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Master Thesis

on the topic of

Modelling and optimization of ship's fuel consumption using Random Forest Regression (RFR)

Submitted to the Faculty of Engineering
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by

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1 Introduction

The research on efficient ship operation is a direction that is being actively pursued by marine industry stakeholders as efficient ship operations equates to increase in profitability. One of the determining factors is the reduction of Fuel Oil Consumption (FOC). FOC takes up considerable portion in ship's operating cost. This is clearly indicated through findings made by Ronen [1] and Stopford [2]. The former mentioned that FOC consumption of a large ship potentially constitute to 75% of the total ship operating cost while the latter noted that FOC makes up to two-thirds of vessel voyage cost and over one-quarter of vessel's overall cost.

With that, maritime industry stakeholder actively searches for inexpensive approach to reduce FOC. As such, they investigate ways to optimise operational measures as technical solutions are expensive [3]. The operational measures include the inclusion of weather/environmental routing, speed optimisation, trim optimisation and virtual (just-in/time) arrival policy [3]. It is noted by Beşikçi et al. [4] that lowering ship speed will have the greatest impact in fuel economy, reducing the ship speed by $2-3knots$ could halve the operating cost of shipping company [2, 5]. Beşikçi et al. further elaborated that the main cause of this is the nonlinear relationship between ship speed and fuel consumption. Ronen [1, 6] and Wang et al. [7] approximated that fuel consumption can be derived through third order function of the ship speed.

Due to volatility and ever-increasing bunker fuel price, developing a model that could accurately predict ship speed would be beneficial to forecast the ship's FOC. The model could potentially help maritime industry stakeholder make decisions at the most opportune moment. Data driven i.e., machine learning approaches have been attempted by several authors in different literatures to model fuel consumption and reported good results in its predictive performance [4,8–11]. However, powerful machine learning models are usually unintuitive making it difficult to interpret its decisions [12]. This brings us to Random Forest, a powerful model that offers partial interpretability in their decisions. With this consideration, modelling using Random Forest will be the focus of this thesis.

1.1 Research Objective, Contributions and Boundary

This thesis aims to predict the ship's speed captured by Automatic Identification System (AIS) using random forest model. In this study, this speed shall be designated as the ship's Speed Over Ground (SOG). The modelling uses fused hourly data from AIS information of Hammershus Ro-Ro ferry and local meteorological weather data in region of travel. Subsequently, the ship actual speed, which is designated as speed through water (STW), shall be derived from the predicted SOG to enable estimation for fuel consumption over different journey periods. The modelling is performed in `Python` programming language using machine learning packages `sklearn` offered by Pedregosa et al. [13].

Using this approach, we shall raise the following research questions (RQs), namely:

- **RQ1**. Is it feasible to fuse AIS data and meteorological data to accurately predict the ship's SOG ?
- **RQ2**. During modelling, which parameters have the greatest impact in increasing the model's predictive performance ?
- **RQ3**. During evaluation, what are the performance measures that should be considered to help us gain the most information out of the model's behaviour ?

To answer the research questions, the following research boundaries are set:

- Random forest has the capability to solve both classification and regression problem. Because the target variable, SOG, is continuous, we will only adopt the regression algorithm of random forest.
- The focus of this work is a detailed study on the performance and possible optimisation configuration of random forest as predictor for the target variable. As such, we will not perform exhaustive comparison study between different machine learning models.
- The estimation for fuel consumption shall be done using simple formulation by Ronen [1, 6]. This thesis will not consider the more comprehensive method such as the method proposed by Kim et al. [14] as the focus of this work is to estimate the SOG using random forest-
- The Hammershus Ro-Ro ship sails between port of Køge, Rønne, Ystad and Sassnitz. However, we will only consider the journey between port of Køge, Rønne and Ystad as part of the data for the voyage between port of Rønne and Sassnitz are missing.

The use of AIS data provides the following contributions as indicated by Rakke [15]:

- Avoid expenses of purchasing (possibly) unaffordable ship information from online database and shipping companies.
- Independent of commercial parties, as information are available in public domain.

Additionally, this work will provide the following contribution:

- Robust modelling approach that requires minimal data pre-processing and minimal model configuration.

2 Theoretical Background

This chapter deals with the past and present research in the relevant area which include literature review. This includes the significance of precise modelling of the ship's speed and its subsequent use in forecasting the ship's operation. The theoretical background of Random Forest Regression will be discussed in this chapter.

2.1 Literature Review

The work by Yan et al. [16] provides a thorough review of the different attempts that have been made by different authors to predict different parameters of ship's operation, this includes ship's fuel consumption. Per definition by Haranen et al. [17], the modelling of ship operation is categorised into White Box Model (WBM), Black Box Model (BBM) and Grey Box Model (GBM). Machine learning approach is categorised as BBM, BBM approach is defined as purely data driven approach requiring no prior knowledge about the ship operation. The literature review by Yan et al. [16] indicated that about 42% of the research utilised BBM model based on machine learning approach.

Majority of the BBM approach based on ML is dominated by ANN [16]. However, there are literatures that considered decision tree-based modelling approach to predict fuel consumption. Some example of decision tree based modelling include Decision Tree (DT), Random Forest (RF) and Extra Tree (ET). Soner et al. [18] implemented tree-based model, which include bagging, random forest (RF), and bootstrap. In their work, they used data captured from onboard sensors of a ferry to predict speed through water and fuel consumption per hour. From the test dataset, the random forest model described root mean square error (RMSE) of 0.34 Knots during its prediction of Speed Through Water (STW). Yan et al. [19] used random forest (RF) model to minimise fuel consumption for a voyage of a dry bulk ship. The model use ship operational data and sea and weather data from noon report and EMCWF. The prediction performance report from this literature reported mean absolute percentage error (MAPE) of 7.91%.

The research by Gkerekos et al. [9] highlighted the performance of different machine learning models to predict ship's fuel consumption per day using both noon data and automated data logging and monitoring (ADLM) system from a bulk carrier. This research concludes that tree based model displayed good prediction performance on both noon data and sensor based data. Using default parameters, RF model obtained R^2 score of 87.55% and 96.26% for noon-data datasets and sensor-based data respectively. It is also noted that it that the data from a 3-month period in ADLM system would be sufficient to create a model with better performance than the model generated by noon data from a collection period of 2.5 year. This literature also concluded that automatic sensor-based data have the potential to increase the model accuracy score, R^2, by $5-7\%$ across different machine learning models.

Li et al. [3] performed more extensive research on the effects of data fusions between meteorological data, ship voyage data and AIS data on different machine learning models to predict the ship's FOC. This research highlighted the advantage of fusing meteorological data and ship voyage data. The evaluation on different model performance indicated that RF are among preferable model candidate that could be used in commercial scale due to its good prediction capability and robustness against different datasets. The findings in this research reported that R^2 score are above 96% when deployed on the best datasets and achieved R^2 score in range between $74\% - 90\%$ over test data. This literature also exhibited the robustness of RF, as it attained the lowest standard deviation at 0.015 of the R^2 score when evaluated against random splits of datasets.

Abebe et al. [10] used different approach in their research by predicting the ship's Speed Over Ground (SOG) instead of FOC. In this work, AIS data and noon-report weather data from 14 tracks and 62 ships are used for the SOG prediction. The observation showed that RF model achieved RMSE of 0.25 knots, while using 489 seconds for training. Decision tree achieved RMSE of 0.36 knots, taking up 52 seconds for training. This shows that RFR outperforms DTR at cost of computational power.

This literature review described the capability of Random Forest Regressor to predict fuel consumptions and ship speed, irrespective of data source and type of data used. Promising results from different performance measures across different literatures indicated the capability random forest model as predictor. As such, this thesis aims to find optimisation possibilities to extract maximum prediction performance from random forest. Due to the nonlinear, third order function estimate of fuel consumption [1, 6]. Accurate prediction of ship speed is paramount to ensure optimal ship operation resulting in increase of profitability.

2.2 Decision Tree

Decision tree is a non-parametric model that can perform both classification and regression tasks for discrete variable and continuous variable respectively. It is a powerful algorithm, capable of fitting complex datasets. The model requires very little to no data pre-processing [12,20]. Decision tree is a white box model[1] [12]. In machine learning sense, this means that the model is intuitive, and the structure of the model is interpretable. Thus, the structure of the model can be analysed in detail. To understand random forest, understanding how decision tree operates is necessary as the principle working of random forest stems from decision trees [12, 21]. In this thesis, we shall only discuss the underlying principle of regression tree.

[1]This is not to be interchanged with the definition described by Haranen et al. [17] regarding modelling of ship operation.

To train Decision Trees, `Scikit-Learn` [13] uses the *Classification and Regression Tree* (CART) algorithm [22]. Partition space shown by Figure 1 are used to illustrate the decision of CART algorithm. This process can be alternatively represented by the binary tree of Figure 2, observation that satisfies the condition are assigned to the left branch and the opposite is assigned to the right branch. The binary tree representation can be especially helpful when multiple input variables are involved, as the responses can be represented by a single tree [20].

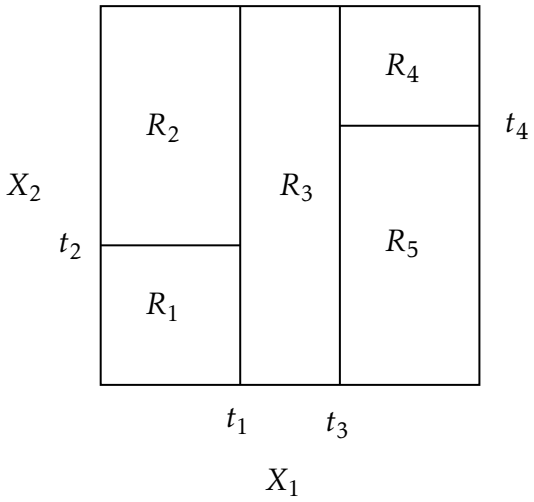

Figure 1: Example of partition space [20]

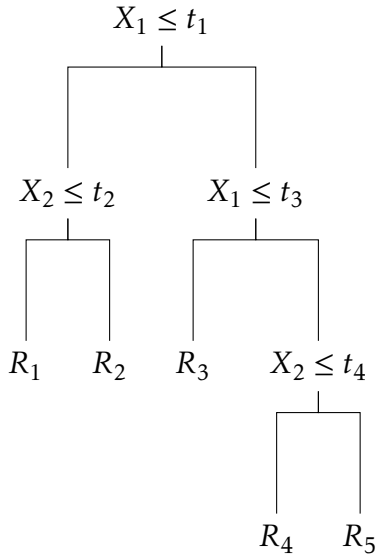

Figure 2: Example of partition tree [20]

Now, we need to understand the principle of selection for the feature k_t and threshold t_k. We shall first start with the principle of selection of the threshold t_k. Assuming a case with single feature k and response Y, with m data points. The algorithm starts by looking for possible thresholds. This is determined by calculating the splitting value.[2]. Then, the mean of data points of the left and right partition space is calculated as seen in Figure 3. This step is then followed by calculating the mean squared error (MSE) of each data points in its respective partition space. Subsequently, the MSE from the respective partition space is summed. The process is then recursively repeated until a threshold t_k that produce minimum sum of MSE is determined. This algorithm is defined by the following cost function $J(k, t_k)$. [12]:

$$J(k, t_k) = \frac{m_{\text{left}}}{m}\text{MSE}_{\text{left}} + \frac{m_{\text{right}}}{m}\text{MSE}_{\text{right}} \begin{cases} \text{MSE}_{\text{node}} = \sum\limits_{i \in \text{node}} (\hat{y}_{\text{node}} - y^{(i)})^2 \\ \hat{y}_{\text{node}} = \frac{1}{m_{\text{node}}} \sum\limits_{i \in \text{node}} y^{(i)} \end{cases} \tag{1}$$

Once complete, then the regions is further split into two more regions and this process is recursively continued until a stopping rule is applied. The stopping rule are either when the tree reaches the maximum depth, (This is controlled by the parameter `max_depth` in `Scikit-Learn`), or when it cannot find a split that can further

[2]For example, suppose there are data points at $k = [0.2, 0.4]$, then the splitting value is the value in between, i.e., $t_k = 0.3$

reduce MSE. This best split also corresponds to the best possible fit to the predicted value. Same principle is also applied when multiple features are present. Consider there are k_t features, then for each respective features $k_1, k_2, \ldots, k_t$, The MSE for each of the features is calculated using the cost function $J(k, t_k)$. The feature that can ***minimise*** the cost function will be selected as the root of the tree. The tree is then grown further by recursively repeating this process [12, 20].

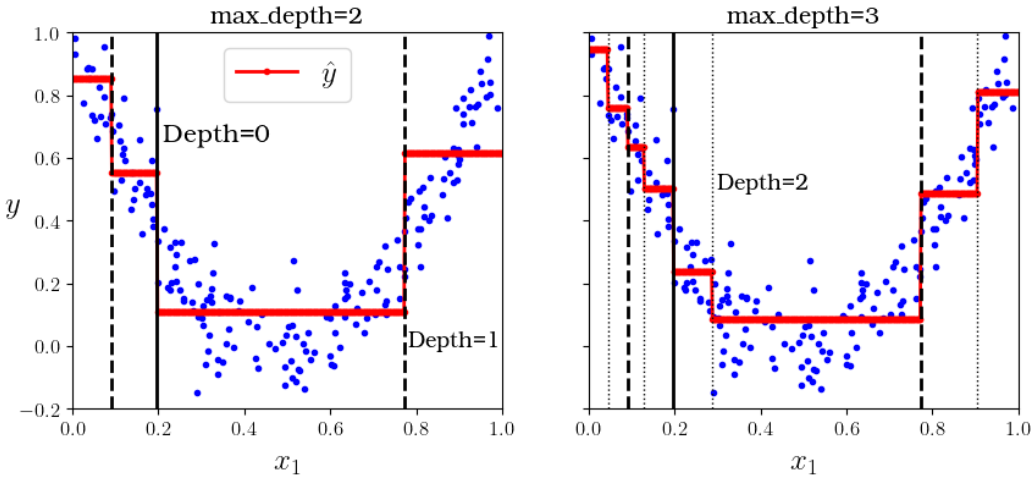

Figure 3: Prediction of two Decision tree regression models [12]

While powerful, decision tree unfortunately suffers from overfitting when the model is unconstrained. Decision tree makes very few assumptions regarding the training data. Therefore, it will adapt to the training data and fitting it very closely [12]. Additionally, an individual tree tends to be unstable, when the data is altered, a completely different set of splits might be found [20, 23]. Therefore, it is necessary to regularise i.e., restrict the decision tree's freedom during the training. Overfitting could be reduced by controlling how deep the tree can grow through the `max_depth` parameter. Additionally, setting the amount of minimum number of samples a leaf node has, through `min_samples_leaf` can alleviate overfitting as well, as shown in Figure 4. However, to address the fundamental drawbacks of decision tree, we shall look into random forest.

2.3 Random Forest

To understand random forest, the concept of ensemble method shall first be understood. Ensemble is defined as group of predictors such as classifier or regressor. Predictions are aggregated across multiple predictors, for regression task, the prediction is the average across the predictors. This principle is applied to random forest, a group of decision trees is trained on different random set of training data. For regression task, this means the prediction value is the average of the prediction across the decision trees. Such ensemble of decision trees is called ***Random Forest*** [20, 24, 25].

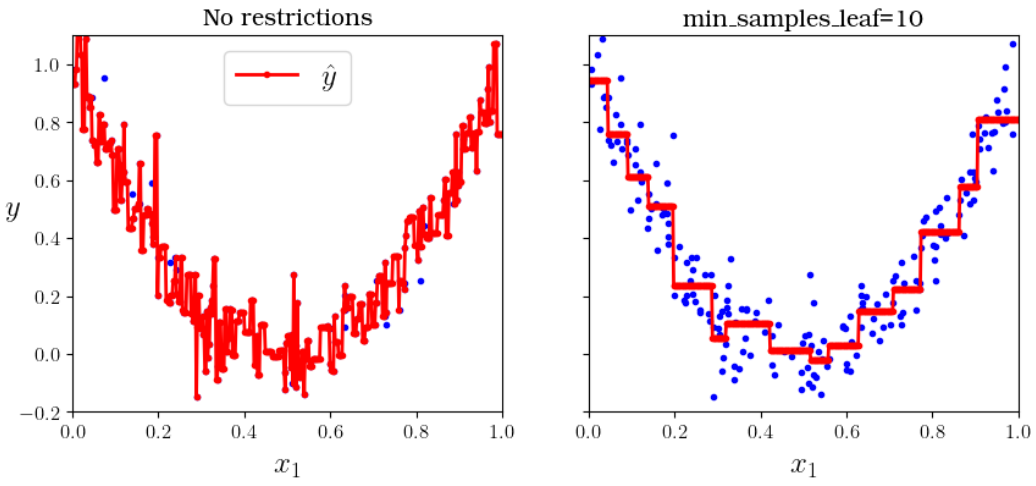

Figure 4: Regularising a Decision Tree regressor [12]

Ensemble methods achieve the best performance, when the predictors are as independent to one another. In statistical sense, this can be achieved by reducing correlation among the trees. This can be realised by adding randomness during tree construction process. For this purpose, random forest utilise *bagging* [26] method (short for *bootstrap aggregating*) during the training process. First, bootstrap sample is created, this means that a sample of the dataset is randomly selected and allowed to appear more than once. This sampling technique is referred to as sampling *with* replacement. Once the predictor are trained, then the prediction of the new instance is *aggregated* across the predictors. [12, 20, 23]

To add further randomness, random forest involves random selection of input features k that are considered to split the tree. This means that the feature k that will be used to split the tree is selected from this random subset of feature. The selection for the best feature to be used as the root of the tree and its subsequent node, as well as the stopping rule for the tree's growth is similar to that of decision tree. [12,20,23]

These measures introduced in random forest address the tendency of decision tree to overfit. In fact, the instability of decision tree mentioned in Section 2.2 is exploited in random forest to gain randomness during construction of the tree. Experience from Hastie et al. [20] shown that random forest requires minimal parameter tuning to achieve good performance while Kuhn et al. [23] reported that tuning parameter does not have a drastic effect on performance.

However, what random forest gains in predictive performance, loses in interpretability. Random forest is generally considered as Black Box Model (BBM) [12,21] [3]. The randomness means that it is challenging to describe the decisions made during the selection of the samples and also during the selection of the input features.

[3]Again, not to be interchanged with the definition described by Haranen et al. [17] regarding modelling of ship operation.

Nevertheless, the interpretability of a single tree in a random forest still holds. As it is still possible to traverse through the tree to reach the predicted value. Additionally, extra-trees (Extremely Randomized Trees) is introduced by Geurts et al. [27] to further randomise random forest. The key difference lies on how each split is selected, in extra-trees each tree split is selected in random instead of searching for the best split. Extra-trees also does not bootstrap the samples, which mean it samples *without* replacement.

Overview of the tree-based model discussed in Section 2.2 and Section 2.3 can be summarised in Table 1:

Model	**Decision Tree**	**Random Forest**	**Extra-Trees**
Number of trees	1	Many	Many
Features considered for split at each node	All features	Random subset of features	Random subset of features
Bootstrapping	Not applied	Yes	No
Split Rule	Best split	Best split	Random split

Table 1: Comparison of tree based model

2.4 Ship speed

2.5 Modelling

3 Research Methodology

In this chapter the methodology used to develop the model will be discussed. The discussion on different parameters in the vessel's journey data will be discussed here. This includes the mining and merging of the features. The method used to develop the ship's speed model will be discussed in this chapter. This consists of the parameter used to develop the model. Ultimately, the model is then used to predict the ship's fuel consumption.

3.1 Data Preprocessing

- Two data sources are imported. `AIS_weather_H_ok2_copy.csv` and `AIS_weather_h_rename_copy.csv`. The information from the latter comma delimited file will be used for calculating the ship Speed Through Water (STW). The information required is the true north current direction. Which is obtained from the vector component of the Northward and Southward current.
- This dataframe will be merged with the main dataframe from the file `AIS_weather_H_ok2_copy.csv`.
- Omission of the journey data between Ronne and Sassnitz
- SOG threshold is applied to omit ship mooring and maneuvering to accurately represent the ship's steady state operation [4, 9, 10, 28]. This threshold is selected as 5 knots according to [10]
- The AIS data from June is filtered. This data will be used as validation data to check the model's performance.

3.2 Data Analysis

- The features are represented in a histogram plot. For the feature Current speed, anomaly is detected. Certain spike is detected around $0.01 - 0.03\,\mathrm{m/s}$. Reasons unknown. The data is retained, including the spike, until a definitive answer can be found.
- OPEN QUESTION : What is the necessity of feature standardization / normalization ? Normalization is required for ANN as model training requires the value between 0 and 1. But in case of RFR, there is no such requirement. Through testing, data standardization also does not seem to improve the model's performance.

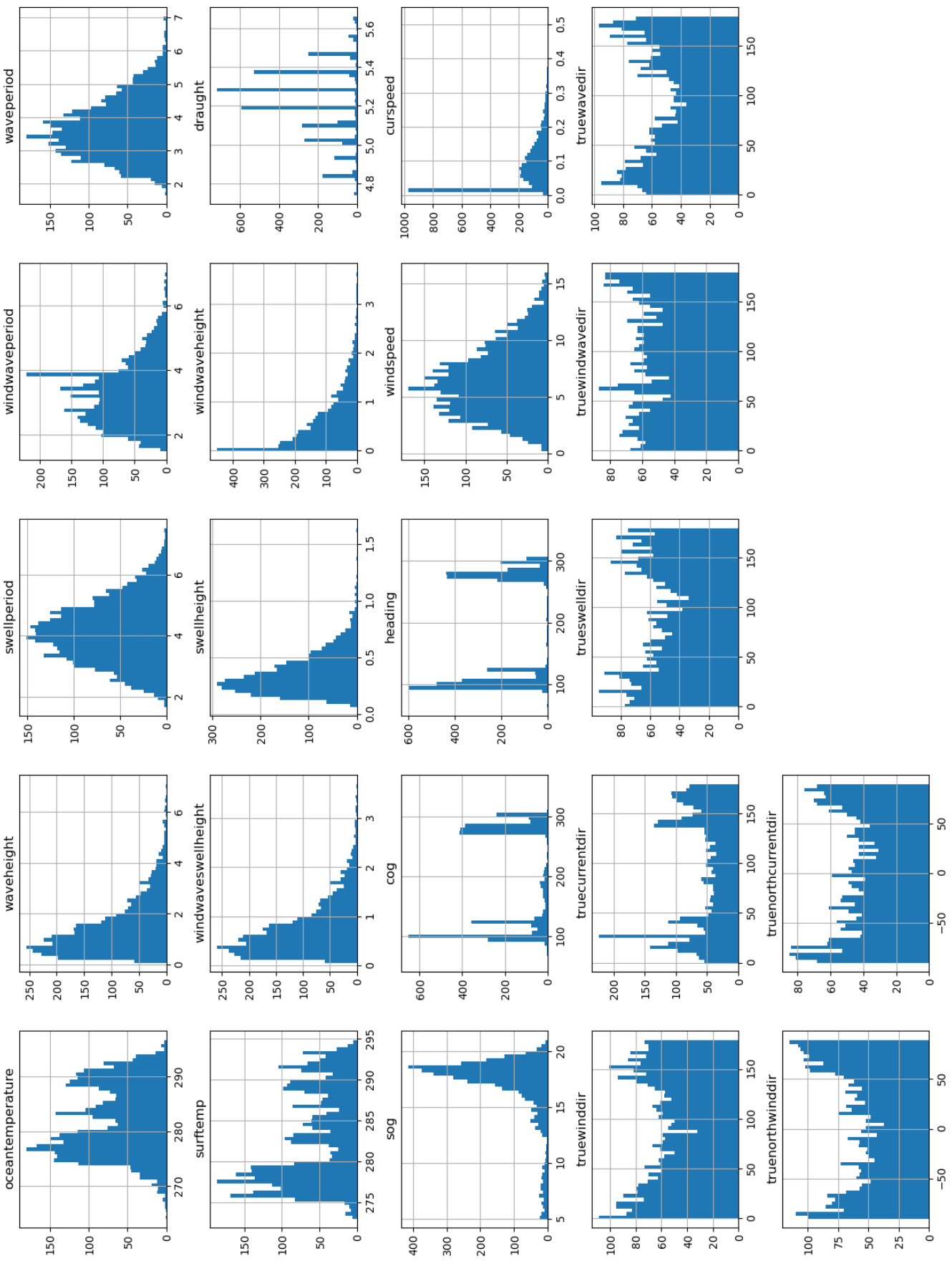

Figure 5: Histogram of the features

- The correlation of the features against SOG are determined. It is found that :
  - Draught
  - Course Over Ground (COG)
  - heading
  - Wind Speed
  - Current Speed
  - True Current direction

  Have relatively stronger correlation to SOG compared to other features, albeit the correlation is a weak one
- The correlation between the features is displayed using the following the heat map. From the heat map it can be observed that between these features:
  - Waveheight and wind wave swell height
  - Waveheight and wind wave height
  - Windwaveswellheight and wave period

  Have a strong correlation between each other.
- Open topic:
  - Feature reduction is possible, [10] suggested high feature correlation filter, the filter suggest that two features which has a high correlation (> 90%) is to be combined into a single feature. But the author is unsure whether this combination is physically sensible. Hence, this filter is yet to be applied for feature reduction.
  - Some of these features can be connected through wave equations, but the author has not found an equation which could relate these features.
- The random forest regressor could not function when `NaN` values are present. With that, the missing values are filled in using the `imputer` function. The missing values are filled in by means of `KNN`.

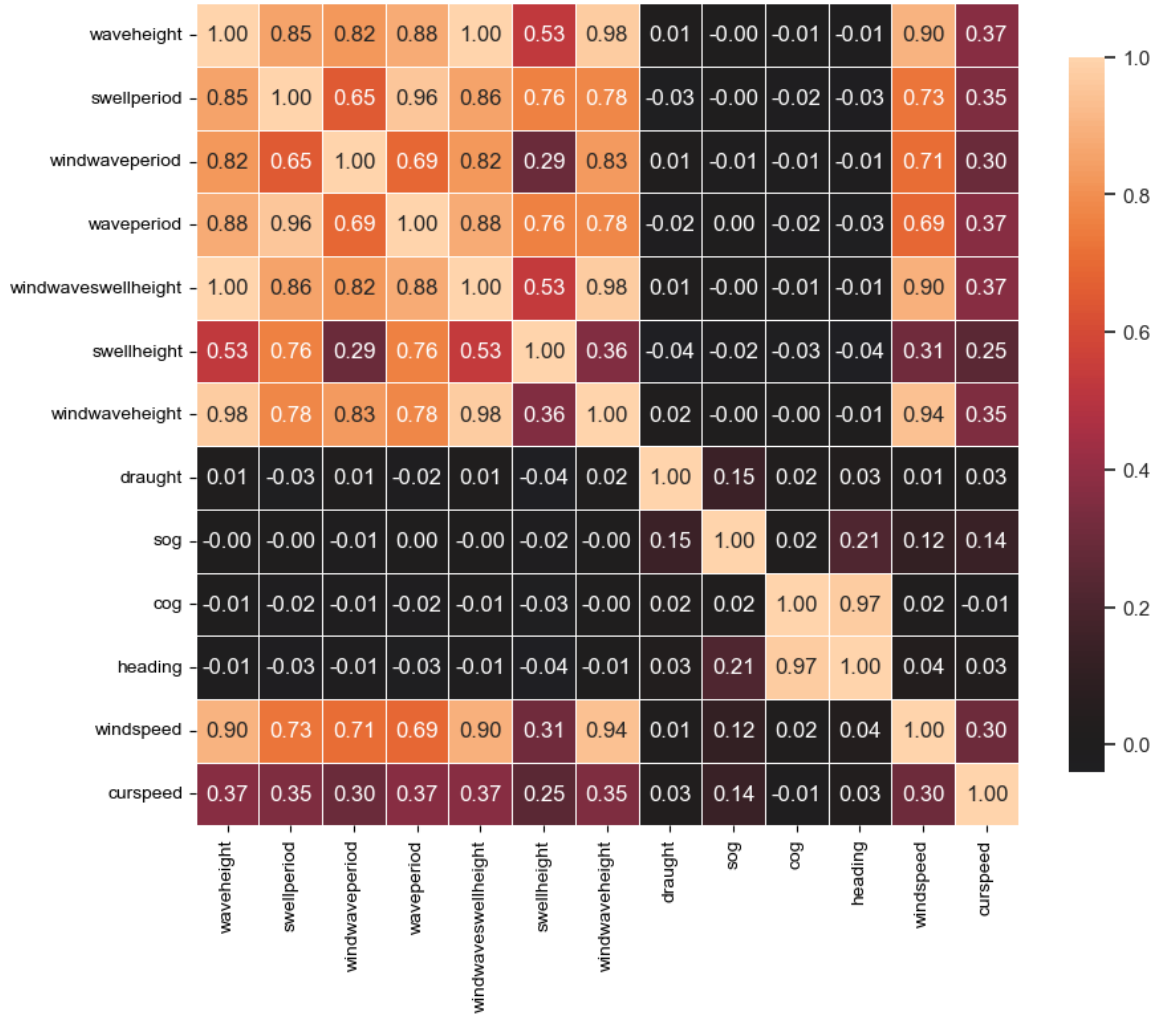

Figure 6: Correlation Heat Map

3.3 Modelling

- The data is split into 80:20 ratio. But considering the validation data, it is split into approximately 73:18:9.
- The model is then trained using Random Forest Regression (RFR). Additional training is also performed using Decision Tree Regressor (DTR). DTR model performance will be used as a benchmark as it is also a tree-based modelling method with similar methodology to RFR.
- The computational time of DTR is significantly faster than RFR Model Evaluation

3.4 Predicting STW

- The ship's Speed Through Water STW can be calculated using vector component of the SOG and current speed. The direction used will be according to True North. [28, 29]
- SOG represents the speed of the ship with reference to the ground, while the STW represent the ship's speed with reference to water.
- SOG also can be termed by the ship's speed that is captured by the GPS, and does not consider any effect of the current
- This means that the ship's STW will be greater than the ship's SOG when there is current moving against the ship's movement direction and vice versa
- The vector decomposition can be defined from the following equations, which is based on the equation by [28]:
  - The ship's SOG V_g can be decomposed into V_g^x and V_g^y, which represents the x and y components of the SOG respectively using the ship's course heading (COG) β *with respect to True North*:

$$V_g^x = V_g \sin(\beta) \tag{2}$$

$$V_g^y = V_g \cos(\beta) \tag{3}$$

  - To consider the effect of sea current. The current speed V_c will also be decomposed to x and y components respectively using the current direction γ *with respect to True North*:

$$V_c^x = V_g \sin(\gamma) \tag{4}$$

$$V_c^y = V_g \cos(\gamma) \tag{5}$$

  - from here the ship' STW V_{wx} and V_{wy} component can be found from the following equation:

$$V_w^x = V_g^x - V_c^x \tag{6}$$

$$V_w^y = V_g^y - V_c^y \tag{7}$$

  - The magnitude of the STW can be readily obtained from the following vector synthesis

$$V_w = \sqrt{(V_w^x)^2 + (V_w^y)^2} \tag{8}$$

- This principle is applied to the following Python script. 4

```
1
2       # Convert SOG from [Knots] to [m/s]
3
4       dfprog["vgms"] = dfprog["sog_pred"]/1.9438
5
6       # Convert the angles from [Degrees] to [Radians]
7
8       rad_gamma = np.deg2rad(dfprog["gamma"])
9       rad_cog = np.deg2rad(dfprog["cog"])
10
11      # Decomposition in x-component
12
13      dfprog["vgx"] = dfprog["vgms"] * np.sin(rad_cog)
14      dfprog["vcx"] = dfprog["curspeed"] * np.sin(rad_gamma)
15      dfprog["stw_x"] = (dfprog["vgx"] - dfprog["vcx"])
16
17      # Decomposition in y-component
18
19      dfprog["vgy"] = dfprog["vgms"] * np.cos(rad_cog)
20      dfprog["vcy"] = dfprog["curspeed"] * np.cos(rad_gamma)
21      dfprog["stw_y"] = (dfprog["vgy"] - dfprog["vcy"])
22
23      # Vector synthesis and reconversion to [Knots] from [m/s]
24
25      dfprog["vwms_p"] = np.sqrt(dfprog["stw_x"]**2 + dfprog["stw_y"]**2)
26      dfprog["stw_pred"] = dfprog["vwms_p"]*1.9438
27
28
```

4 Result and Discussion

The result of the research is discussed in this chapter. This comprises model validation and how different statistical metrics are used to analyze the model's performance.

4.1 Model Evaluation

The model are tested against four metrics, namely:

- R^2 : Indicate model fit. Best Score = 1
- Explained Variance `EV` : Indicate amount of variance in model. Best Score = 1
- Mean Absolute Error `MAE` : Indicate how much error a model makes in its prediction. Best Score = 0
- Root Mean Square Error `RMSE` : Same as MAE, more sensitive to outlier. Best Score = 0
- Median Absolute Error `MAD` : Check robustness against outlier. Best Score = 1

The result is summarized in the following table

Model	RFR	DTR	LR
R^2	0.9328181446941499	0.8526085810220092	1
EV	0.932872958708872	0.8526260247615258	2
MAE	0.5546347329650284	0.8108982427834758	3
RMSE	0.7095480848510665	1.5566896535262504	4
MAD	0.38484635910000087	0.5475717149999983	5

Table 2: Model performance

Model	RFR	DTR	LR
R^2	0.9328181446941499	0.8526085810220092	1
EV	0.932872958708872	0.8526260247615258	2
MAE	0.5546347329650284	0.8108982427834758	3
RMSE	0.7095480848510665	1.5566896535262504	4
MAD	0.38484635910000087	0.5475717149999983	5

Table 3: Model performance

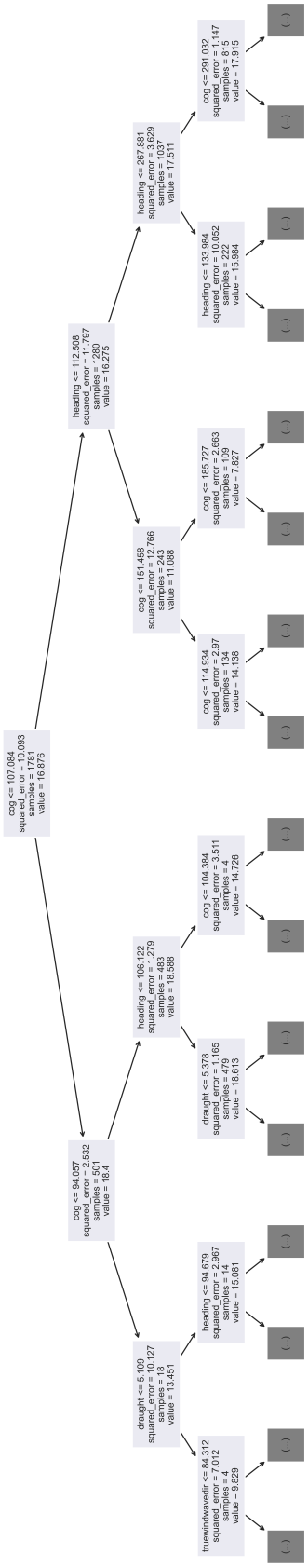

Figure 7: Correlation Heat Map

5 Summary and Outlook

In this chapter the summary of this research will be discussed. This section includes reflections of the research process and presents any possible suggestions and recommendations in this line of research. This chapter concludes this thesis.

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Declaration in lieu of oath

I hereby solemnly declare that I have independently completed this work or, in the case of group work, the part of the work that I have marked accordingly. I have not made use of the unauthorised assistance of third parties. Furthermore, I have used only the stated sources or aids and I have referenced all statements (particularly quotations) that I have adopted from the sources I have used verbatim or in essence.

I declare that the version of the work I have submitted in digital form is identical to the printed copies submitted.

I am aware that, in the case of an examination offence, the relevant assessment will be marked as 'insufficient' (5.0). In addition, an examination offence may be punishable as an administrative offence (Ordnungswidrigkeit) with a fine of up to €50,000. In cases of multiple or otherwise serious examination offences, I may also be removed from the register of students.

I am aware that the examiner and/or the Examination Board may use relevant software or other electronic aids in order to establish an examination offence has occurred

I solemnly declare that I have made the previous statements to the best of my knowledge and belief and that these statements are true and I have not concealed anything.

I am aware of the potential punishments for a false declaration in lieu of oath and in particular of the penalties set out in Sections 156 and 161 of the German Criminal Code (Strafgesetzbuch; StGB), which I have been specifically referred to.

Section 156 False declaration in lieu of an oath

Whoever falsely makes a declaration in lieu of an oath before an authority which is competent to administer such declarations or falsely testifies whilst referring to such a declaration incurs a penalty of imprisonment for a term not exceeding three years or a fine.

Section 161 Negligent false oath; negligent false declaration in lieu of oath

(1) Whoever commits one of the offences referred to in Sections 154 to 156 by negligence incurs a penalty of imprisonment for a term not exceeding one year or a fine. (2) No penalty is incurred if the offender corrects the false statement in time. The provisions of Section 158 (2) and (3) apply accordingly.

Place,date

Signature