UNIVERSITÄT DUISBURG ESSEN

Offen im Denken

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
of University Duisburg Essen

by

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1 Introduction

The research on efficient ship operation is a direction that is being actively pursued by marine industry stakeholder 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 optimisation parameter has 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 of random forest as predictor for the target value. As such, we will not perform exhaustive comparison test 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 such as method proposed by Kim et al. [14]. The comprehensive methodology by Kim et al. [14] use ISO standards to perform the estimation. However, some information for the estimation are not available in our dataset.
- 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.

If satisfactory solutions can be met for the bounded research questions, this thesis will provide the following contributions like the work previously done 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.
- 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 research to estimate ship fuel consumption is an active field of research. The summary of previous research compiled by Kim et al. [11] gives a good overview of the methodology used to estimate Fuel Oil Consumption (FOC). For example, Beşikçi et al. [4], Jeon et al. [8] and Kim et al. [11] utilised ANN to estimate FOC and reported good results by comparing ANN model's performance against Multiple Linear Regression model. It will be also sensible to compare the performance of ANN model against other machine learning models.

The research by Gkerekos et al. [9] showcased the performance of different machine learning models to predict ship's (FOC) using both noon data and automated data logging and monitoring (ADLM) system. This research concludes that Decision Tree Regressor (DTR) based model, namely Random Forest Regressor, (RFR), and Extra Tree Regressor, (ETR), displayed good prediction performance. Gkerekos et al. [9] also suggested that automatic sensor based data have the potential to increase the model accuracy score, R^2, by $5-7\%$.

Li et al. [3] performed a 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 RFR are among preferable model candidate to be used in commercial scale due to its good prediction capability and robustness against different datasets.

The research presented by Gkerekos et al. [9] and Li et al. [3] both used machine learning method to estimate the ship's FOC. Abebe et al. [10] used different approach in their research by predicting the ship's Speed Over Ground (SOG) instead of FOC. Abebe et al. [10] fused AIS satellite data and noon-report weather data for the SOG prediction. The evaluation from this research shows that machine learning methods can also be applied to predict SOG. Findings from this research also show good prediction performance of RFR.

This literature review indicated the capability of Random Forest Regressor to predict SOG and FOC. However, the difference of the data source as well as the data type used for modelling will result different result in model performance. From the literature review, good prediction performance from RFR can be expected. With that, this thesis will present the strength and limitations of RFR and provide general suggestions to improve the prediction performance of random forest model.

2.2 Random Forest Regressor (RFR)

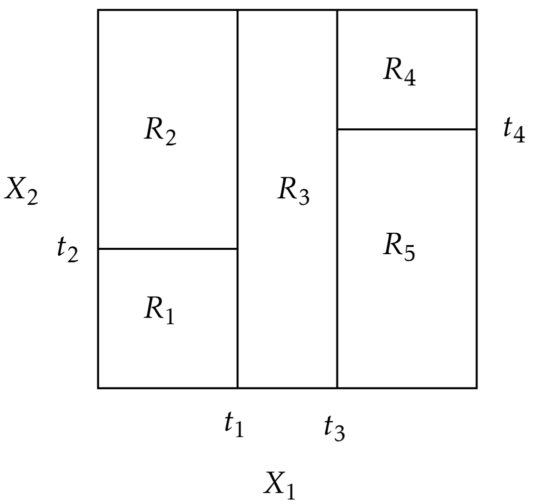


Figure 1: Example of partition space

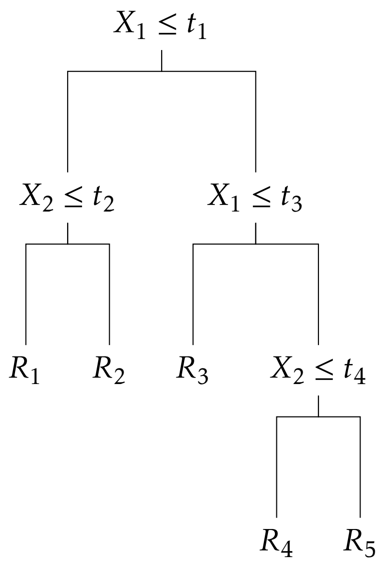
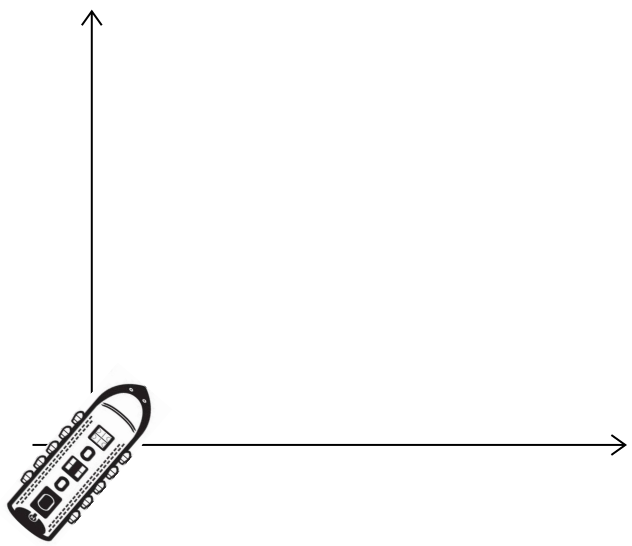


Figure 2: Example of partition tree



Suppose the following decision tree regressor

2.3 Ship speed

2.4 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, 16]. 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 $0.01 - 0.03$ 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.

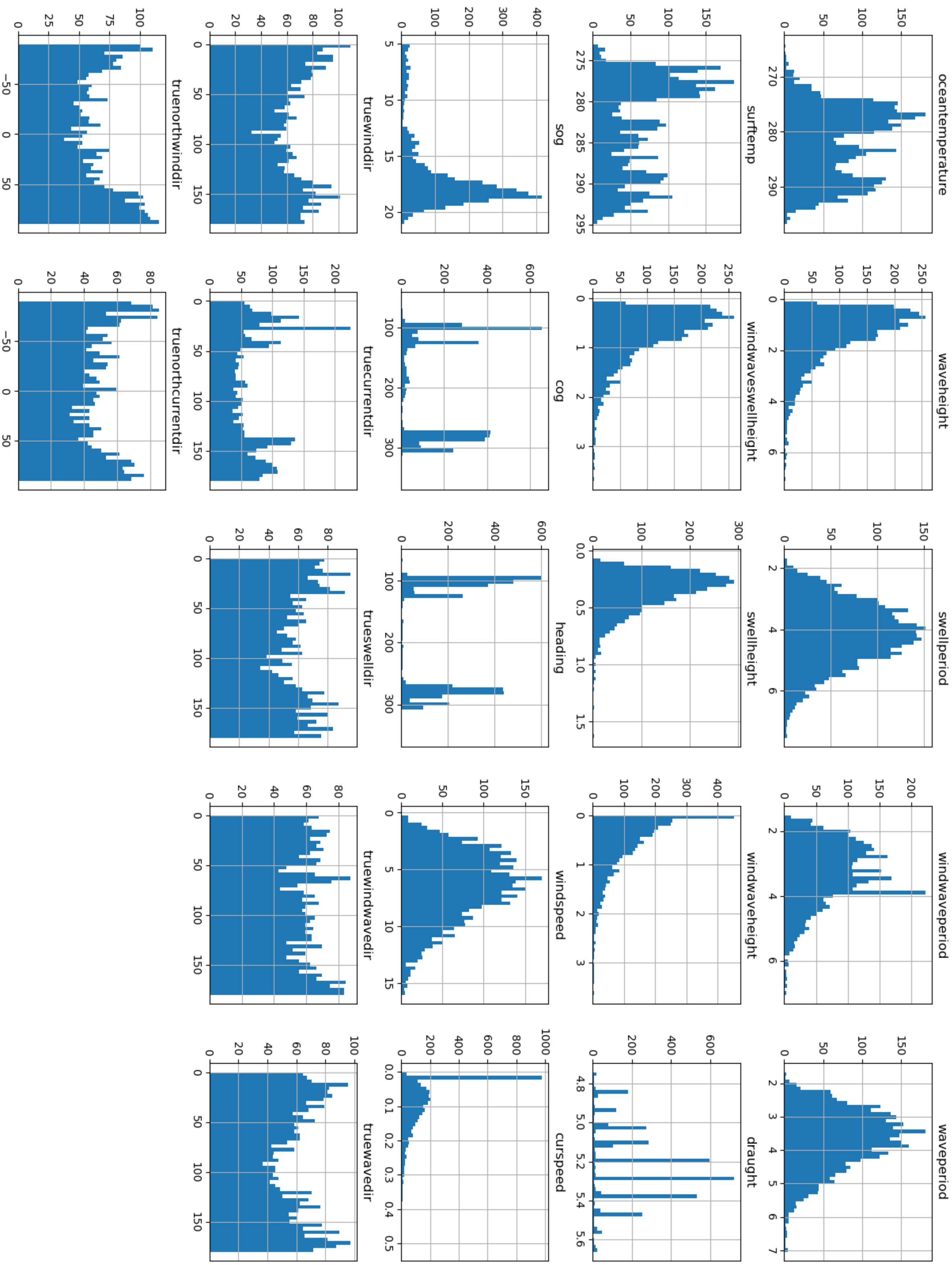


Figure 3: Histogram of the features

- 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`.

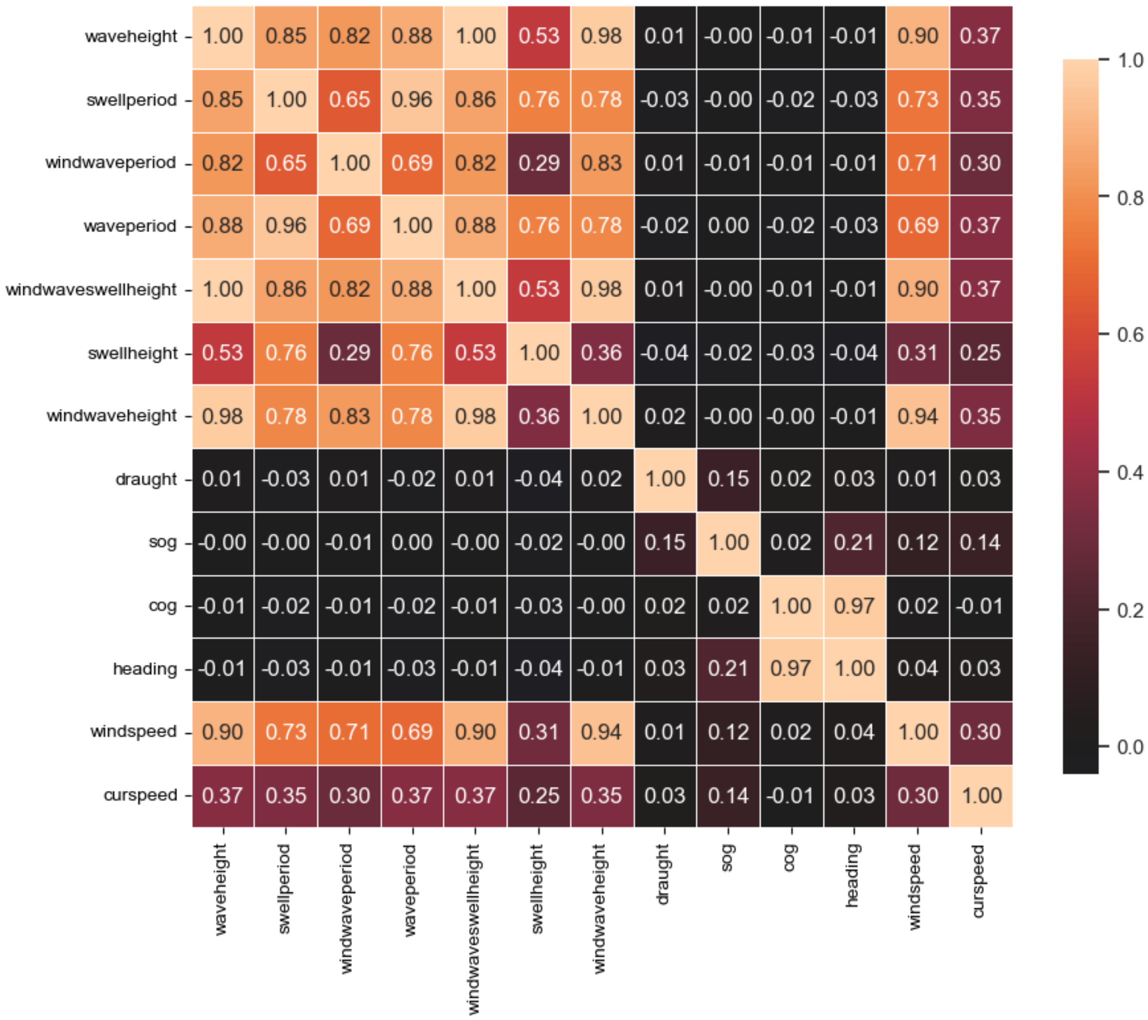


Figure 4: Correlation Heat Map

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. [16, 17]
- 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 [16]:
  - 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*:

$$V_g^x = V_g \sin(\beta) \tag{1}$$

$$V_g^y = V_g \cos(\beta) \tag{2}$$

  - 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*:

$$V_c^x = V_g \sin(\gamma) \tag{3}$$

$$V_c^y = V_g \cos(\gamma) \tag{4}$$

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

$$V_w^x = V_g^x - V_c^x \tag{5}$$

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

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

$$V_w = \sqrt{(V_w^x)^2 + (V_w^y)^2} \tag{7}$$

- This principle is applied to the following Python script. 3

```

        # Convert SOG from [Knots] to [m/s]

        dfprog["vgms"] = dfprog["sog_pred"]/1.9438

        # Convert the angles from [Degrees] to [Radians]

        rad_gamma = np.deg2rad(dfprog["gamma"])
        rad_cog = np.deg2rad(dfprog["cog"])

        # Decomposition in x-component

        dfprog["vgx"] = dfprog["vgms"] * np.sin(rad_cog)
        dfprog["vcx"] = dfprog["curspeed"] * np.sin(rad_gamma)
        dfprog["stw_x"] = (dfprog["vgx"] - dfprog["vcx"])

        # Decomposition in y-component

        dfprog["vgy"] = dfprog["vgms"] * np.cos(rad_cog)
        dfprog["vcy"] = dfprog["curspeed"] * np.cos(rad_gamma)
        dfprog["stw_y"] = (dfprog["vgy"] - dfprog["vcy"])

        # Vector synthesis and reconversion to [Knots] from [m/s]

        dfprog["vwms_p"] = np.sqrt(dfprog["stw_x"]**2 + dfprog["stw_y"]**2)
        dfprog["stw_pred"] = dfprog["vwms_p"]*1.9438

```

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 1: 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 2: Model performance

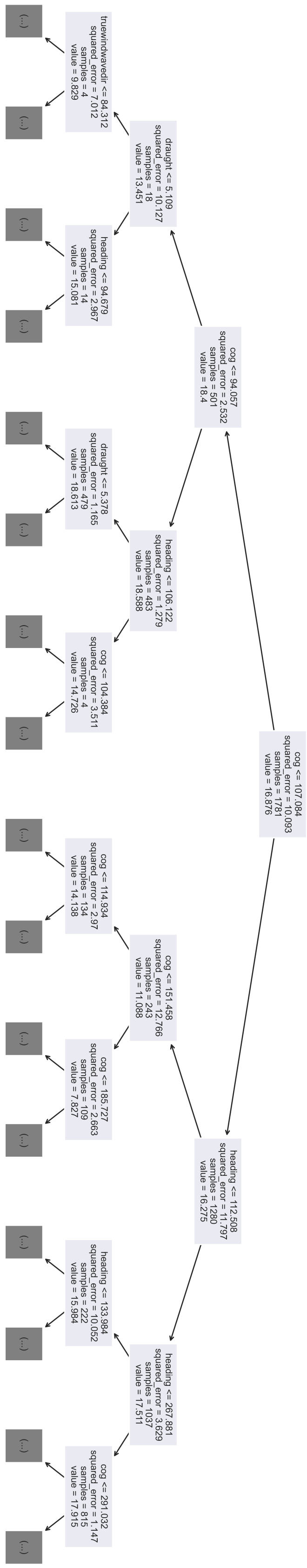


Figure 5: Correlation Heat Map

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