ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

PROPOSING AN OPERATIONAL DATA ANALYTICS APPROACH IN SHIP MANAGEMENT

Ph.D. THESIS

Ömer SÖNER

Department of Maritime Transportation Engineering

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GEMİ YÖNETİMİNDE BİR OPERASYONEL VERİ ANALİZİ YAKLAŞIMI ÖNERİSİ

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Ömer SÖNER, a Ph.D. student of İTU Graduate School of Science Engineering and Technology student ID 512152008, successfully defended the dissertation entitled "PROPOSING AN OPERATIONAL DATA ANALYTICS APPROACH IN SHIP MANAGEMENT", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my spouse and family,

FOREWORD

First of all, I would like to express my gratitude to my wife due to her encouragements in the course of thesis.

I am also grateful to thesis advisor Assoc. Prof. Dr. Metin ÇELİK and Assoc. Prof. Dr. Emre AKYÜZ for their involvement in this dissertation. Next, I appreciate Prof. Dr. Ş. İlker BİRBİL, Dr. Pelin BOLAT, and Dr. Kadir ÇİÇEK, for their constructive comments and contributions to research content as the members of the thesis monitoring committee.

April 2019 Ömer SÖNER

TABLE OF CONTENTS

Page

ABBREVIATIONS

ANN : Artificial Neural Network
EEDI : Energy Efficiency Design Index
EEOI : Energy Efficiency Operational Index
GAM : Generalized Additive Model
GHG : Greenhouse Gas
GMM : Generalized Method of Moment
GP : Gaussian Process
GPS : Global Positioning System
IMO : International Maritime Organisation
ITTC : International Towing Tank Conference
KPI : Key Performance Indicator
LNG : Liquefied Natural Gas
LR : Linear Regression
MARPOL : International Convention for the Prevention of Pollution from Ships
MEPC : Marine Environmental Protection Committee
MLR : Multiple Linear Regression
PCA : Principal Component Analysis
PCR : Principal Component Regression
PLS : Partial Least Squares
RF : Random Forest
RMSE : Root Mean Squared Error
RSS : Residual Sum of Squares
SEEMP : Ship Energy Efficiency Management Plan
SOG : Speed Over Ground
STW : Speed Through Water

SYMBOLS

$\mathbf{n}$	: The number of distinct data points
$\mathbf{p}$	: The number of variables
$\mathbf{x}_{ij}$	: The value of the $j\ th$ variable for the $i\ th$ observation
$\mathbf{y}_i$	: The $i\ th$ observation of the variable that is to be predicted
$\boldsymbol{\lambda}$	: Tuning parameter
$\boldsymbol{\beta}_p$	: Coefficient
$\hat{\mathbf{y}}_{\mathbf{R_j}}$	: Mean response for the training observations within the $j\ th$ region
$\boldsymbol{X_j}$	: Predictor
$\boldsymbol{s}$	: Cut point
$\boldsymbol{\lvert T \rvert}$	: Number of the terminal nodes of the tree
$\boldsymbol{\alpha}$	: Tuning parameter for tree
$\boldsymbol{R_m}$	: The predictor space corresponding to the mth terminal node
$\boldsymbol{B}$	: Separate training sets

LIST OF TABLES

Page

LIST OF FIGURES

PROPOSING AN OPERATIONAL DATA ANALYTICS APPROACH IN SHIP MANAGEMENT

SUMMARY

Over 80 % of global trade by volume and more than 70 % of its value has been carried by the shipping industry. In addition, demand for the maritime transportation mode is still expected to increase in the forthcoming years. Despite these facts, maritime transportation shareholders are under the increasing pressure to improve their overall service quality, while ensuring the competitive cost with the other transportation modes. More importantly, maritime transportation is expected to facing with the global overcapacity (the supply of ship capacity increased faster than demand). Its cause the pressure on the on freight rates and profits. Environmental protection and social awareness is another substantial component at this perspective, which environmentally sustainable transportation modes is demanded. Specifically, International Maritime Organization (IMO) has implemented the new regulatory regime, which aimed to improve a ship energy efficiency through life cycle of a ship starting from with ship design process and includes its service time. To improve a ship operational efficiency, and to decrease the ecological footprint of its activity, maritime researchers have focused on the ship operational performance monitoring since it would lead to improving fuel savings rate with relatively low initial investments and correspondingly low risk. Beyond that, ship operational performance monitoring might also be extended to optimization of operations, maintenance, delivery plans, charter party analysis, and vessel benchmarking. Thus, ship performance monitoring is an increasingly growing research area since it has a huge potential to improve a wide range of aspects in maritime industry.

Despite the mentioned benefits, current ship operational performance monitoring has several fundamental obstacles that make it impractical for ship owners and ship management companies to improve ship efficiency. At this point, data quality and utilized data analysis techniques are main concerns. Most of the time, ship operational data sets consist of the noon-reports. However, it is well-known that noon-reports are not capable of the providing sufficient data quality to investigate ship operational performance monitoring. Beyond that, utilized data analysis models in performance monitoring of ships are categorized as a theoretical, statistical, and hybrid models. Theoretical models have limited capacity to explain the complex behaviors of a dynamic ship system, since they heavily depend on the deterministic mathematical formulations. Moreover, current statistical models that have been implemented on the ship operational performance monitoring are considered as a black box that relations between the ship operational factors are not explained. Besides, low prediction accuracy is another issue for the implemented statistical models.

Because of these reasons, this thesis is aimed to develop a ship operational performance monitoring system based on the advanced statistical methods. As indicated earlier, reliable ship operational data is pre-condition for ship performance monitoring. Automatic data acquisition system based data set has been investigated to

improve system reliability. In order to optimize ship operation, ship operation characteristic and important variables, outputs, and their relation must be determined. Therefore, shrinkage methods and tree-based methods have been utilized for the ship operational performance monitoring. Shrinkage methods are one of the two statistical estimation methods particularly capable of providing interpretable models than the ordinary least squares. The tree-based methods, on the other hand, can be used on situation where the parameters are non-linear related, such as ship operational data. It guarantees to remove redundant and irrelevant variables (variable selection) to improve the prediction accuracy.

As a result; shrinkage methods (Ridge and Lasso) enable to minimize complexity and to enhance interpretability when comparing to current nonlinear models. The tree based model has considerable superiority since the model provides high accuracy rate. In the thesis, the concept of tree based models; bagging, random forest and bootstrap are deployed and the bootstrap gives the most accurate prediction rate than the others. Since statistical learning approaches can be used for the prediction and interference, identifying the best model depend on the user perspective and motivation.

GEMİ YÖNETİMİNDE BİR OPERASYONEL VERİ ANALİZİ YAKLAŞIMI ÖNERİSİ

ÖZET

Denizcilik endüstrisi global ticaret hacminin yüzde 80'ini ve değerinin yüzde 70'inden fazlasını taşımaktadır. Dahası, önümüzdeki yıllarda deniz yolu taşımacılığına olan talebin artması beklenmektedir. Bu gerçeklere rağmen, deniz yolu taşımacılığı paydaşları, diğer taşıma modları ile rekabetçi bir maliyet sunmaları beklenirken, genel hizmet kalitelerini de arttırma baskısı altındadır. Daha da önemlisi, deniz taşımacılığının küresel kapasite arz fazlası ile karşı karşıya kalacağı düşünülmektedir. Bunun neticesinde navlun fiyatları ve kar oranları üzerindeki baskılar artacaktır. Öteyandan, deniz çevresinin korunması ile ilgili uluslararası regülasyonlar nedeni ile denizcilik endüstrisindeki taşıma maliyetleri yükselme eğilimi göstermektedir. Özellikle, Uluslararası Denizcilik Örgütü (IMO), gemi tasarım sürecinden başlayarak bir geminin yaşam döngüsü boyunca enerji verimliliğini arttırmayı amaçlayan düzenleyici regülasyonları yürürlüğe sokmuştur. Bu kapsamda, Deniz Çevre Koruma Komitesi (MEPC), tam potansiyel verimlilik ve çevresel faydalar elde etmek için Enerji Verimliliği Tasarım Endeksi'ni (EEDI), Enerji Verimliliği Operasyonel Endeksini (EEOI) ve Gemi Enerjisi Verimliliği Yönetim Planını (SEEMP) geliştirmiştir. Tüm bu ana sebepler gemilerin operasyonel verimliliğini artırmayı ve gerçekleştirilen taşıma faaliyetlerinin çevreye olan olumsuz etkilerinin azaltılmasını gerekli kılmaktadır. Bu bağlamda gemi operasyonel performans izlenmesi denizcilik literatüründe her zaman yoğun bir şekilde işlenen konuların başında yer almıştır.

Gemi operasyonel performans izlemesinin diğer yöntemlere göre nispeten düşük ilk yatırım maliyeti gerektirmesi ve düşük risk taşıması en önemli avantajları olarak karşımıza çıkmaktadır. Bunların ötesinde, gemi operasyonel performans izlemesi, gemi operasyonların optimizasyonu, bakım ve teslimat planları, charter parti analizi ve gemi kıyaslama işlemlerine de genişletilebilir. Bu sebeple, gemi performans izlemesi, denizcilik endüstrisinde geniş kapsamlı uygulama alanlarını geliştirme konusunda büyük bir potansiyele sahiptir. Ancak, denizcilik literatüründe gemi operasyonel performans izlemesine yönelik çalışmaları incelediğimizde, bu çalışmalarda geliştirilmesi gereken önemli noktaların olduğunu ve denizcilik şirketleri için bu yaklaşımları işlevsiz kılan yönler olduğu tespit edilmiştir.

Sensör teknolojisindeki ilerlemelerin yol açtığı otomatik veri toplama sistemleri, denizcilik endüstrisinde veriye ulaşma sorununu ortadan kaldırmıştır. Ancak, gemi operasyonel performans izlemesi özelinde denizcilik literatürü incelendiğinde, gerçekleştirilen çalışmaların genellikle sensör verileri yerine noon-reportlardaki (öğlen raporu) veri kaynaklarına dayandırıldığı gözlemlenmektedir. Halbuki, bir çok bilimsel çalışma noon report kaynaklı verilerin bu konudaki yetersizliklerini ve eksikliklerini ortaya koymaktadır. Noon reportların hergün için sadece tek veri noktası sunması, kısıtlı sayıda değişken içermesi ve insan kaynaklı hatalara açık olması en çok altı çizilen dezavantajlarındandır. Dolayısı ile, otomatik veri toplama sistemlerinden elde edilen verilerin kullanılması, gemi operasyonel performans izlemesi

çalışmalarında elde edilecek sonuçların güvenirliliği ve hassasiyeti açısından büyük önem taşımaktadır.

Diğer bir önemli husus ise kullanılan veri analiz yöntemleri ile ilgilidir. Gemi operasyonel performans izlemesinde kullanılan teorik modeller, gemi performansına etki eden değişkenler arasındaki ilişkileri basite indirgeyerek söz konusu ilişkileri belirli varsayımlara dayandırmaktadırlar. Teorik yöntemler özellikle gemi dizayn aşamasında sıklıkla başvurulan yöntemler olarak karşımıza çıkmaktadırlar. Ancak, büyük oranda varsayımlara dayandırılmış olmaları ve büyük miktar ve çeşitlilikteki sensör verilerini analiz etmedeki yetersizlikleri, yeni metotların kullanılması gerekliliğini ortaya çıkarmıştır. İstatistiksel yöntemler ise bu bağlamda kullanılan daha gelişmiş yöntemler olarak karşımıza çıkmaktadır. Genel itibari ile, istatistiksel yöntemler tahmin ve çıkarım yapmak için kullanılırlar. Gemi operasyonel performansını iyileştirebilmek adına istatistiksel yöntemlere dayalı bir karar destek sistemi oluşturmanın gerekliliği aşikardır. Bazı durumlarda ise (charter parti analizi vb.), kullanılacak yakıt miktarına ilişkin hassas tahminlerde bulunmakta önem arz etmektedir. Ancak, gemi operasyonel performansının çok sayıda değişkene bağlı olması ve bu değişkenler arasındaki ilişkilerin doğrusal olmaması, çıkarım yapmayı zorlaştırmaktadır. Dahası, istatistiksel yöntemler kara kutu (black box) şeklinde ifade edilen yapılar sunduğundan çıkarımda bulunmayı güçleştirmektedirler. Doğrusal olmayan ilişkiler yapılan tahminlerin doğruluk düzeylerini de önemli ölçüde etkilemektedir. Denizcilik literatüründe, daha yüksek doğruluk oranlarına sahip istatistiksel çalışmalara olan ihtiyaç açıkca ortaya konmuş ve bu konuda daha fazla çalışma yapılması gerekliliği tartışılmıştır.

Bahsi geçen eksikliklerin ve uygulama zorluklarının üstesinden gelebilmek bu çalışmanın temel amaçını oluşturmaktadır. Bu kapsamda; otomatik veri toplama sistemlerinden elde edilen veriler analiz ederek veri kaynaklı eksiklikler giderilmesi amaçlanmıştır. Dahası, gelişmiş istatistiksel yöntemler kullanılarak daha yüksek doğruluk oranlarına ulaşılmasının yanı sıra çıkarım yapmaya olanak sağlayan metotlar kullanılması amaçlanmaktadır.

Bu kapsamda analiz edilen veriler Faroe Adaları'ndaki bir feribot'dan 16 Şubat - 12 Nisan 2010 tarihleri arasında bir araştırma projesi kapsamında toplanmıştır. Gemi, başkent Torshavn'dan en güneydeki ada Suduroy'a belirli bir rota üzerinden her gün iki veya üç sefer yapmaktadır ve herbir sefer ortalama 1 saat 55 dakika sürmektedir. Gemi üzerine farklı noktalardan veri elde etmek için sensörler yerleştirilmiş ve bu sensörler üzerinden toplam 254 sefer verisi toplanmıştır.

Elde edilen verilerin incelenmesi için öncelikle shrinkage metotları (Ridge ve Lasso) kullanılmıştır. Shrinkage metotlarının seçilmesinin nedeni; model karmaşıklığı azaltan ceza terimi (penalty term) içermesi, böylelikle değişken seçimine imkan tanımasıdır. Dahası, kısıtlı sayıdaki değişkeni içeren modeller sağladığı için varyansı azaltıp daha yüksek oranda bir tahmin yapılmasına da imkan sağlamaktadır. Böylelikle, yüksek doğruluk oranından feragat etmeden, karar destek sistemine temel oluşturan model elde edilebilmektedir. İkinci olarak, ağaç tabanlı (tree-based) modeller çıkarımların temel olarak amaçlanmadığı, daha ziyade hassas tahminlerin gerek duyulduğu durumlar için kullanılmıştır. Bu bağlamda, bagging, random forest and bootstrap yöntemleri kullanılmıştır. Bu yöntemler parametrik olmadıklarından kompleks yapıdaki sistemler üzerinde daha etkili sonuçlar elde edilebilmektedir. Dahası, istatiksel yöntemlerde var olan varsayımlara (normal dağılım, sabit ortalama ve standart sapma gibi) da gerek duyulmaması en önemli avantajlarındandır. Gemi operasyonel performansı dinamik değişkenlere bağlı kompleks bir problem olduğu için bu türdeki modellerin kullanılması uygun görülmüştür. Sonrasında, elde edilen sonuçlar aynı verileri kullanan diğer çalışmalar ile karşılaştırılmış ve kullanılan modellerin etkinlikleri değerlendirilmiştir.

Bu doğrultuda, shrinkage modelleri ile yapılan analiz sonuçunda beklendiği gibi belirli sayıda değişkenin yer aldığı modeller elde edilmiş ve bu modeller kullanılarak elde edilen tahmin değerleri diğer çalışmalarda elde edilenlerde rekabet edebilir düzeyde olduğu saptanmıştır. Daha da önemlisi, model karmaşıklığı azaltılmış olduğu için karar destek sistemi olarak kullanılması mümkün olan bir model geliştirilmesine imkan tanınmıştır. Bu ise gemi operasyonel performans izlemesi çalışmalarının karar destek sistemi olarak uygulabilirliğini artıran önemli bir katkı olarak değerlendirilmektedir. Tree-based modeller kullanılarak elde edilen sonuçların doğruluk dereceleri diğer çalışmalarla kıyaslandığında ise bazı noktalarda daha iyi sonuçlar verdiği görülmüştür. Dahası, değişkenlere ait birer önem sırası sağlıyor olması da bir diğer önemli avantaj olarak karşımıza çıkmaktadır. Dolayısı ile, çalışmada elde edilen sonuçlar hedeflenen amaçların gerçekleştirildiğini ortaya koymaktadır.

İstatistiksel yöntemlerin değişkenler arasındaki ilişkileri, kullanılan veriler aracılığıyla öğrendiği dikkate alınacak olursa, daha uzun süreli ve daha fazla değişken kullanılması ileriki çalışmalarda dikkate alınması gereken noktalar olarak karşımıza çıkmaktadır.

1. INTRODUCTION

Since ships have carried over 80 % of global trade by volume and more than 70 % of its value, the importance of maritime transportation has steadily growing (UNCTAD, 2017). The Review of Maritime Transport 2017, to illustrate, forecasts global maritime transportation to increase by 2.8 per cent in 2017, with total volumes reaching 10.6 billion tons (UNCTAD, 2017). In addition, demand for the maritime transportation mode is still expected to increase in the forthcoming years, related with the world economic growth. On the other hand, maritime transportation shareholders are under the increasing pressure to improve their overall service quality, while ensuring the competitive cost with the other transportation modes. More importantly, maritime transportation is expected to facing with the global overcapacity, which implies the supply of ship capacity increased faster than demand, and its cause the pressure on the on freight rates and profits. Environmental protection and social awareness is another substantial component at this perspective, which environmentally sustainable transportation modes is demanded (UNCTAD, 2017).

International Maritime Transportation (IMO) has developed a sustainable maritime concept regarding the handle the continues challenges that the shipping industry have been faced with the mentioned segments. This concept is mainly aimed to identify the various goals that must be met to achieve sustainable growth and development in maritime industry. At this perspective, reducing fuel consumption in shipping operations is a one of the key objectives so that it would enable to improve ship operational efficiency, as well as decrease the environmental impact of ships, and eventually lead to sustainable maritime transportation. Figure 1.1 shows the changes at oil prices over the time. Global crude oil demand as well as the negative effect of fluctuating oil price on the consumers paid is growing. Thus, the fuel costs of the ship operations are also expected to increase with respect to the fluctuated oil prices. Considering the fact that fuel cost as percentage of a ship’s total operation is one of the major components, operating the more efficient ships and investigating the reliable practices of ship management for optimal operation strategies is urgently needed now more than ever (Jafarzadeh and Utne, 2014; Soner et al., 2018a; Soner et al., 2018b).

Moreover, new amendments have been implemented by the Marine Environmental Protection Committee (MEPC) on the International Convention for the Prevention of Pollution from Ships (MARPOL) to minimize the particular gases emission from ships. For example; Energy Efficiency Design Index (EEDI) stands for new ships and the Ship Energy Efficiency Management Plan (SEEMP) for all ships. Energy Efficiency Operational Indicator (EEOI) is a voluntary technical measure for ships in operation (Faber et al., 2011).

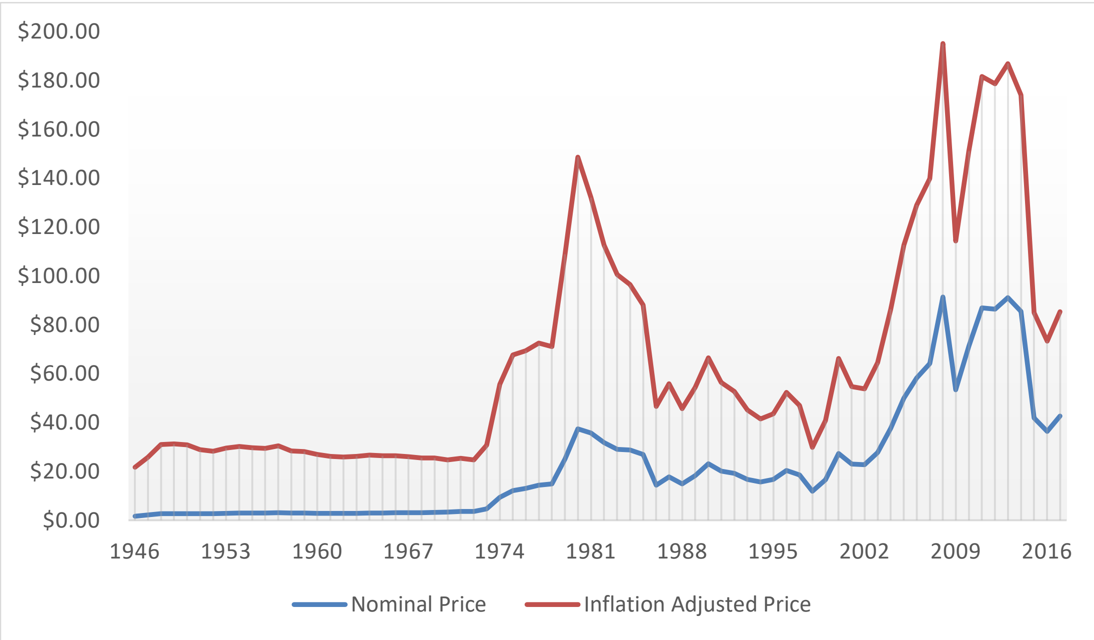

Figure 1.1 : Inflation adjusted oil price chart, (McMahon, 2018).

Comparing to the improving the fuel efficiency, which are structural, operational, technical, and alternative fuels, controling of operational measures offers great potential to fuel saving on board. There is a relatively low initial investments and a correspondingly low risk (Aldous, 2016). The recent and future technologies and innovations, employing batteries and electric motors, returning to wind propulsion, using the liquefied natural gas (lng) or nuclear propulsion are other options that have been investigated.

Ships operate within dynamic working conditions so that its operational performance realted with the various independent factors. Ship conditions, environmental conditions, and loading conditions are the major component of these factors. Relations between these variables are nonlinear that’s why linear based approaches would not provide demanded assistance. Therefore, advance statistical models are required to be implemented in such complex problem (Soner et al., 2018a; Soner et al., 2018b).

Besides, along with the advances of the sensor technologies and automatic data acquisitions systems, utilizing the capable advance tool in ship operational performance monitoring have become a necessity, since theoretical models are not structured to solve nonlinear problems. Considering the problem characteristic, it is clear that there is a gap between the problem requirements and utilized models in the ship operational performance monitoring. Therefore, the research is aimed to investigate the certain statistical models capability in the ship operational performance monitoring to fulfil the gaps in the literature (Soner et al., 2018a; Soner et al., 2018b).

1.1 Motivations Behind Thesis

There are significant benefits that ship operational performance monitoring would be provide for shipping industry. Apart from the motivations related to fuel efficiency and environmental policy, operational real time optimization, maintenance trigger, evaluating technological interventions, operational delivery plan optimization, fault analysis, charter party analysis, and inform policy are other particular applications with the scope of the ship operational performance monitoring (Aldous, 2016; Soner et al., 2018a; Soner et al., 2018b).

Operational real time optimization is mainly based on the adjusting the controllable variables with respect to the uncontrollable conditions to optimize ship operations. Weather routing, slow steaming, and trim and propeller pitch optimizations are some of the operational real time optimization applications (Armstrong, 2013; Maloni et al., 2013). Moreover, ship operational performance monitoring can determine the dry docking intervals and hull and propeller maintenance or conversion to improve the hull and propeller performance, as a maintenance trigger. Ship operational performance monitoring enables to evaluate the technological intervention by comparing the prior and post analysis of newly installed technology on ships. Operational delivery plan optimization implies the longer term and ship fleet perspective to optimize operational parameters. Ship operational performance monitoring can identify abrupt changes in ship performance so that make timely repairs possible, which is considered fault analysis. Under the time charterer, frequent dispute between owners and charterers is fuel consumption for a given speed might be overcome by taking advantage of the ship performance monitoring (Soner et al., 2018a; Soner et al., 2018b). Lastly, ship performance monitoring might also lead to inform authorized parties to prove complying with regulations and conventions (Hasselaar, 2011; Aldous, 2016).

Despite the mentioned benefits, current ship operational performance monitoring has several fundamental obstacles that make it impractical for ship owners and ship management companies to improve ship efficiency. At this point, data quality and adapted data analysis techniques are mainly mentioned concerns (Pedersen and Larsen, 2009-a, Soner et al., 2018-b). Most of the time, ship operational data sets consist of the noon-reports, as a traditional approach (Pedersen and Larsen, 2009-a; Aldous et al., 2015). However, it is well-known that noon-reports are not capable of the providing sufficient data quality to investigate ship operational performance monitoring. Noon-reports' shortcomings are clearly underlined in the literature. To illustrate; frequency of recording, required to human intervention, and provide restricted number of features are some of them (Erto et al., 2015; Soner et al., 2018a). On the other hand, automatic data acquisition system can provide high quality of data which are interrelated with different ship operational factors (Aldous et al., 2015; Soner et al., 2018b).

Beyond that, utilized data analysis models in performance monitoring of ships are categorized as a theoretical, statistical, and hybrid models (Aldous, 2016). Theoretical models have limited capacity to explain the complex behaviors of a dynamic ship system, since they heavily depend on the deterministic mathematical formulations (Coraddu et al., 2017; Soner et al., 2018b). Moreover, current statistical models that have been implemented on the ship operational performance monitoring are recognized as a black box that relations between the ship operational factors are not explained (Hasselaar, 2011, Soner et al., 2018a). Besides, low prediction accuracy is another argue that for the implementation of statistical models (Aldous, 2016). The hybrid models, on the other hand, combine the theoretical and statistical models (Leifsson et al., 2008; Soner et al., 2018a).

In this facts, this study is aimed to develop a ship operational performance monitoring system based on the advanced statistical methods. As mentioned previously, reliable ship operational data is pre-condition for ship performance monitoring. Automatic data acquisition system based data set has been investigated to improve system reliability.

In order to optimize ship operation, ship operation characteristic and important variables, outputs, and their relation must be determined (Soner et al., 2018a; Soner et al., 2018b). Therefore, developed model will be capable of provide high prediction accuracy rate and interpretable ship operational performance model to overcome the mentioned drawbacks. As a result, this thesis has a great potential to contribute both shipping literature and industry.

1.2 Thesis Objectives

The main objective of the study is to investigation of potential in advance statistical learning methods that are capable of the predict ship operational performance with high accuracy. Besides, it is also aimed at developing a model that is as accurate for predictions as easy-to-interpret. Considering the ship performance depends on the various interrelated factors (environment, loading, and ship condition), having an interpretable model is also desirable. Therefore, the thesis focusses on the statistical learning models that can eliminate the unrelated factors (variable selection) in the ship operational performance. Moreover, statistical learning models heavily depend on the data quality, since they establish a model based on the collected (train) dataset. The thesis has also taken advantage of the high quality ship operational data, which collected from the automatic data acquisition system on-board ship. In this perspective, the objectives of the thesis are i) to investigate the current ship performance monitoring models ii) to identify the research gaps in the ship performance monitoring iii) to propose advance ship operational performance monitoring iv) to demonstrate and test the proposed monitoring model v) to compare of the prediction accuracy of the proposed and existing ship performance monitoring models (Soner et al., 2018b).

1.3 Thesis Layout

Chapter 1 discuss the research potential, motivations, and recent development with detailes. Within the chapter, the requirements of the sustainable maritime concept are highlighted. Significance of the ship performance monitoring in this concept is thoroughly discussed. Moreover, drivers of the ship performance monitoring, which stem from international maritime regulations, economic and environmental concern, are elaborately investigated. Section 1.1 covers the motivations behind the thesis. The benefits and industrial application of the ship operational performance monitoring are exemplified with the related research in this sub-section. Section 1.2, on the other hand, express the thesis objectives, which are specified to clear the contributions of the thesis.

Chapter 2 reviews the existing ship performance monitoring research by classifying the studies with regard to the utilized models. Respectively, section 2.1 stands for the theoretical model based studies, section 2.2 stands for the statistical learning based studies, and section 2.3 stands for the hybrid model based studies. Section 2.4 underlines the shortcomings in the examined studies and identify literature gaps with respect to the requirements of the ship operational performance monitoring.

Chapter 3 describes the available data set that has been used in the thesis. Detailed information about the ferry where data collected from is also given in this chapter. Section 3.1 is focuses on the data collection system and specifications. Section 3.2 explains the data pre-processing techniques that transforms the raw data into desirable data format to conduct the required analysis.

Chapter 4 provides the technical background about the implemented statistical models. Section 4.1 is concerned with the regression based models; Lasso and Ridge models, respectively. Section 4.2 is concerned with the tree based models; Random Forest, Bagging, and Boosting, respectively. Section 4.3 demonstrates how the methods performance are measured.

Chapter 5 demonstrates the practical applications of the thesis. The proposed ship operational performance monitoring models are described. Visualization of the applications are displayed so that prominent variables are identified in this chapter. Comparison of the prediction accuracy of the proposed and existing ship performance monitoring models is also conducted.

Chapter 6 highlights the critical findings and summarize the aims and objectives of the thesis. Further, recommendations for the future work are also suggested in this chapter.

2. LITERATURE REVIEW

The aim of this chapter is to underpin the motivational drivers of the thesis. For this reason, recent state of-the-art ship operational performance monitoring literature have been critically examined in detail in order to justify the literature gaps. Moreover, it is also intended to show that ship operational performance monitoring is worth of attention to accomplish sustainable maritime concept.

In the literature, the utilized methods on ship operational performance monitoring studies are clustered and reviewed under three sections. The models, theoretical, statistical and hybrid, have been investigated to comparatively identify the strength and weakness of the model elaborately within the different sub-section, respectively.

2.1 Theoretical Model Based Studies

In the theoretical based models, hydrodynamic relations have been implemented to assess ship performance in relation with the environmental and ship's loading conditions. With these models, dynamic ship working environment is simplified in order to the reducing the problem complexity. In addition, the theoretical models are based on assumptions and uncertainties associated with interaction ship operational factors (Harvald, 1983; Soner et al., 2018a; Soner et al., 2018b). Generally, theoretical models are used in the ship design phase for determining ship characteristics; main engine size, propeller and hull dimension etc. Then, sea trials are dedicated to verify the model outcomes. Even if the numerous performance analysis methods utilize the identical hydrodynamic relations to calculate ship performance, the main differences between them are how they correct the calculated ship performance (Harvald, 1983; Hasselaar, 2011).

One of the first research that based on the theoretical model have been conducted by Telfer (Telfer, 1926). In the study, Generalized Power Diagram (GPD) has been introduced. GPD enables to demonstrate ship power, ship speed and propeller revolutions for a particular wake fraction in one diagram. Since the ship working environment and ship state is subject to continuous change, the wake fraction should be adjusted periodically. Besides, GPD is not only used for the ship speed calculation but also using to transform ship operational performance data to design speed or power (Hasselaar, 2011).

One of the early online data collecting system has been developed by Journée et al., (1987) and Journée (2003) to predict ship performance with theoretical models. Kim et al., (2001) have conducted a research that develop a computer program to analysis ship resistance increase with respect to the ship motion, wave diffraction, wind, steering, drifting, water temperature and salt content, deviation of displacement, hull and propeller surface roughness, and shallow water. The research mainly depends on the Taniguchi-Tamura's Method, which aimed to correct wind resistance with related to the analysis of speed trial results (Taniguchi and Tamura, 1966). Apart from the other theoretical models, the effect of the reduced ship speed on hull resistance is taking into account with this method. Moreover, semi-theoretical models are also derived from the regression analysis of random model and full-scale data, which accessible at the Netherlands Ship Model Basin (Holtrop and Mennen, 1982). The research has conducted extensive towing tank tests and dedicated ship trials to develop the model (ITTC, 2002).

In addition to these, certain theoretical based studies suppose propulsive efficiency and ship speed is constant (Aertssen and Sluys, 1972; Andersen et al., 2005). Despite the assumption of the constant propulsive efficiency, basic corrections are considered, such as; shallow water, draft deviations, and resistance due to waves, and wind (Hasselaar, 2011). In order to take propeller efficiency into account, propeller open-water diagram would be used to convert the performance to standard conditions by measuring the engine RPM, delivered power, ship speed, and laws of propeller action (Hasselaar, 2011).

A theoretical study is implemented to optimize trim conditions through the computational evaluation system called SoLuTion (Lee et al., 2014). The study has taken advantage of the Reynolds Stresses Model (RSM) so as to a good estimation of the wake distribution. The study comperes the model of the trim optimization with the towing test results to evaluate the model accuracy. Another research focuses on the bulk carriers to optimize trim configuration with respect to the three loading conditions at different speed range (Moustafa et al.,2015). The study is based on the empirical models that developed by Holtrop-Mannen (Holtrop and Mennen, 1982). Martelli et al., (2014), on the other hand, have developed multi-physic simulation platform to represent the dynamics of a twin-screw ship. The simulation platform enables to capture the ship heel angles within the turning circles and it represents simplified behavior of the two propeller shafts during maneuvers. Besides, a new approach in engine-propeller matching is developed by using numerical tools and available hardware resources (Coraddu et al., (2011).

2.2 Statistical Learning Based Studies

Statistical learning models are mainly concerned with the high prediction accuracy rate and model interpretability (Petersen et al., 2012-a; James et al., 2013). Statistical methods learn relations between the ship operational factors from the collected dataset. Therefore, these methods highly depend on the training data quality. Moreover, statistical learning models require a large amount of data both in terms of variety (number of different measured variables) and volume (size of the data) (Karlaftis and Vlahogianni, 2011; Coraddu, et al., 2017; Soner et al. 2018a). Take modeling complex datasets with possible nonlinearities (ship operational environment etc.) into account, the statistical learning models would be regarded as more flexible compared to theoretical models. Moreover, statistical learning models are excessively desirable since a-priory knowledge of the underline physical system is not required and they make possible to reveal some kind of hidden information that cannot be easily extracted with a theoretical model (Coraddu et al., 2015; Soner et al. 2018b).

A large amount of data that collected from the sensors and data acquisition systems are needed in order to an adequate investigation for ship performance monitoring. Data handling process (data pre-preparation) has paramount importance with this regard. Due to various nonlinearities among ship performance, ship operational datasets are usually obtained in unstructured formats (Perera and Mo, 2016). Thus, Perera and Mo is focused on the sensor fault identification, data compression and expansion to improve the quality of the process (Perera and Mo, 2016-a). Principal component analysis (PCA), which is a non-parametric method that extracts relevant information from complex data sets, is utilized in this study. Perera and Mo (2016-b), on the other hand, have emphasized the burden of ship operational data transfer to shore based data analysis centers for further processing and storage. Thus the study suggests autoencoder system architecture (a deep learning approach) to compress ship performance and navigation information to reduce the data set (Perera and Mo, 2016-b). Moreover, ship speed power performance under relative wind profiles is also investigated by Perera and Mo, (2016-c).

Sasa et al., (2015) have taken advantage of the EUT (Enhanced Unified Theory) and a numerical simulations of ship motions to estimate the frequency spectra of the roll and pitch motions in following waves. In addition, multiple linear regression analysis is also implemented to recognize the correlation among particular parameters related with the ship speed loss and the fuel consumption (Sasa et al., (2015). Erto et al., (2015) have also conducted a multiple linear regression based analysis in order to predicting and controlling the ship fuel consumption. Utilized dataset has been collected from a cruise ship and it covers navigational data: speed over ground (SOG), apparent wind speed and direction etc., and engine data: main engine and diesel generator rpm, thrust power, and temperature etc. (Erto et al., 2015).

Pedersen and Larsen (2009-a) and Pedersen and Larsen (2009-b) have utilized the Artificial Neural Networks (ANN) to predict propulsion power. Pedersen and Larsen (2009-b) take ship peed through the water, wind speed and direction, seawater temperature, air temperature water depth, wave height and direction as a set of input variables from four different loading conditions. Pedersen and Larsen (2009-a) have taken advantage of the four independent data set, with different loading conditions, for the analysis. It is assumed that the ship performance including the hull and propeller fouling was constant, so their effect not included in the analysis (Pedersen and Larsen 2009-a).

Petersen et al., (2012-a) and Petersen et al., (2012-b) have analyzed the same high-quality sensor data collected from a ferry over a period of two months. ANN and Gaussian processes (GP) have been implemented to modelling for ship propulsion efficiency by Petersen et al., (2012-a). Petersen et al., (2012-b), on the other hand, have aimed to predict main energy consumption under realistic operational conditions in order to trim optimization.

Brandsæter and Vanem, (2018) have aimed to predict ship speed under the environmental condition with full scale sensor measurements of shaft thrust. Linear regression, projection pursuit (PPT) and generalized additive models (GAM) have been implemented in this study for the comparison purposes (Brandsæter & Vanem, 2018). Ahlgren & Thern, (2018) take advantage of the machine learning (linear regression with the Tree Pipeline Optimization Toiol) model for predicting the fuel oil consumption. Utilized data set have been obtained on the cruise ship engine operating in the Baltic Sea. Utilized sensors was newly installed mass flow meters, as well as an extensive set of logged time series data from the machinery logging system (Ahlgren & Thern, (2018).

2.3 Hybrid Based Studies

Hybrid modelling methods combine the white-box and black-box modeling methods. In the literature, different expressions have been used for the hybrid modelling, to illustrate; grey-box modelling, semi-physical modelling, and semi-mechanistic modelling etc. (Leifsson et al., 2008). Duarte et al., (2004) have consider the hybrid modelling based on the combination of mechanistic models with Multivariate Adaptive Regressive Splines (MARS), Artificial Neural Networks (ANN), and Regression Analysis (RA). In order to evaluate the performance of the various combinations of modules and hybrid approaches two simulated case studies are performed, and the mechanistic model/MARS combination has the lowest prediction errors.

Te Braake et al., (1998) have also used to white-box and black-box modeling to predict the process states. The study underlines the fact that availability of enough dataset is pre-request for the nonlinear black-box modeling. On the other hand, where the process conditions are not allowing to measure the variables and outfits then semi-mechanistic models become preferable (Te Braake et al., (1998). Leifsson et al., (2008) has implemented a grey-box modeling approach for the simulation of ocean vessels (medium sized container vessel) in order to the improve the prediction of the vessel fuel consumption. Utilized grey-box modeling combines conventional analysis models, which based upon the theoretical formulation (a white-box modeling), with a feed forward neural network (a black box modeling). Moreover, these two models combine together not only in parallel but also in series, as well. Despite the potential advantages of the grey box modelling, the model has slightly improved the prediction of the vessel speed (Leifsson et al., 2008).Coraddu et al., (2017) have compared the white, black and grey box modelling approaches performance when they predict the ship fuel consumption. The investigated dataset have been obtained in real operations from the onboard ship automation systems to optimize the trim of a vessel in real conditions. The study result shows that black box modeling has superior prediction accuracy rate over two other modellings (Coraddu et al., 2017). Regularized Least Squares (RLS), the Lasso Regression, and the Random Forrest (RF) have been exploited in this research as a black box modelling. Coraddu et al., (2015), on the other hand, implemented RLS as a black box modelling for the same problem in a grey box modeling approach. The study discusses that white box modelling neglects the critical aspect of the ship fuel consumption. Therefore, black box modelling provides great potential at this perspective.

2.4 Discussion on Literature Review

Although there are considerable studies may improve the ship fuel efficiency, there is still a gap in improving ship operational performance from the point of view of model interpretability and estimation accuracy (Aldous et al., 2015; Lepore et al., 2017; Wang et al., 2018; Soner et al. 2018a; Soner et al. 2018b). Table 2.1 illustarte the methods used in the ship performance monitoring studies (Soner & Celik, 2017). As can be seen in the table, there are particular statisticals methods that could be used for this issue. However, there are numerous factors that affect the operational performance of the ship such as wind speed, wind angle, wave height, air pressure, and cargo weight. Given that some of them are highly correlated, they increase the variance and bias that can lead to complex modeling and low accuracy. Therefore, utilized methods should handle the these problems.

In order to provide the high prediction accuracy, nonlinear models should be selected, whereas; the relations among the features are not explained in these models. Therefore, it is not possible to intervene in ship operation when using non-linear models. Nevertheless, when looking for interpretability, statistical models offer significant difficulty to monitor the operational performance of the ship. (Soner et al. 2018b). For example, shrinkage models predict coefficients that shrink to zero. Therefore, they reduce variance and improve prediction accuracy. Feature selection can help increase accuracy and reduce unnecessary model complexity. The decision tree is a nonparametric model which means that there is no assumption about space distribution and classifier structure. (Song and Ying, 2015; Soner et al. 2018a). The decision tree can be used in cases where parameters such as operational data of ships are not linear.

It guarantees to remove unnecessary and irrelevant variables (variable selection) to increase the accuracy of the prediction (Ramezankhani et all., 2016). As a result, the thesis based on shrinkage methods and tree based methods for monitoring ship operational performance (Soner et al. 2018a; Soner et al. 2018b).

Table 2.1 : Methods that used in reviewed articles.

Year/Author	Regression		Regularization Based Regression		Tree-Based Methods			Non-linear ANN	Monte Carlo	GMMs	PCA	Other
	LR	MLR	Ridge	Lasso	Bagging	RF	Boosting					
2008 Leifsson et al.								x				x
2009-a Petersen and Larsen								x				
2009-b Petersen and Larsen		x						x				
2010 Hasselaar	x	x										x
2012-a Petersen et al.								x		x		
2012-b Petersen et al.								x				x
2012 Hansen	x	x										x
2014 Mak et al.												x
2015 Coraddu et al.												x
2015 Mak et al.												x
2015 Aldous et al.									x			
2015 Lu et al.												x

Table 2.1 (continued) : Methods that used in reviewed articles.

Year/Author	Regression		Regularization Based Regression		Tree-Based Methods			Non-linear ANN	Monte Carlo	GMMs	PCA	Other
	LR	MLR	Ridge	Lasso	Bagging	RF	Boosting					
2015 Erto et al.		x										
2015 Sasa et al.		x										
2016 Perera										x	x	
2017 Coraddu et al.				x		x						x
2017 Perera and Mo										x		x

3. DATA REQUIREMENTS

3.1 Data Collection System

Data collection system is installed on a ship which is performing a few trips forward and backward in a regular schedule from the Tórshavn to Suduroy in the Faroe Islands (Petersen, 2011; Petersen et al., 2012a). Each trip takes about 2 hours. The ship was equipped with four main engines, 3360 kW (13,440 kW) and four auxiliary engines 515 kW (Petersen, 2011). The service speed of the ship is 21 kn and the total length is 135.00 m, the width is 22.70 m and the width of the main deck is 5.60 m. (Petersen, 2011). Moreover, she is equipped with two controllable pitch propellers and two rudders (Petersen, 2011). Data collection timeline includes a 2-month period between February 16, 2010 through April 12, 2010 (Petersen et al., 2012a). The ship's operational performance is related not only to ship conditions (ie machinery) but also to additional features such as weather conditions and loading conditions (Orihara and Tsujimoto, 2017). Therefore, numerous features should be considered to improve the operational performance of ship. The devices that were used to collect data were: Doppler speed log, gyrocompass, GPS (Global Positioning System), main fuel pipe flow meter, rudder angles, wind, and propeller pitches (Petersen, 2011). In addition, an inclinometer was used to measure the ship's trim, and two-level meters were placed on the sides of the ship. Table 3.1 demonstrates the collected ship operational features (Propulsion modelling, 2017).

There are some costs for each data collection point: cabling, connections, software, storage, etc. Thus, while measuring all relevant signals is important, in each case there is also a limiting cost and complexity factor to consider (Petersen, 2011). Brief information about the considering features are given, as follows;

Trim is defined as the aft and forward draughts difference, which results in a positive aft trim. In addition, the displacement and speed are kept constant when a vessel is trimmed, i.e. no additional ballast is added and the power consumption varies when the resistance is changed when trimmed. At a given condition, the optimal trim is the trim angle where the required propulsion power is lower than any other trim angle at that condition (Abouelfadl and Abdelraouf, 2016). Considering the data used in this study, an inclinometer was installed in the engine room to measure the vessel's trim (Petersen, 2011).

In addition, the system is fitted with two level measuring devices on the ship's sides. They use radio waves to measure the distance to the surface of the sea (Petersen, 2011).

Wind, on the other hand, has nature that is highly fluctuating. The relevance of ship operating fluctuations is limited primarily to longitudinal high-energy wind turbulences with relatively long periods and dimensions, so that the entire ship can be assumed to be affected. Visual estimates, forecast information or direct measurement using an anemometer can be used to estimate the wind speed. A continuous reading of the apparent wind speed and direction is needed for performance monitoring. Therefore, visual observations are not appropriate for performance monitoring (Hasselaar, 2011).

A rudder is a primary surface for controlling a ship. Due to the high and low pressure regions generated by the water flow, a force is generated when a rudder is turned to some angle. The flow decreases in speed on one side of the rudder while on the other it increases. Therefore, movements of the rudder add drag to the hull and increase strength. Minimizing the number of times the rudder is used and saving fuel will be the amount of rudder angle applied to keep the course or execute a course change.

SOG is a non-critical performance monitoring parameter because it is not associated with the ship's actual performance. However, it is used to validate speed by measuring water and to identify currents. STW, on the other hand, is one of the most important parameter of performance analysis. The following techniques on ships can be used to measure STW; such as doppler logs, electromagnetic logs, acoustic correlation logs etc. (Hasselaar, 2011).

Pitch effectively converts the propeller shaft's torque to thrust by deflecting or accelerating the astern water. In view of ship motions generated by external waves, long, regular waves like swell have the greatest influence on motions. Therefore, pitch is especially important for performance monitoring as a major contributor to wave resistance and propulsive characteristics changes (Hasselaar, 2011).

True course or true heading is expressed as angular distance between 000 ° and 360 ° from the true North clockwise.

Table 3.1 : Available raw dataset features (Propulsion modelling, 2017).

Features	Units
Fuel density	kg/l
Fuel temperature	C
Fuel volume flow rate	L/s
Inclinometer trim angle	degrees
Latitude	degrees
Longitude	degrees
Port level measurements	m
Starboard level measurements	m
Speed through water (STW)	kn
Port propeller pitch	-10 - 10 V
Port rudder angle	-10 - 10 V
Speed over ground (SOG)	Km/h
Speed over ground (SOG)	Kn
Starboard propeller pitch	-10 - 10 V
Starboard rudder angle	-10 - 10 V
Track degree magnetic	degrees
Track degree true	degrees
True heading	degrees
Wind angle	degrees
Wind speed	m/s

The true heading is the course used in the chart and the compass course is the course that the helmsman will steer with the navigation compass. The magnetic course refers to the north of the magnet. The course applies through the water to the direction. Wind, sea, and current, however, may defer a vessel from its intended course on Earth. Track is Earth's intended (horizontal) direction of travel. The track consists of one or a series of course lines from the starting point to the destination along which a journey is intended to continue. (Bole, Nicholls, and Dineley, 2013). is the number of samples (Soner et al., 2018a; Soner et al., 2018b).

3.2 Data Pre-processing

The data set obtained consist of 254 trips in the timeline. The data set is organized in a window size of 3 minutes (total 9001 windows) to capture changes in variables before analyzing the operational data set (Petersen, 2011; Petersen et al., 2012a; Petersen et al., 2012b).

In addition, feature extraction was performed to obtain the mean, variance and derivative of the variables (Petersen et al., 2012a). As mentioned, the system collected values from many sources. Therefore, it is possible to lose some values. At least one sample should be provided in each window to provide each required entry. Otherwise, the window is removed to deal with missing values. Outliers were specified at acceptable intervals for each entry. If a value is out of range, it is dropped (Petersen, 2011). In addition, the feature extraction process, the average of an entry, such as retrieving the variance or derivative is carried out by simple mathematical operations (Petersen et al., 2012a). While the variance of the feature expresses how much the signals in a window change, the increase or decrease in a signal in a window will be understood by the derivative of the feature. For example, the variance of surface distance measurements will give an idea of the pattern of waves surrounding the ship (Petersen, 2011). Because the wind direction contains a circular discontinuity, headwind and cross wind are used to reflect the measurements. Therefore, headwind and crosswind are produced in terms of relative wind speed and angle (Petersen, 2011). Application and problem properties have an impact on the window size (Petersen, 2011). Some research found a window size of 10 minutes, which would be more appropriate for their application (Leifsson et al., 2008; Pedersen and Larsen, 2009). The data set obtained for this study was arranged in a window size of 3 minutes (total of 900 windows) (Petersen et al., 2012a). Different indicators can be used to evaluate vessel performance. Generally, ship speed or fuel consumption is used for this perspective. This study takes into account fuel consumption and STW to monitor ship operational performance.

3.3 Data Description

In this sub-section, application data set is presented with the detailed figures. Figure 3.1, Figure 3.2, and Figure 3.3 shows a scatter diagram showing the relationship between STW with trim, draft, and heeling (Soner et al., 2018b).

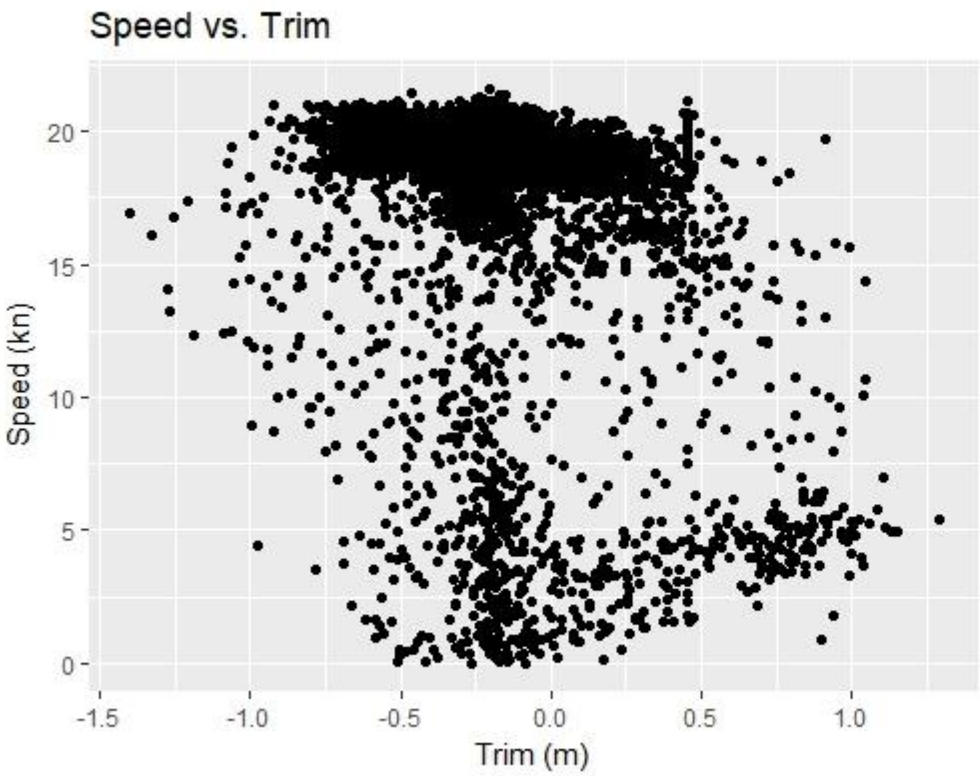

Figure 3.1 : Scatter plots of the ship STW versus trip.

The relationship between speed and related properties is not linear as expected.

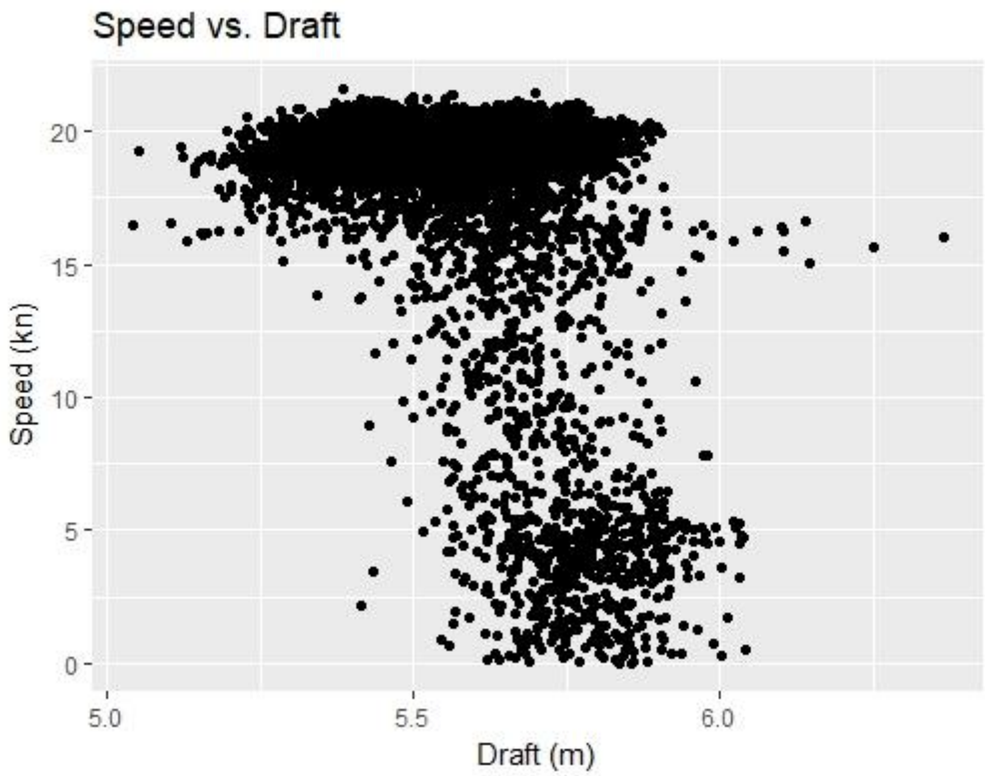

Figure 3.2 : Scatter plots of the ship STW versus draft.

Distribution as shown in the chart, trim is between -1.5 to 1.25, and draft mostly spread between 5.0 to 6.0 meters' (Soner et al., 2018b).

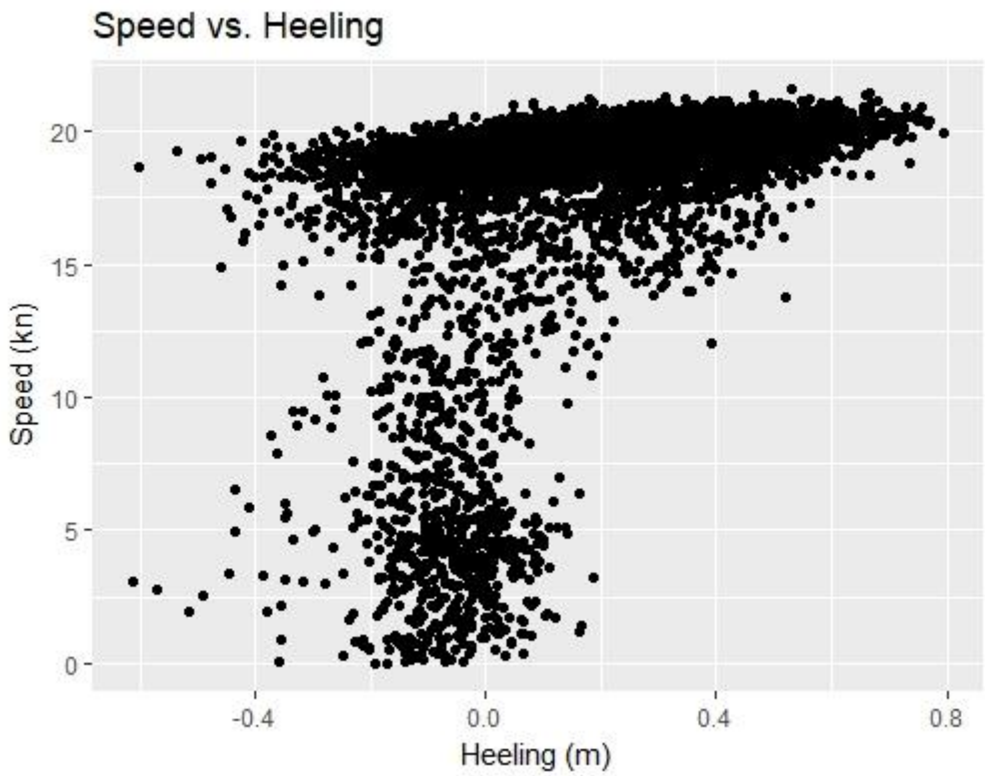

Figure 3.3 : Scatter plots of the ship STW versus heeling.

On the other hand, heeling tend to increase STW. Furthermore, the data set includes mainly STW sample is between 15 knots to 20 knots (Soner et al., 2018b).

With basic figures, summary statistics can define a complicated set of data. After the data is obtained, it is important to understand the data before applying algorithms and making predictions. The minimum (Min), 1st quartile (1st Qu), median, mean, 3rd quartile (3rd Qu), and maximum (Max) have been used for the summary statistic.

Table 3.2 demonstrates the summary statistic of the features. Mean or average is a central data trend, i.e. a number that spreads a whole data, the average data values. While the minimum is the lowest data value, the highest data value is the maximum. The median (or 50th percentile) for the sorted data values is the "middle number." The 75th to 25th percentile difference (the 3rd and 1st quartiles). This represents the range of 50% of the data in the middle. It serves as a robust data variation measure. As a branch of descriptive statistics, data visualization makes complex data more accessible, understandable and usable.

Table 3.2 : Summary statistic of the features.

Features	Statistics					
	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Speed	0.00	18.69	19.46	18.13	19.93	21.59
Fuel	0.1928	0.5977	0.6306	0.5967	0.6478	0.7110
Fuel Mass Flow Rate	0.1786	0.5544	0.5840	0.5529	0.6003	0.6580
Ahead Speed	-19.47	18.45	19.38	17.43	19.89	21.58
Trim	-1.40257	-0.29875	-0.19321	-0.17835	-0.09085	1.29117
Port Pitch	0.05548	81.44289	83.34849	78.68136	84.91733	89.58378
Starboard Pitch	0.01	80.66	82.67	77.38	84.11	88.70
Port Rudder	-74.10195	-0.84585	-0.34845	-1.86341	0.06516	44.61400
Starboard Rudder	-60.89206	-0.86545	-0.40670	-0.20063	0.04032	77.09591
Heeling	-0.6131	0.0541	0.2222	0.2074	0.3644	0.7945
Draft	5.042	5.448	5.563	5.561	5.666	6.366
Port Level	4.530	5.607	5.809	5.784	5.986	6.507
Starboard Level	4.513	5.203	5.361	5.369	5.513	6.302
Longitude	-6.982	-6.733	-6.679	-6.691	-6.633	-6.532
Latitude	61.53	61.61	61.76	61.76	61.90	62.06
Headwind	-13.97	4.77	10.49	10.93	16.84	35.80
Crosswind	-25.1039	-6.7292	-0.1009	-1.6452	2.8555	18.4672

For further understanding, colored figures are also provided. Figure 3.4 demonstrates the ship speed against the trip and the fuel consumed presented by the colored points. As shown in Figure 3.4, speed change is extremely constrained (Soner et al., 2018b). Therefore, measurements below 15 knots ship speed can be considered outliers. At the points when the ship achieves high speed, fuel consumption likewise increments, however, there are a few data points that show otherwise.

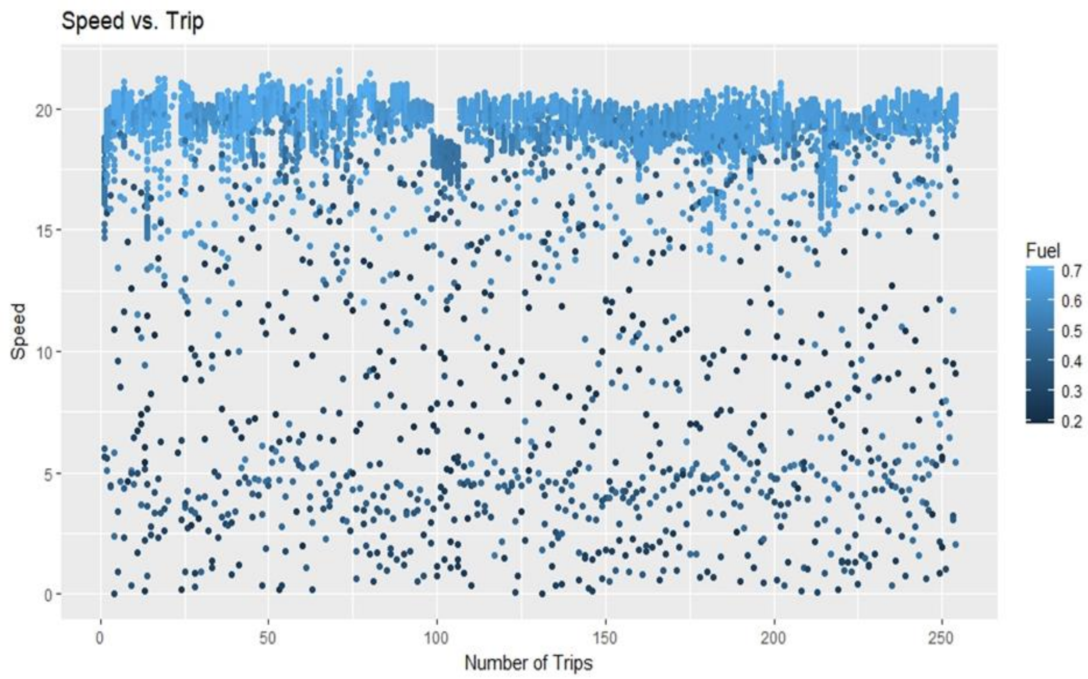

Figure 3.4 : For ship speed [knots] versus trip number.

Figure 3.5 shows the average speed for each trip. Average speeds up to 20 knots from 16 knots fluctuate.

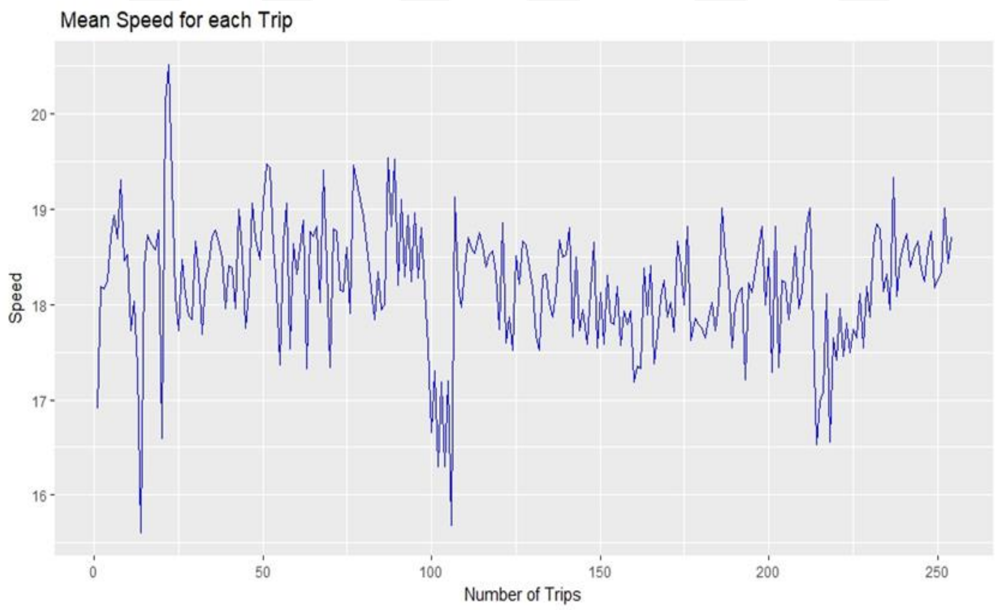

Figure 3.5 : Mean speed [knots] for each trip.

Another way to summarize data, as an input into a more advanced analysis, and as a diagnosis for advanced analysis, a correlation matrix also has been used. The correlation between each feature, to illustrate the relationship between ship operational data are presented in Figure 3.6. The strength and direction of the linear relationship between two variables are measured by correlation. The coefficient of correlation values may vary from -1 to + 1. The closer it is to + 1 or -1, the closer the relationship between the two variables is.

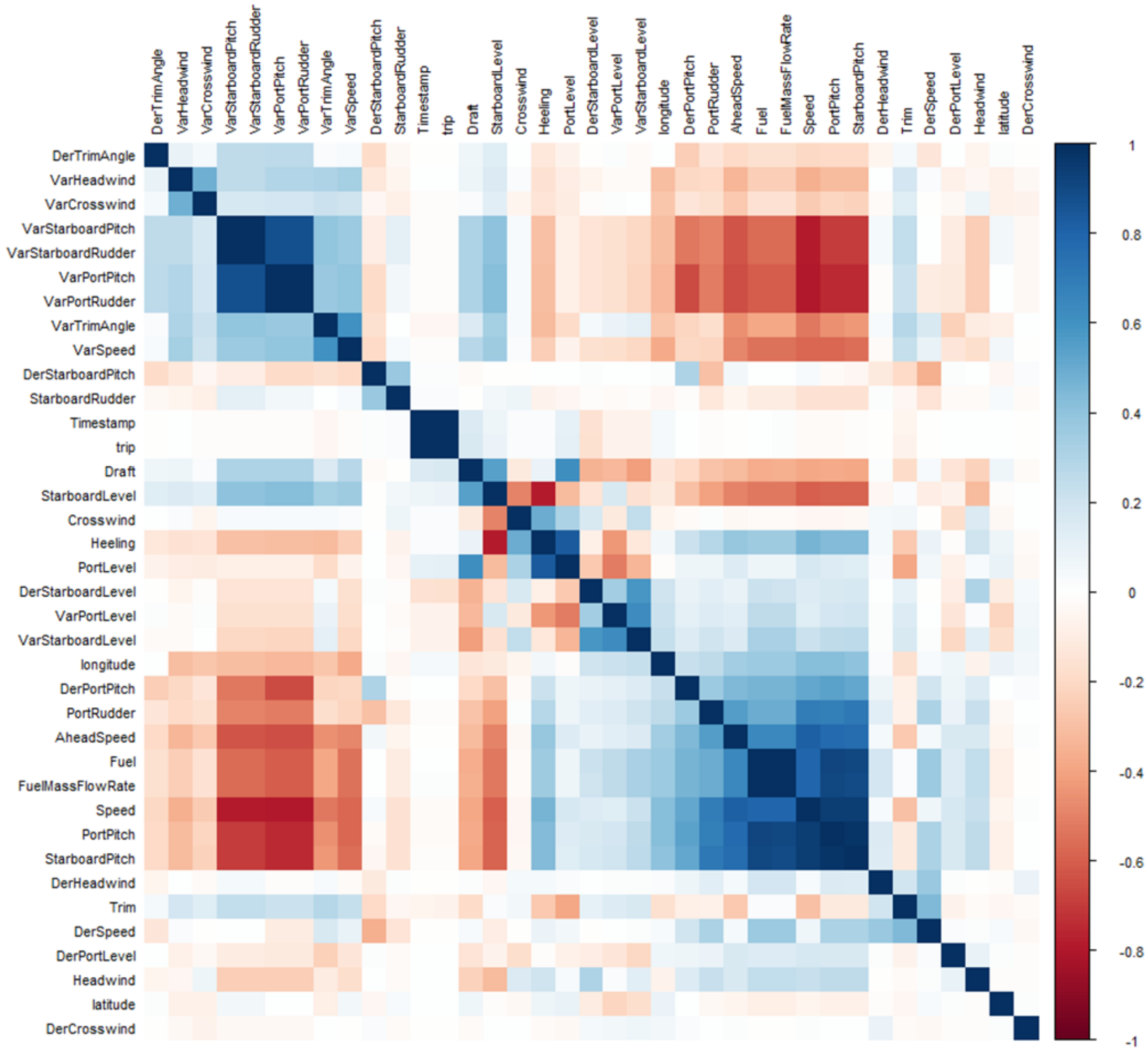

Figure 3.6 : The correlation analysis of the features.

The positive sign means the direction of the correlation, i.e. if one of the variables increases, the other variable should increase as well. Positive correlations are displayed in a blue scale while a red scale displays negative correlations. There are complex interactions. The fuel, environmental conditions, trim, pitch, and draught are physically inextricably releted. Because of the non-linear relationships among the different features, ship performance monitoring is considered, as a complex problem.

4. ADVANCED STATISTICAL LEARNING METHODS

It has developed statistical models to monitor the operating performance of the ship. The scope of this study, however, is primarily intended to develop a model that is easy to interpret and accurate for prediction (Soner et al., 2018a; Soner et al., 2018b). Prediction and interpretation are the main objectives of the use of statistical learning methods (James et al., 2013). In some cases, inference is the main objective of the analysis to elicit the relationship between each respondent and the predictor. On the other hand, the prediction aims to high accuracy rate when predicting the response. However, there is limited research focusing on this issue regarding ship operational performance monitoring. In recent years, there have been various statistical methods proposed to monitor ship operational performance. In this thesis, shrinkage methods and tree-based methods have been utilized for the ship operational performance monitoring (Soner et al., 2018a; Soner et al., 2018b). According to James et al., (2013) shrinkage methods, is one of two statistical learning methods that can provide more interpretable models from ordinary least squares (James et al., 2013). Tree-based methods can be used where parameters such as ship operational data are in a non-linear state. It guarantees to remove unnecessary and irrelevant variables (variable selection) to increase the accuracy of the prediction. (Ramezankhani et all., 2016). The next sub-sections give brief description about these methods (Soner et al., 2018a; Soner et al., 2018b).

4.1 Ridge and Lasso Methods

In the shrinkage methods, predicted efficiencies are regularized or shrunken toward zero when all the features are used to fit a model. Despite the negligible increasing in bias, shrinkage models can severely reduce a model variance. Hence, they enhance the overall performance of a model. Ridge regression and the Lasso are well known shrinkage models used in statically learning (James et al., 2013; Pereira et al., 2016, Lepore et al., 2017). Equation 4.1 for Ridge regression and equation 4.2 for Lasso are provided to describe technical background of models (James et al., 2013). In the equations, y_i defines the ith observation of the variable that is to be predcited, x_{ij} represents the value of the jth variable for the ith observation, where $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, p$; coefficients $\beta_0, \beta_1, \ldots, \beta_p$, RSS for the residual sum of squares, and λ is a tuning parameter ($\lambda \geq 0$).

As clearly depicted in the equations, the Ridge and the Lasso are modified version of the least squares. The modification is made by adding a penalty term to the objective function to regularize the estimated coefficients. In spite of the Lasso penalty based on the absolute coefficients ($\lambda \sum_j |\beta_j|$), the Ridge regression penalty term is depending on the squared coefficients ($\lambda \sum_j \beta_j^2$) (Hoerl and Kennard, 1970; James et al., 2013). Tuning parameter λ need to be selected with the fact that when $\lambda = 0$, the penalty term has not enough effect on the model. Therefore, it creates the least squares estimates, whereas as $\lambda \rightarrow \infty$, the impact of the shrinkage penalty grows, and the Ridge regression coefficient estimates will approach zero but not exactly to zero (unless $\lambda = \infty$) (James et al., 2013).

$$\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 = RSS + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{4.1}$$

On the other hand, the Lasso is a relative recent alternative to Ridge regression which tackles with disadvantage by forcing some of the estimated coefficient to be exactly equal to zero when the tuning parameter λ is sufficiently large (Tibshirani, 1996; James et al., 2013; Lepore et al., 2017). Hence, the Lasso is expected as a feature selection or variable selection model.

$$\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij}\right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| = RSS + \lambda \sum_{j=1}^{p} |\beta_j| \tag{4.2}$$

In the literature, there have been various models proposed with respect to the choosing a good value of λ, while it is a critical step for both methods (Pereira et al., 2016, Cule and De Iorio, 2012; Hastie et al.,2009). Cross-validation enables a quick way to handle this issue when comparing to the other techniques (James et al., 2013; Pereira et al., 2016). In this study, it is performed cross-validation error for each value of λ. Thereafter, it can be selected the tuning parameter value for which the cross-validation error is smallest (James et al., 2013).

4.2 Tree-Based Methods

Generally, in clustering and regression problems, tree based model approach can be used (Breiman, 1984; Dietterich, 2000). There are two basic main steps defined for a regression tree. While the predictor space is considered as the first one which is required to split district and non-overlapping, predictions are defined as the second step which are formed from the mean output values of the training monitoring falling into each section which might have any shape. Equation (4.3) states Residual Sum of Square (RSS).

$$RSS = \sum_{j=1}^{J} \sum_{i \in R_j} \left(y_i - \hat{y}_{R_j}\right)^2 \tag{4.3}$$

where $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, p$ ((n gives the number of data points; p states the number of variables), y_i denotes the response variable for the ith observation, $\hat{y}_{R_j}$ is the mean response for the training observations within the $j\,th$ region (James et al., 2013). In order to determine splitting points and splitting variables, recursive binary splitting is conducted (Maindonald and Braun, 2006; Lepore et al., 2017). In the first step, predictor X_j and the cut point s are determined for splitting the predictor space into the regions $\{X | X_j < s\}$ and $\{X | X_j \geq s\}$minimize the RSS. The pair of half-planes can be depicted as follows for any j and s.

$$R_1(j,s) = \{X | X_j < s\} \text{ and } R_2(j,s) = \{X | X_j \geq s\} \tag{4.4}$$

The value of j and s can be used to decrease the equation.

$$\sum_{i:\, x_i \in R_1(j,s)} \left(y_i - \hat{y}_{R_1}\right)^2 + \sum_{i:\, x_i \in R_2(j,s)} \left(y_i - \hat{y}_{R_2}\right)^2 \tag{4.5}$$

where $\hat{y}_{R_1}$ and $\hat{y}_{R_2}$is the mean response for the training observations in $R_1(j,s)$ and $R_2(j,s)$ sequentially (James et al., 2013). According to the James et al. (2013), the process can be kept going until some stopping criteria is reached. In this paper, the process is considered as continuing till region does not involve more than five observations. Although this process enables high prediction accuracy on the training set, a tree might over-fit the data. Hence, a good strategy is to grow an extensive large tree T_0, and then prune it back to get a subtree (James et al., 2013). There corresponds a subtree $T \subset T_0$ such that for each value of α

$$\sum_{m=1}^{|T|} \sum_{i:\, x_i \in R_m} \left(y_i - \hat{y}_{R_m}\right)^2 + \alpha|T| \tag{4.6}$$

is as small as possible (James et al., 2013). Here $|T|$ states the number of the terminal nodes of the tree T, R_m can be defined as the subset of predictor space corresponding to the mth terminal node, and $\hat{y}_{R_m}$ is the predicted response related with R_m (James et al., 2013). Complexity of subtree can be managed by tuning parameter α and it is quite applicable to the training data. Predcition of α can be performed by tenfold cross-validation. Final tree is $T_{\hat{\alpha}}$ (Friedman et al., 2001).

Bagging, random forest, and boosting

High variance can be considered as the major limitation of decision tree although it has some advantages. Averaging a set of observations reduces variance is calculated $\hat{f}^1(x), \hat{f}^2(x), \dots, \hat{f}^B(x)$ by using B separate training sets and average them to get a single low-variance statistical learning model adopting following equation.

$$\hat{f}_{\text{avg}}(x) = \frac{1}{B} \sum_{b=1}^{B} \hat{f}^b(x) \tag{4.7}$$

As the accessing the multiple training sets is rarely probable, it is not always applicable (James et al., 2013). At this point, bootstrap is capable of taking recurring samples from the single training data set. In this context, B different bootstrapped training data sets are created (James et al., 2013). Furthermore, the technique can be trained on the bth bootstrapped training set to obtain $\hat{f}^{*b}(x)$ and finally average all the predictions. Following equation is used.

$$\hat{f}_{\text{bag}}(x) = \frac{1}{B} \sum_{b=1}^{B} \hat{f}^{*b}(x) \tag{4.8}$$

The bagging method can take benefits of the bootstrap to produce various datasets from the original dataset. The random forest is also taking benefits of the bootstrap. Besides, the predictors of restricted random (i.e. $\sqrt{p}$) are considered to use at each split for décor-relating the trees in the random forest (James et al., 2013). On the other hand, the boosting method uses an extensive version of the original dataset to construct each tree. Equation (4.9) show aforementioned point.

$$\hat{f}(x) = \sum_{b=1}^{B} \lambda \hat{f}^{b}(x) \tag{4.9}$$

Shrinkage parameter λ slows the learning process. It is also called as learning rate. Hence, a wide range of shaped tree can be gathered by utilizing boosting. The shrinkage parameter (λ) and number of tress are determined by cross-validation in this paper. Whilst the slow learner statistical methods are adopted, the boosting will increase their accuracy when comparing to the bagging and random forest (James et al., 2013).

4.3 Performance Measure

To evaluate the statistical model performance, the use of a data set different from that used for the model is very important. The data must, therefore, be divided into two sizes: training and testing. The train data set is used for model training, and the model performance is evaluated using the test set. Fuel consumption and ship speed are model responses in this study and other variables are considered input variables. To guide the comparison of a similar study with Petersen et al., (2012a) and Petersen et al., 2012b), a root - mean - square error (RMSE) was adopted. It is also a convenient measure for the performance of statistical methods and provides a common basis for these studies. The RMSE calculated according to equation 4.10.

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{f}(x_i))^2}{n}} \tag{4.10}$$

Each where, y_i denotes the *ith* observation of the variable, $\hat{f}(x_i)$ gives prediction that $\hat{f}$ states for the ith observation and n is the number of samples (Soner et al., 2018a; Soner et al., 2018b).

5. MODELING OF SHIP PERFORMANCE MONITORING SYSTEM

Mentioned advanced statistical models and collected dataset are analyzed in this section. The following sub-section provides detailed explanation about the practical application of the methods.

5.1 Practical Application of Shrinkage Methods

The Ridge and Lasso models are applied by utilising the dataset collected from the ferry. Since choosing the tuning parameter is a fundamental part of the two methods, the tenfold cross-validation is utilized. STW corresponding mean square error of the setting parameters for Ridge and Lasso model are presented in Figure 5.1. (Soner et al., 2018b).

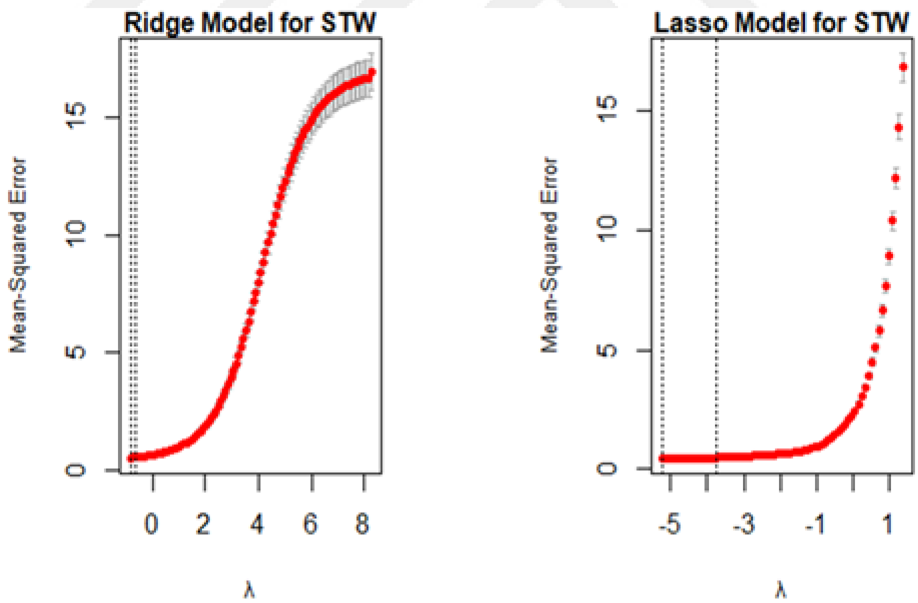

Figure 5.1 : MSE across tuning parameter of STW for Ridge and Lasso.

Table 5.1 presents the number of features that shown in the shrinkage models. The changes in the coefficients according to the tuning parameter are shown in Figure 5.2 and Figure 5.3 for the Ridge and Lasso regression when predicting fuel consumption. Although most of the features do not have an important value, it makes it difficult to interpret the model, all features are shown in the Ridge regression model (Soner et al., 2018b).

Table 5.1 : Number of the features in the shrinkage models.

No	Features	No	Features
1	Derivative of crosswind	15	Trim
2	Derivative of headwind	16	Heeling
3	Variance crosswind	17	Starboard level
4	Port rudder	18	Starboard rudder
5	Derivative of starboard level	19	Variance of starboard level
6	Derivative of port level	20	Derivative of port pitch
7	Derivative of trim angle	21	Crosswind
8	Variance of headwind	22	Headwind
9	Variance of port pitch	23	Port level
10	Draft	24	Variance of port level
11	Variance of starboard rudder	25	Variance of port rudder
12	Variance of starboard pitch	26	Port pitch
13	Derivative of starboard pitch	27	Starboard pitch
14	Variance of trim angle		----

According to the figure 5.2; the derivative of headwinds, derivative of crosswind, derivative trim angle and variance of trim angle significantly affects the ship performance regarding fuel consumption in the Ridge regression. For instance, derivative of trim angle, it requires extraordinary consideration during a voyage. Trim angle is very important to ensure maximum fuel efficiency because the vessel must know the exact trim to keep it in the narrow and optimum trim range. Otherwise, fuel consumption will increase drastically (Soner et al., 2018b).

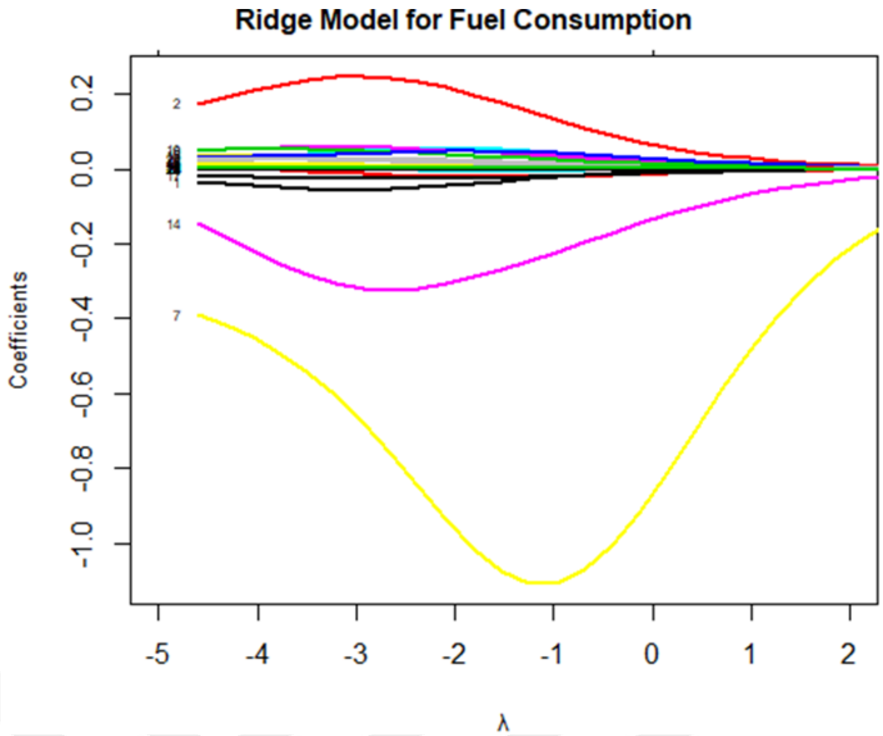

Figure 5.2 : Influence of λ on the estimated coefficients for Ridge model for fuel consumption.

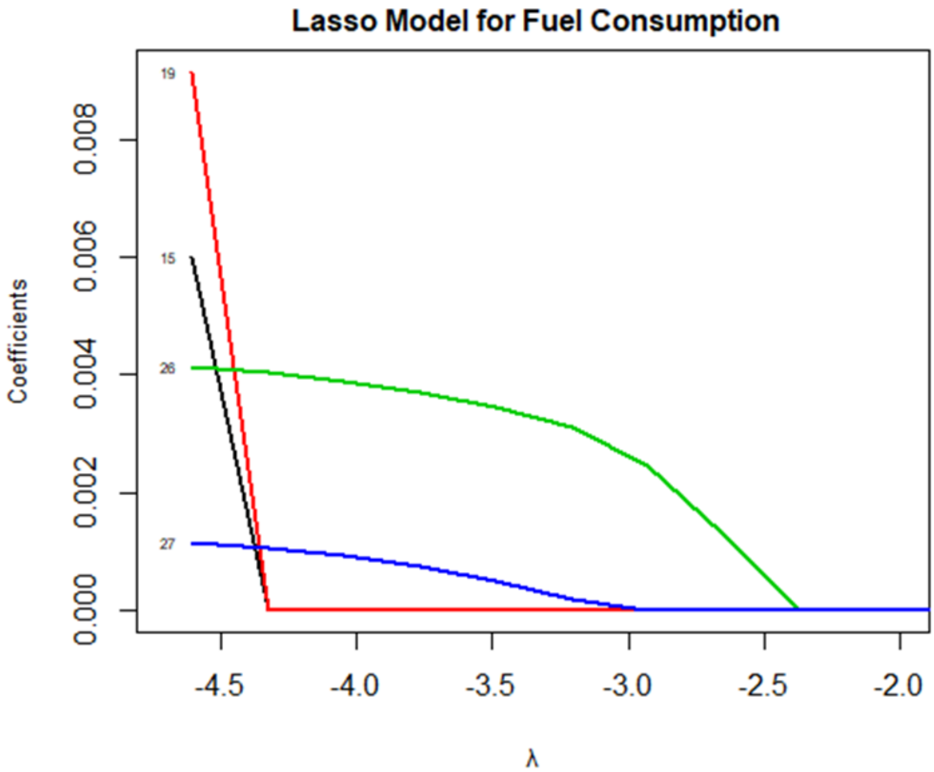

Figure 5.3 : Influence of λ on the estimated coefficients for Lasso model for fuel consumption.

On the other hand, the Lasso model chose only a few features and provided a better interpretable model. The Lasso model coefficients are presented in Figure 5.3. As portrayed in the figure, it uncovers that change of variance of starboard level, trim, port pitch and starboard pitch considerably affect ship operational performance. The variance of starboard level has a remarkable effect on reducing fuel consumption. The variance of starboard level is measured from the special automatic data acquisition system that installed in starboard draft marks. In parallel with the increasing the resistance and decrease speed through the voyage, they have a considerable effect on the fuel consumption of the ship. Trim is also a vital parameter that influences ship operational performance. The point of the optimum trim on-board ship is to lessen the resistance of sea water or increment the all-out productivity so as to pick up from trimming. The optimal trim for the vessel is the trim angle in a particular case where the desired propulsion power is lower than the other trim angles in this case (Abouelfadl and Abdelraouf, 2016).

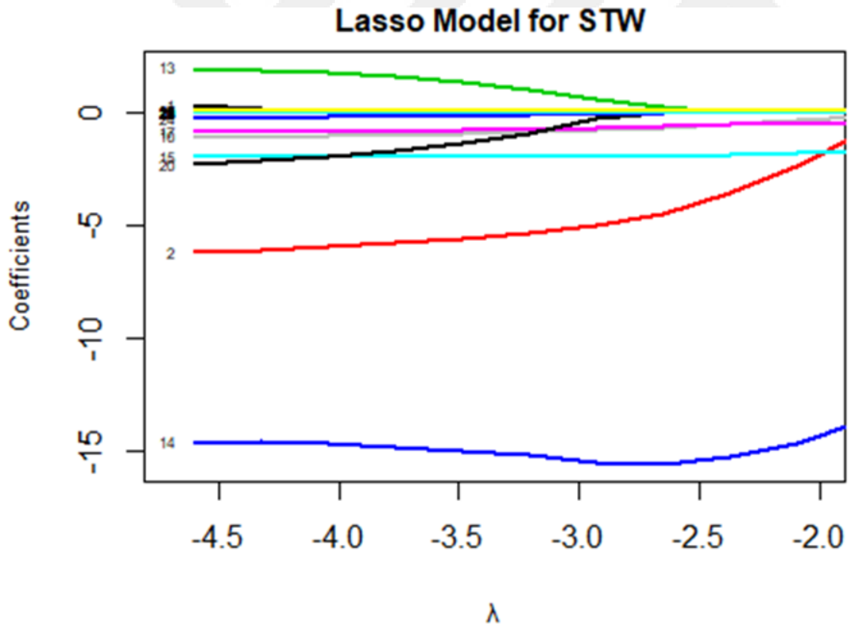

Figure 5.4 : Influence of λ on the estimated coefficients for Lasso model for speed.

Furthermore, the figure 5.4 and figure 5.5 shows the changes in coefficients when predicting ship speed. Derivative of headwind, derivative of starboard pitch and variance of trim angle appears to have significant effects on ship speed during ship operational performance monitoring with regard to Lasso and Ridge models (Soner et al., 2018b).

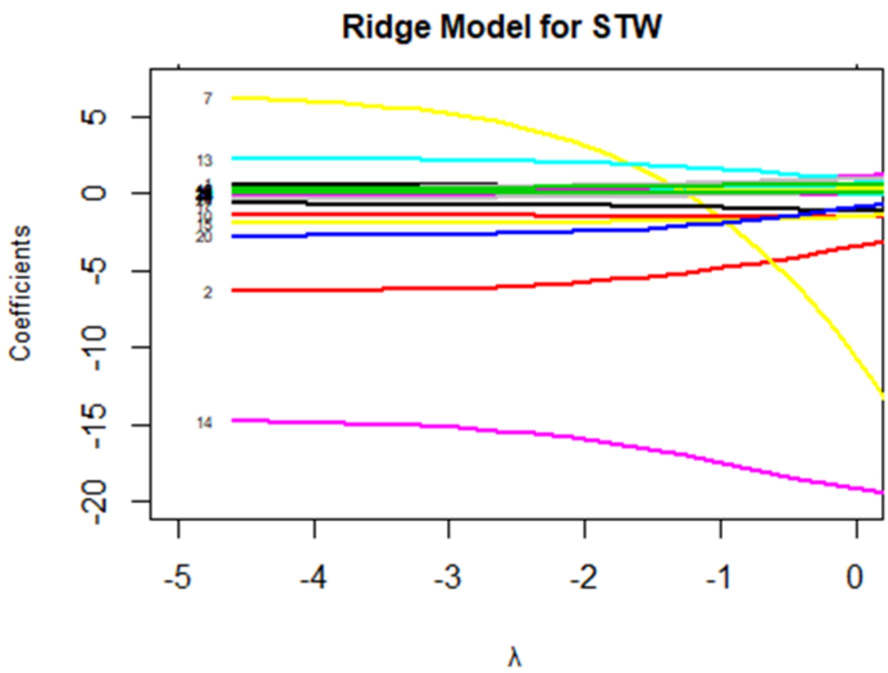

Figure 5.5 : Influence of λ on the estimated coefficients for Ridge model for speed.

The headwind derivative has a negative impact on the speed of the ship as the headwind blows against the travel direction. The headwind reduces the speed of the ship and increases the time needed to reach the port of arrival. Due to the lateral movement of the ship caused by cross currents, the starboard pitch also reduces the ship's speed. Another paramount feature is the variance of the trim angle, which can reduce the ship's speed, since trimming the ship by bow will increase the resistance in general (Soner et al., 2018b).

5.2 Practical Applications of Tree-Based Methods

Firstly, training data set is used to predict STW based on heeling, crosswind, headwind, trim, draft, port pitch, and starboard pitch to illustrate the regression tree. Figure 5.6 shows a regression tree fitting the training data. It consists of a series of rules splitting from the top of the tree. The regression tree only demonstrates the features that meet the splitting conditions. The top split assigns observations having starboard pitch <55 to the right branch, and smaller to the left. Observations with greater than starboard pitch >55 are also further subdivided by starboard pitch <81. Moreover, headwind and starboard pitch are also subdivided on the left branch. Overall, the tree has stratified or segmented speed into six predictor space regions. The regions are known as terminal nodes or tree leaves in accordance with the tree analogy.

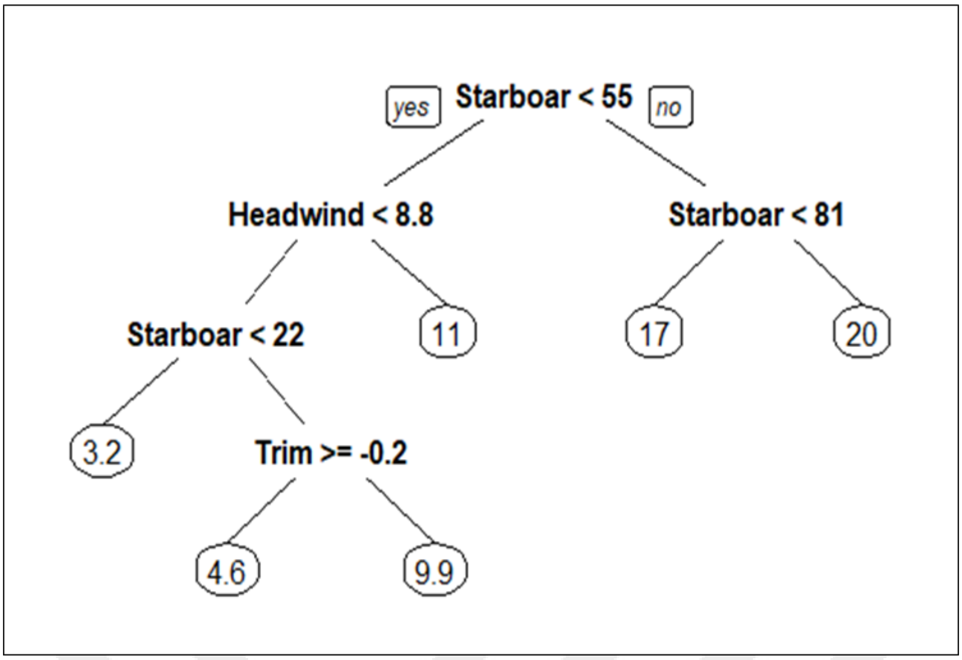

Figure 5.6 : Regression tree analysis for the STW.

In order to monitor ship operational efficiency, tree-based models have been performed on high-frequency ship operational data. In addition to the high predictive accuracy, the most important operational efficiency variables are also revealed by the models used. The results of the models were compared with each other and similar studies in order to demonstrate the performance of the bagging, random forest and bootstrap on the ship's operational performance monitoring. Figure 5.7, Figure 5.8 and Figure 5.9 thus illustrate the variable importance of bagging, random forest and bootstrap for speed through water (Soner et al., 2018a).

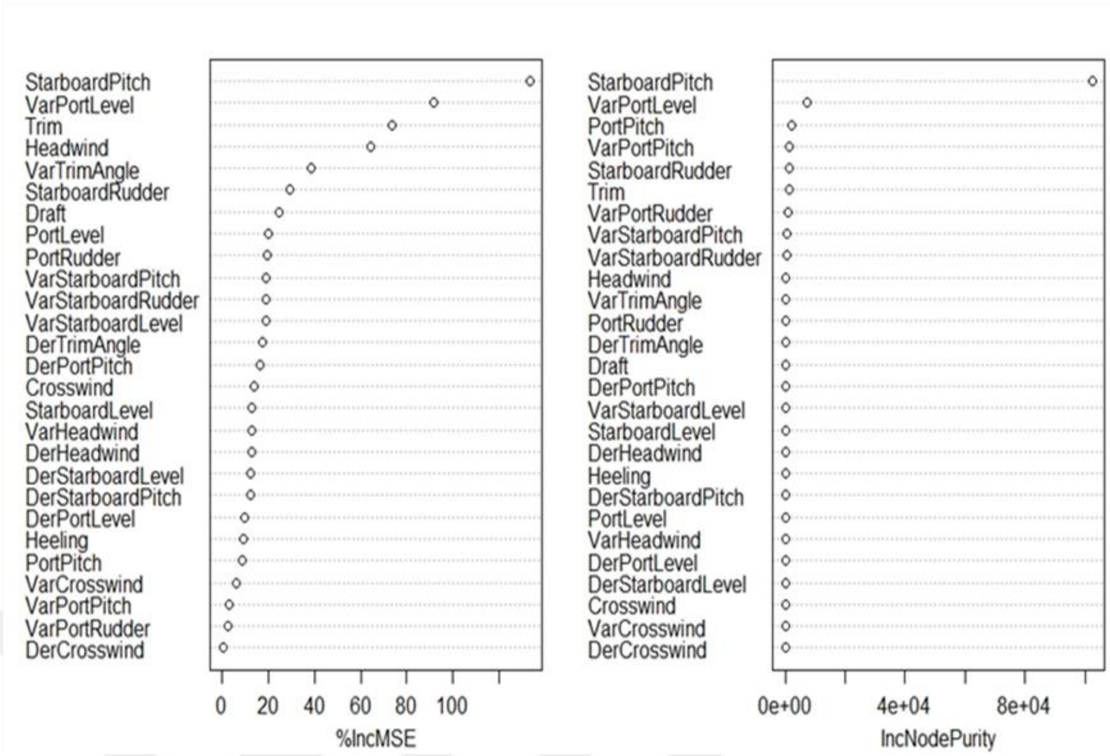

Figure 5.7 : Variable importance assigned by bagging.

Depending on the bagging model, the most critical variables for the % IncMSE are the starboard pitch, trim, headwind, starboard rudder and draft. According to IncNodePurity, the pitch and rudder of port and starboard are the most important variables in Figure 5.7 and Figure 5.8. Headwind, trim, port and starboard pitch are of paramount importance according to Figure 5.7. In Figure 5.8, on the other hand, the the starboard and port pitch as well as trim has a significant effect on ship operational performance. In particular, ship trim poses major challenges in monitoring the performance of ship operations (Soner et al., 2018a).

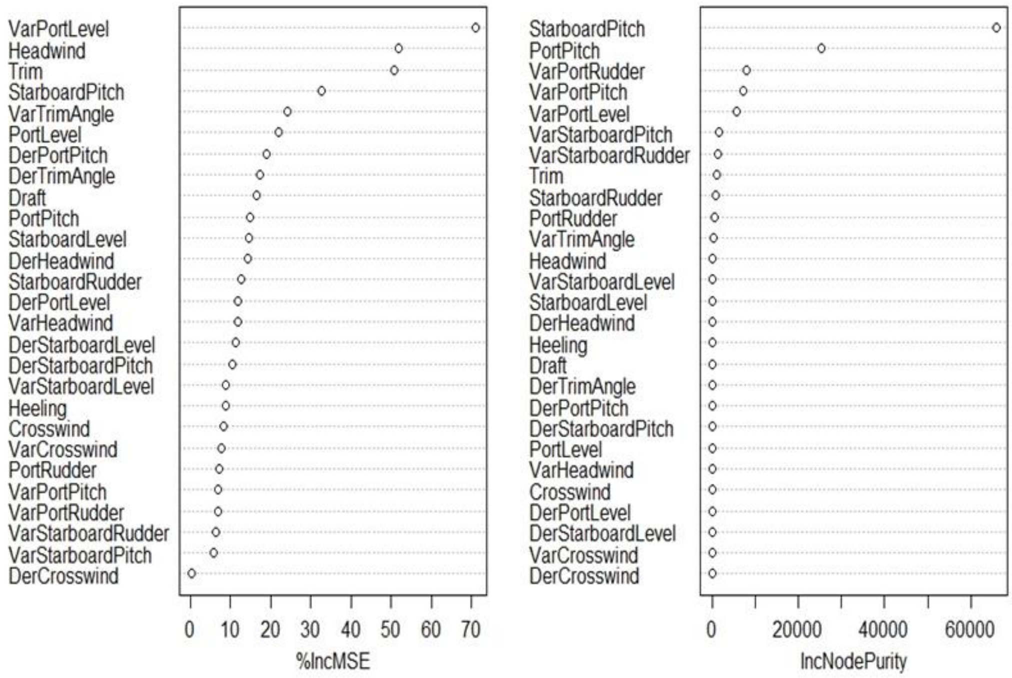

Figure 5.8 : Variable importance assigned by random forest.

The impact of trim optimization plays an important role in reducing fuel consumption, as it reduces sea water resistance and increases overall efficiency. Starboard and port pitches also have a significant impact on fuel consumption. The main engine of the ship is started with a pitch of the blade set at zero, which can increase fuel consumption. Reduce the load on different engine rolls and shafts if the vessel is equipped with controllable pitch control (Soner et al., 2018a).

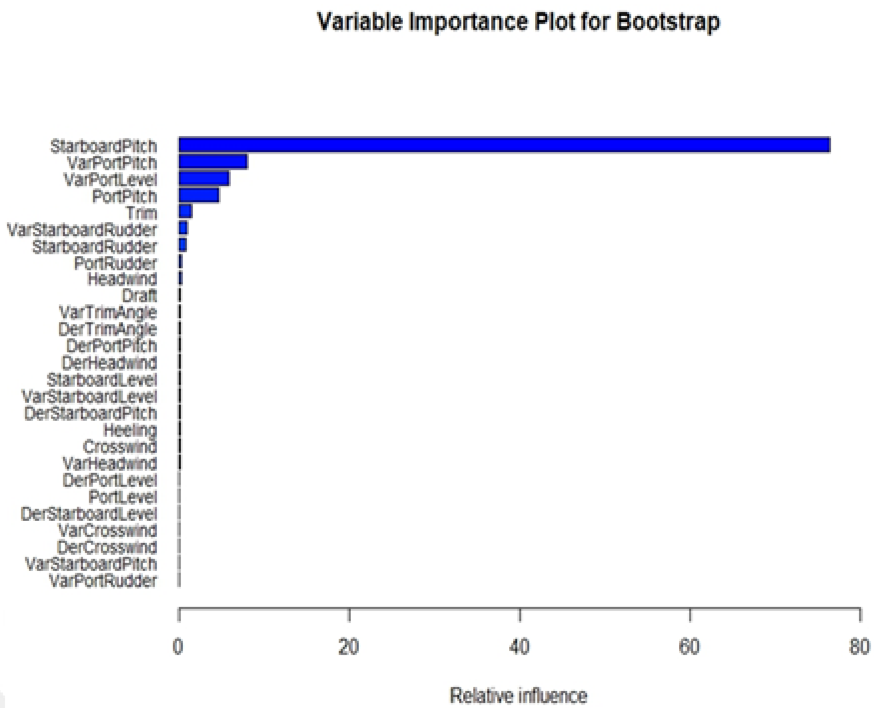

Figure 5.9 : Variable importance assigned by bootstrap.

5.3 Performance Measure of the Applied Methods

The test data sets are used to assess the performance of the model. Figure 5.10 and Figure 5.11 therefore illustrate the predicted vs. ship speed and fuel consumption for Lasso and Ridge models. The performance of the model is then checked by the test dataset. Table 5.2 shows the RMSE for all the models that have been utilized. (Soner et al., 2018a; Soner et al., 2018b).

Table 5.2 : RMSE for utilized methods.

Models	RMSE for Speed (kn)	RMSE for Fuel (L/h)
Bootstrap	0,32	41,3
Random Forest	0,34	43,5
Bagging	0,35	45,2
Lasso	0,45	44,6
Ridge	0,52	48,7

After comparative analysis of the ship's speed and fuel consumption with the Ridge and Lasso models, three main features are highlighted: Trim, starboard and port pitch and headwind and crosswind. In other words, trim, pitch and wind are prominent. The different configuration of the trim and pitch have a significant impact on the fuel consumption of ships, as the analysis findings show (Soner et al., 2018b).

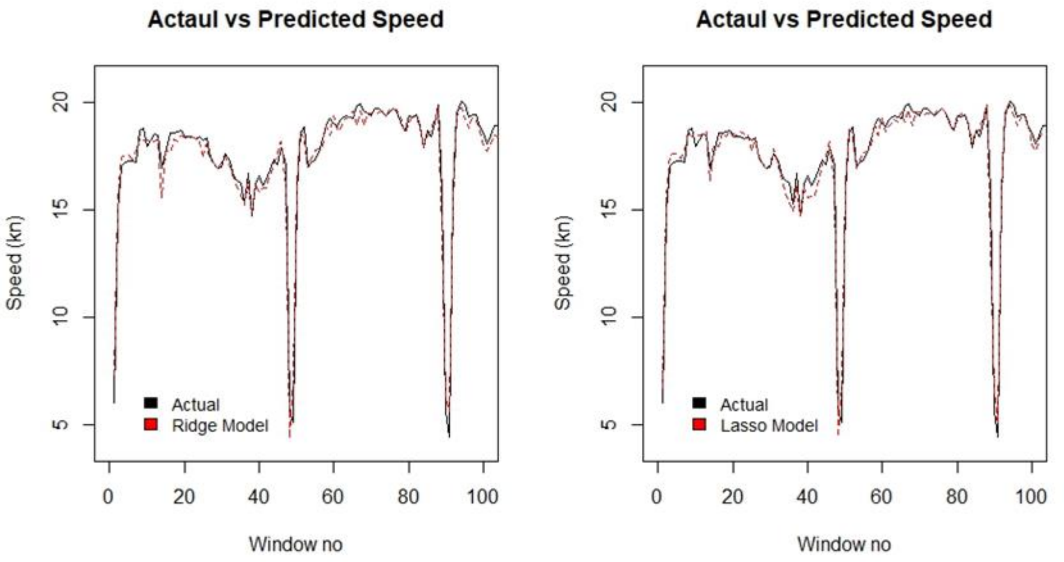

Figure 5.10 : Actual vs predicted speed for Lasso and Ridge models.

The optimum trim and pitch on-board ship is to minimize the resistance of sea water and improve overall performance, in particular ship speed. Therefore, the lowest fuel consumption is provided for the trim and pitch. In the light of comparative analysis of the ship's operational performance, the results show that efficient ship performance depends on the operation and environmental condition.

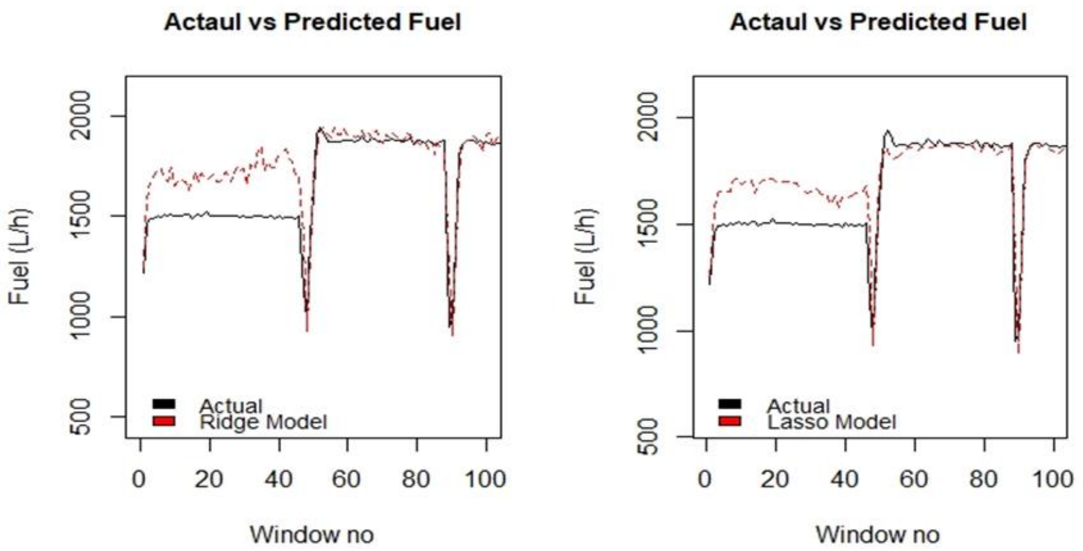

Figure 5.11 : Actual vs predicted fuel for Lasso and Ridge models.

Figure 5.12 also shows the predicted and actual water speed values for the tree-based models. Bootstrap performed far better results compared to other tree-based models, according to Figure 5.12 (Soner et al., 2018a).

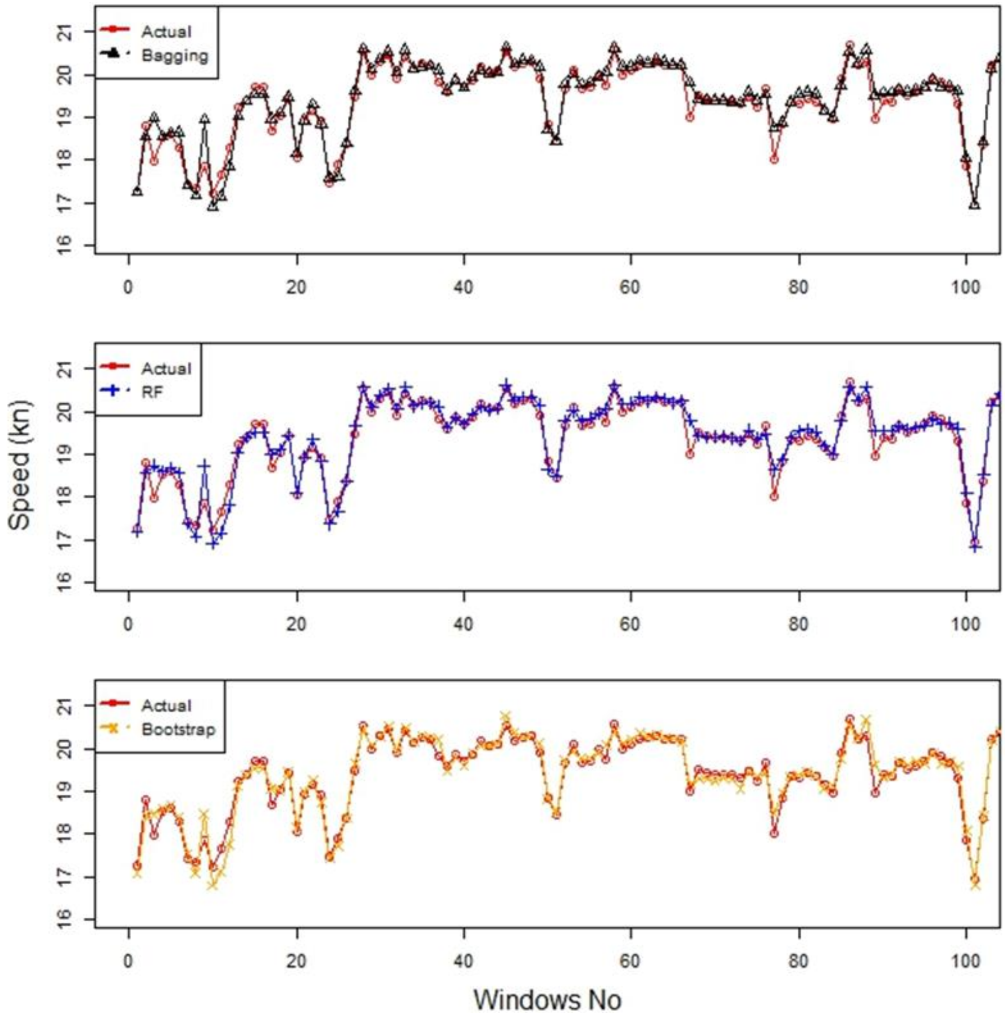

Figure 5.12 : The predicted versus actual STW for tree-based models.

As shown in the figure, the bootstrap provides a predictive rate more accurately than bagging and random forest (Soner et al., 2018a).

5.4 Comparison with the Similar Studies

The results of the study can be compared with similar studies, such as Petersen et al. (2012a); Petersen et al. (2012b), since they are based on the same dataset. Study performance of Petersen et al., (2012a); ANN speed 0.32 and fuel 41.1 and GP speed 0.76 and fuel 51.4 RMSE. In addition, the performance results of Petersen et al. (2012b) using the instantaneous ANN speed model are 0.38 and 47.2 for fuel RMSE.

Moreover, the current relative error in fuel consumption for ANN models is 1.50 percent, and 1.87 percent for the GP (Petersen et al., 2012a). The present relative error in the fuel consumption of Bootstrap model is 1.50 percent, and 1.77 percent for the Ridge model. This means that average consumption of the ship is predicted as a 2753 liters of fuel per hour by the Bootstrap model with an error rate 41.3. Compared to the other studies, Lasso and Ridge models provided a competitive accuracy rate. In addition, they provide a better rate of accuracy compared to the GP. Since instantaneous ANN and ANN provide a high precision rate rather than explain the relationship between the features, their ability to improve operational performance is limited in interference. On the other hand, the model used in the thesis can be a selection of features that provides a relatively high rate of accuracy and, more importantly, indicates the relationships between the features. The proposed model can therefore be used as a decision support system for the efficiency of ship operation.

On the other hand, tree - based models provide nearly the same result (bootstrap) as other studies. Because tree - based models allow variable selection (variable sequences of importance), they have a great advantage over similar studies.

6. CONCLUSIONS AND RECOMMENDATIONS

In order to save fuel consumption, ship management companies are interested in ship operational efficiency (Yu et al., 2017). As the cost of fuel has a major impact on ship management sustainability, fuel efficiency becomes a priority. Moreover, reducing the air pollution caused by ship is one of the paramount objectives of IMO. The Annex VI under the MARPOL convention requires energy efficieny and performance enehancement of ship. In recent decades, advanced data analytics, digitalization, and big data have gained enormous momentum in the maritime industry to improve ship operational efficiency (Gracia et al., 2017; Thun et al., 2017). Since the optimisation of ship operations begins with the monitoring of ship operational performance, the study aims at presenting statistical modelling which is adopting shrinkage and tree-based models for ship operational performance monitoring (Soner et al., 2018a; Soner et al., 2018b).

6.1 Conclusion

Monitoring the operational performance of ships is essential to improve the energy efficiency of ships in the maritime sector. This study adopts statistical methods for monitoring ship operational performance, including shrinkage and tree-based methods. The strength of the methods lies behind the theories that allow not only the complexity of the model to be minimized, but also the usual sum of square errors, which are limited to the sum of the absolute coefficients. The utilized dataset has been previously analysed for the ship propulsion efficiency and trim optimization by the Petersen et al. (2012a) and Petersen et al. (2012b). The dataset was gathered from ferry ship which performed consecutives voyages in two months' periods. The automatic data acquisition system (sensors) was installed to the ship to obtain the real ship operational data. The numerical parameters were measured with the sensor such as ship speed, wind, fuel density, fuel temperature, port propeller pitch, true heading, etc (Soner et al., 2018a; Soner et al., 2018b).

The shrinkage models (the Ridge and Lasso) allow to minimize the complexity of the model and improve interpretability when compared to current non - linear models in the view of the test dataset. The models based on the tree have considerable superiority since the models provide a high rate of accuracy. The concept of tree - based models is used in the study; bagging, random forest and bootstrap are used and the bootstrap provides the most precise prediction rate than the others.

The test data set results show that the starboard pitch, port pitch and trim have significant effects on the performance of the ship. In particular, ship trim poses great challenges in monitoring the operational performance of ships. The impact of trim optimization plays an important role in reducing fuel consumption, as it reduces marine water resistance and increases overall efficiency. Starboard and port pitches also have a significant impact on fuel consumption. The main ship engine starts with a pitch of the blade set to zero. This can increase fuel consumption and reduce the load on different engine bearings and shafts if the vessel is equipped with controllable pitch control (Soner et al., 2018a; Soner et al., 2018b).

Since the ultimate objective of ship performance monitoring is to improve the operational efficiency of the ship, the proposed model should also provide the information required for the inference. The proposed methods would improve the operational efficiency of the ship in view of the findings. As a result, the identification of the best model depends on the user perspective and motivation, as statistical learning approaches can be used for prediction and interference (Soner et al., 2018b).

6.2 Recommendation for Future Studies

Although parameters affecting ship operational performance pose a serious challenge to ship management companies, future research can be extended to include an interface design to transform the instant monitoring features into control actions from the point of view of ship operational performance. The proposed models for the monitoring of ship performance can be extended to DSS in order to develop a practical ship performance management concept. In addition, the proposed methods could also be extended to other logistics and maritime systems. The task of data acquisition is achieved in research-oriented studies at this stage, while existing ships still have major challenges on board. On the other hand, statistical analysis is being used to determine and implement measures to improve performance in real time. Further studies can be carried out on data acquisition and control measures.

In addition, since the statistical learning methods learn from the data set used, the use of the additional variables could improve the ability of the model. The requirement for long-term data collection also limits the efficiency of the model. Therefore, additional variables with long-term data collection should be considered in order to obtain more accurate and efficient modelling (Soner et al., 2018c).

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