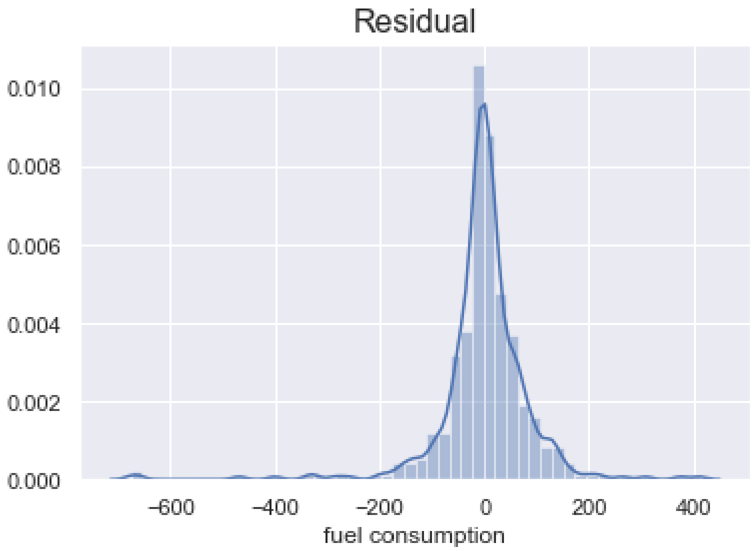
```
y_hat = tpot.predict(X_train)
```

```
plt.scatter(y_train, y_hat)
plt.xlabel('Target validation',size=18)
plt.ylabel('Prediction validation',size=18)
plt.show()
```



```
sea.distplot(y_train - y_hat)
plt.title("Residual", size=16)
```

```
Text(0.5, 1.0, 'Residual')
```

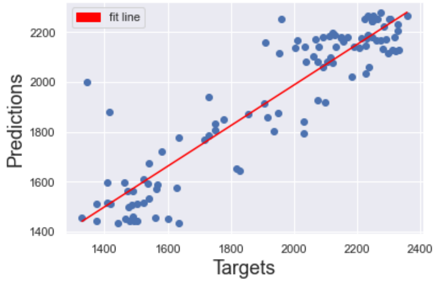



```
import matplotlib.patches as mpatches
```

```
test_yhat = tpot.predict(X_test)
```

```
test_yhat = tpot.predict(X_test)
```

```
plt.scatter(y_test, test_yhat)
plt.xlabel('Targets',size=18)
plt.ylabel('Predictions',size=18)
plt.plot(np.unique(y_test), np.poly1d(np.polyfit(y_test, test_yhat, 1))(np.unique(y_test)), color='red', label='fit line')
red_patch = mpatches.Patch(color='red', label='fit line')
plt.legend(handles=[red_patch])
plt.show()
```



```
In [29]: y_test_panda = pd.DataFrame(data = y_test)
```

```
In [30]: from sklearn.metrics import mean_squared_error
```

```
In [32]: y_test_panda = y_test_panda.rename(columns={'fuel consumption' : 'Target'})
```

```
In [33]: y_test2 = y_test_panda.reset_index(drop=True)
         y_test.head()
```

```
Out[33]: 220    1904.075188
         312    1415.466667
         664    1635.456204
         508    1915.551418
         254    2319.863014
         Name: fuel consumption, dtype: float64
```

```
data_prediksi = y_test2
data_prediksi ['Prediction'] = test_yhat
```

```
data_prediksi['Residual'] = data_prediksi['Target'] -data_prediksi['Prediction']
data_prediksi['Difference%'] = np.absolute(data_prediksi['Residual']/data_prediksi['Target']*100)
data_prediksi
```

	Target	Prediction	Residual	Difference%
0	1904.075188	1912.109298	-8.034110	0.421943
1	1415.466667	1879.965243	-464.498576	32.815932
2	1635.456204	1432.767585	202.688619	12.393399
3	1915.551418	1857.089352	58.462066	3.051971
4	2319.863014	2181.054340	138.808674	5.983486
...	...	...	...	...
104	2226.484848	2033.656992	192.827856	8.660641
105	2036.642633	2082.446024	-45.803391	2.248966
106	2289.905660	2172.483900	117.421760	5.127799
107	2030.328358	1793.166092	237.162266	11.680981
108	2230.525963	2174.790467	55.735496	2.498760

109 rows × 4 columns

```
data_prediksi.describe()
```

	Target	Prediction	Residual	Difference%
count	109.000000	109.000000	109.000000	109.000000
mean	1929.045190	1929.731713	-0.686524	5.161162
std	325.243011	289.615221	132.263189	6.139158
min	1328.744275	1432.565886	-653.554946	0.010699
25%	1568.869565	1611.152840	-65.636448	1.436654
50%	2036.642633	2076.398833	-0.240283	3.585028
75%	2230.525963	2174.790467	68.134898	7.618826
max	2358.236842	2278.798676	237.162266	48.591855

In [37]:
```
pd.options.display.max_rows = 999
pd.set_option('display.float_format', lambda x: '%.2f' % x)
data_prediksi.sort_values(by=['Difference%'])
```

Out[37]:

	Target	Prediction	Residual	Difference%
42	2245.93	2246.17	-0.24	0.01
97	2248.05	2245.74	2.31	0.10
41	2248.61	2245.08	3.53	0.16
58	2248.16	2252.66	-4.50	0.20
54	2274.09	2278.80	-4.71	0.21
85	2156.40	2161.10	-4.70	0.22
68	1564.38	1569.24	-4.86	0.31
8	1504.10	1509.39	-5.29	0.35
86	2131.55	2139.11	-7.56	0.35
37	2169.89	2177.75	-7.86	0.36
0	1904.08	1912.11	-8.03	0.42

In [38]:
```
mean_squared_error (data_prediksi['Target'], data_prediksi ['Prediction'], squared= False)
```

Out[38]: 131.65686897651884

```
from sklearn.metrics import r2_score
r2_score(data_prediksi['Target'], data_prediksi ['Prediction'])
```

```
0.8346234828401098
```

```
tpot.export('4_feature.py')
```

```
ex = np.array([1000, 100,18000,0,0,0,1,0,0,0,0,0,0,0]).reshape(1,-1)
```

```
tpot.predict(ex)
```

```
array([2192.35806299])
```

```
x_test3 = pd.DataFrame(data = X_test)
```

```
In [97]: xx_test = x_test3.reset_index(drop=True)
         xx_test
```

```
: data_final4 = pd.concat([xx_test,data_prediksi], axis=1)
```

```
: data_final4
```

```
data_final4.columns = [i if '_' not in i else i.split('_')[1] for i in data_final4]
res1 = pd.melt(data_final4, id_vars=['engine load', 'speed','displacement','Target','Prediction','Residual','Difference%'], var_r
res1 = res1[res1['value'].eq(1)].iloc[:, :-1].reset_index(drop=True)
```

```
res1
```

	engine load	speed	displacement	Target	Prediction	Residual	Difference%	sea_condition
0	41.00	11.37	16839.68	2030.33	1839.41	190.92	9.40	moderate sea
1	54.00	12.00	16094.00	1344.99	1998.54	-653.55	48.59	moderate sea
2	40.00	0.75	15103.29	1419.00	1513.05	-94.05	6.63	moderate sea
3	51.00	11.00	13725.00	1904.08	1912.11	-8.03	0.42	slight sea
4	54.00	11.00	18263.50	1415.47	1879.97	-464.50	32.82	slight sea
5	53.00	12.50	16644.60	2319.86	2181.05	138.81	5.98	slight sea
6	55.00	11.75	18442.00	2284.80	2221.21	63.59	2.78	slight sea
7	50.00	13.00	13725.00	2059.78	2104.37	-44.59	2.16	slight sea
8	53.00	13.25	16094.00	2250.97	2263.75	-12.78	0.57	slight sea
9	52.00	11.75	13725.00	2033.90	2142.15	-108.25	5.32	slight sea
10	53.00	12.50	16644.60	2150.16	2181.05	-30.89	1.44	slight sea

```
cols = (['engine load', 'speed', 'displacement','sea_condition', 'Target', 'Prediction',
         'Residual', 'Difference%'])
```

```
res1 = res1[cols]
```

```
res1
```

	engine load	speed	displacement	sea_condition	Target	Prediction	Residual	Difference%
0	41.00	11.37	16839.68	moderate sea	2030.33	1839.41	190.92	9.40
1	54.00	12.00	16094.00	moderate sea	1344.99	1998.54	-653.55	48.59
2	40.00	0.75	15103.29	moderate sea	1419.00	1513.05	-94.05	6.63
3	51.00	11.00	13725.00	slight sea	1904.08	1912.11	-8.03	0.42
4	54.00	11.00	18263.50	slight sea	1415.47	1879.97	-464.50	32.82
5	53.00	12.50	16644.60	slight sea	2319.86	2181.05	138.81	5.98

```
res1.sort_values(by=['Difference%'])
```

	engine load	speed	displacement	sea_condition	Target	Prediction	Residual	Difference%
75	52.00	12.62	15257.60	smooth sea	2245.93	2246.17	-0.24	0.01
47	51.00	13.25	15623.00	slight sea	2248.05	2245.74	2.31	0.10
74	53.00	12.87	14837.80	smooth sea	2248.61	2245.08	3.53	0.16
83	51.00	13.00	14795.00	smooth sea	2248.16	2252.66	-4.50	0.20
81	53.00	13.37	18375.20	smooth sea	2274.09	2278.80	-4.71	0.21
94	51.00	12.75	16094.00	smooth sea	2156.40	2161.10	-4.70	0.22
87	41.00	12.00	15720.14	smooth sea	1564.38	1569.24	-4.86	0.31
58	40.00	11.12	14839.39	smooth sea	1504.10	1509.39	-5.29	0.35
95	50.00	13.00	15623.00	smooth sea	2131.55	2139.11	-7.56	0.35
16	51.00	12.50	16644.60	slight sea	2169.89	2177.75	-7.86	0.36
3	51.00	11.00	13725.00	slight sea	1904.08	1912.11	-8.03	0.42

```
import numpy as np
import pandas as pd
from sklearn.ensemble import GradientBoostingRegressor, RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline, make_union
from tpot.builtins import StackingEstimator
from tpot.export_utils import set_param_recursive


tpot_data = pd.read_csv('Data', sep='COLUMN_SEPARATOR', dtype=np.float64)
features = tpot_data.drop('target', axis=1)
training_features, testing_features, training_target, testing_target = \
            train_test_split(features, tpot_data['target'], random_state=42)
```

```
exported_pipeline = make_pipeline(
    StackingEstimator(estimator=GradientBoostingRegressor(alpha=0.85, learning_rate=0.5, loss="lad", max_depth=9, max_features=0.5,
min_samples_leaf=12, min_samples_split=18, n_estimators=100, subsample=0.9000000000000001)),
    RandomForestRegressor(bootstrap=True, max_features=0.5, min_samples_leaf=7, min_samples_split=9, n_estimators=100)
)
# Fix random state for all the steps in exported pipeline
set_param_recursive(exported_pipeline.steps, 'random_state', 42)

exported_pipeline.fit(training_features, training_target)
results = exported_pipeline.predict(testing_features)
```