

Decision Support Tool for the Tanker Second-hand Market Using Data Mining
Techniques

by

Athanasios A. Karaindros

M.S. Mathematics
University of Rhode Island 1998

B.S. Mathematics
Brandeis University 1997

SUBMITTED TO THE DEPARTMENT OF OCEAN ENGINEERING IN PARTIAL
FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE IN OCEAN SYSTEMS MANAGEMENT
AT THE
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

SEPTEMBER 2005

© 2005 Athanasios A. Karaindros. All rights reserved.

The author hereby grants to MIT permission to reproduce
and to distribute publicly paper and electronic
copies of this thesis document in whole or in part.

Signature of Author: _____

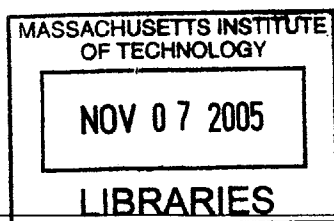
Department of Ocean Engineering
August 31, 2005

Certified by: _____

Henry S. Marcus
Professor of Marine Systems
Thesis Supervisor

Accepted by: _____

Lallit Anand
Professor of Mechanical Engineering
Chairman, Committee for Graduate Students



BARKER

Decision Support Tool for the Tanker Second-hand Market Using Data Mining
Techniques

by

Athanasios A. Karaindros

Submitted to the Department of Mechanical and Ocean Engineering
On August 31, 2005 in Partial Fulfillment of the
Requirements for the Degree of Master of Science in
Ocean Systems Management

ABSTRACT

This thesis proposes an innovative decision support tool intended for market leaders and those anticipating market states of “sale and purchase”. This is feasible with the use of powerful data mining techniques and the construction of explanatory forecasting models. Data mining techniques seek and extract patterns from databases. These patterns can be used to reveal possible interactions between database variables and to predict values for future “sale and purchase” market states as an aid to decision-making. Possible users of such a tool are ship brokers, ship owners, shipyards and general brokers and investors. It is crucial to mention the rising need for decisional tools especially when asset play in shipping seems to increase its proportion among other investment practices.

Thesis Supervisor: Henry S. Marcus
Title: Professor of Ocean Systems

ACKNOWLEDGEMENTS

Throughout the time I have spent in researching, structuring and writing my thesis, a couple of people have taken an interest in my work. I would like to take this opportunity to acknowledge the assistance of these people.

Dr. Henry S. Marcus, acting as my supervisor for the project. I have been able to make great use of his valuable knowledge and ideas. My supervisor was always willing to advise and assist me.

Dr. Nicholas M. Patrikalakis for his help, belief and encouragement throughout the difficult times.

Individuals, who prefer to remain anonymous, from: the Drewry Shipping Consultants, the Lloyds' Group, the Clarksons Research Group, Allied Shipbrokers and AK Shipping & Trading.

Mr. Sydney Levine of Shipping Intelligence.

All the staff in the Department of Ocean Engineering for their support and help.

Finally, I would like to thank my family and friends for their continued understanding, support and encouragement throughout all these years.

CONTENTS

1	INTRODUCTION	10
1.1	GENERALITIES	10
1.2	CHARACTERISTICS OF TANKER SECOND-HAND MARKET	12
1.3	PROBLEM DEFINITION – REPORT STRUCTURE.....	13
2	METHODOLOGY	15
2.1	DATA COLLECTION	15
2.2	DATA PREPROCESSING.....	18
2.3	DATA ANALYSIS AND MODEL DEVELOPMENT	25
3	IMPLEMENTATION RESULTS	27
3.1	ZERO MONTH MODEL.....	27
3.1.1	Form of the Zero Month Model.....	27
3.1.2	Evaluation of the Zero Month Model	29
3.2	SIX MONTHS MODEL	35
3.2.1	Form of the Six Months Model.....	35
3.2.2	Evaluation of the Six Months Model.....	37
4	DECISION SUPPORT TOOL - A CASE STUDY	43
4.1	DECISION SUPPORT TOOL DEFINITION	43
4.2	CASE STUDY.....	44
5	CONCLUSIONS	47
5.1	SUGGESTIONS FOR FURTHER RESEARCH.....	48
	APPENDIX A: NAMES FILES	50
1	ZERO MONTH MODEL	51
2	SIX MONTHS MODEL.....	52
	APPENDIX B: RESULT FILES	53
1	ZERO MONTH MODEL	54
2	SIX MONTHS MODEL.....	62
	APPENDIX C: STATISTICAL ANALYSIS RESULTS.....	70
1	DESCRIPTIVE STATISTICS	71
2	CORRELATIONS.....	72
	REFERENCES	74

LIST OF TABLES

Table 1: Descriptive Statistics for Vessels Characteristics 18
Table 2: Descriptive Statistics for Tanker 5 Years Old Average Price in \$/DWT 21
Table 3: Correlations 23
Table 4: Correlations 29
Table 5: Correlations 36
Table 6: Case Study Results 46

LIST OF FIGURES

Figure 1: The Age Profile of the Tanker Vessels	19
Figure 2: The Tonnage Profile of the Tanker Vessels	19
Figure 3: The Tonnage Profile of the Tanker Vessels	20
Figure 6: The Zero Month Model Fit on the first 20 Training Cases of Tanker Vessels.....	30
Figure 7: The Zero Month Model Fit on the next Training Cases of Tanker Vessels.....	30
Figure 8: The Zero Month Model Fit on the next Training Cases of Tanker Vessels.....	31
Figure 9: The Scatter Plot for Zero Month Model Fit on Training Cases of Tanker Vessels	32
Figure 10: The Zero Month Model Fit on 20 First Testing Cases of Tanker Vessels.....	33
Figure 11: The Zero Month Model Fit on 20 Next Testing Cases of Tanker Vessels.....	33
Figure 12: The Zero Month Model Fit on 20 Next Testing Cases of Tanker Vessels.....	34
Figure 13: The Scatter Plot for Zero Month Model Fit on Testing Cases of Tanker Vessels	34
Figure 14: The Six Month Model Fit on 20 First Training Cases of Tanker Vessels	37
Figure 15: The Six Month Model Fit on 20 Next Training Cases of Tanker Vessels	38
Figure 16: The Six Month Model Fit on 20 Next Training Cases of Tanker Vessels	38
Figure 17: The Scatter Plot for Six Month Model Fit on Training Cases of Tanker Vessels	39
Figure 18: The Six Month Model Fit on 20 First Testing Cases of Tanker Vessels	40
Figure 19: The Six Month Model Fit on 20 Next Testing Cases of Tanker Vessels.....	40
Figure 20: The Six Month Model Fit on 20 Next Testing Cases of Tanker Vessels.....	41
Figure 21: The Scatter Plot for Six Months Model Fit on Testing Cases of Tanker Vessels	41

Synopsis

What is the main issue in the tanker second-hand market? To sell or purchase at the right price, at the right time. To accomplish both goals seems rather difficult especially in the chaotic and volatile system of the world shipping market. The common practice is to use expertise and information in order to follow market trends and stay at the safe side of revolution.

This thesis proposes an innovative decision support tool intended for market leaders and those anticipating market states of “sale and purchase”. This is feasible with the use of powerful data mining techniques and the construction of explanatory forecasting models. Data mining techniques seek and extract patterns from databases. These patterns can be used to reveal possible interactions between database variables and to predict values for future “sale and purchase” market states as an aid to decision-making. Possible users of such a tool are ship brokers, ship owners, shipyards and general brokers and investors. It is crucial to mention the rising need for decisional tools especially when asset play in shipping seems to increase its proportion among other investment practices.

The report will be structured as follows: the first chapter will introduce past research papers in this cognitive field. It is essential to show research innovation and to mention the relative references, and the sources of the data and information. The tanker market will be described with an emphasis on “sale and purchase”. It is crucial to reveal all possible interactions between tanker vessel prices and market state variables such as time charter rates, steel prices etc. Using expert judgment, an initial explanatory model will be constructed in order to build the final database and a function approximation model.

Data pre-processing will take place at the second chapter. By using descriptive statistics methods, we’ll try to define the following:

- final database
- independent and dependent variables
- form of the explanatory forecast model,
- forecast time span and step,
- training, testing and cross validation dataset

Relations among the various parameters as well as between their current and past values or their moving averages are sought out through the calculation of the Pearson correlation coefficient. The main scope is to transfer the biggest proportion of necessary information from the data through the model to the dependent variable and at the same time avoid multicollinearity and congestion problems.

The second chapter will describe and show the application of the methodology (data mining technique). The appropriate variables are then chosen and rule based, piecewise linear, multivariate models are developed in the form of trees using recursive partitioning of the training data set. The explanatory model will be fitted on training data and evaluated with data, out of training sample, using performance criteria. It is crucial to prove goodness of forecast and the ability to generalize. This is a critical issue and it is up to the modeller’s ability to avoid overtraining and achieve generalization.

In the third chapter the results will be presented among with various criteria in order to evaluate model accuracy. After the training and testing process, it is common practice to present the results.

A Decision Support Tool (DST) will be presented in the fourth chapter and applied into predetermined cases. It is very significant to describe the utility and ascendancy of the proposed DST. Various criteria will be assessed in order to evaluate DST.

The conclusions of the report will be presented in the fifth chapter along with suggestions of future research directions.

1 INTRODUCTION

1.1 Generalities

The transportation of bulk liquids by sea generally requires the use of the tankers. The main types of tankers are for the transport of oil products, crude oil, chemicals, wine, molten sulphur or liquid gas.

Oil tankers form by far the largest fleet of specialist bulk vessels. The tanker fleet can be usefully subdivided into six segments: Handymax (10-50,000 dwt), Panamax (50-70,000 dwt), Aframax (70-100,000 dwt), Suezmax (100-200,000 dwt), VLCC (200-300,000 dwt) and ULCC (300,000 dwt). Each of these segments operates as a separate market, and from a ship design viewpoint, each has its own specific requirements. Tankers under 50,000 dwt are mainly operated for the transport of oil products and larger vessels for the transport of crude oil.

There are two different designs for oil tankers, single hull and double hull. Until 1990 almost all crude oil tankers had a single skin, using the hull as the main containment vessel and in 1996, 86% of the tanker fleet was single hull. IMO Regulation 13F required tankers ordered after July 6, 1993 to be of double hull construction as a protective measure against oil loss. The regulation laid down precise rules regarding the width of the double side and double bottom, but the principle was simple enough. There must be a second skin to limit the outflow of oil in the event of collision damage to the outer hull.

Cargo handling is an important aspect of tanker design. Rapid loading and discharge requires powerful pumps. Crude oil tankers rely on shore based facilities for loading, but carry their own cargo pumps for discharge. The pump room is generally located between the cargo tanks and the engine room. A network of pipes run along the deck, linking the cargo tanks to two banks of manifolds, one on each side of the ship. To load or discharge cargo, the manifolds are connected to the shore based pipe system by flexible hoses, which are handled by the ship's cranes. The flow of oil is controlled by valves operated from a control panel on the bridge and must conform to a plan which minimizes stress on the hull. Note that an incorrect load or discharge sequence can literally sink the vessel. Having introduced the market for tanker vessels, we are going to concentrate more on the pricing of tanker vessels rather than their special characteristics and design.

Vessel prices and their movements over time are of great importance to shipowners taking decisions regarding the purchase and sale of vessels. As Stopford (1997) notes, 'Typically, second-hand prices will respond sharply to changes in market conditions, and it is not uncommon for prices paid to double, or halve, within a period of a few months.' Furthermore, investors in the shipping industry rely not only on the profits generated from shipping operations, but also on capital gains from buying and selling

merchant vessels. In fact, some investors consider the latter activity more important than the former one since correct timing of sale and purchase can be highly rewarding compared to operating the vessel.

Shipping is a very volatile and risky market, while shipping cycles and speculative investments, in the newbuilding and S&P markets, compound the industry's volatility. A shipowner's goal in the shipping industry is to improve overall performance, that is to maximize profits (or minimize costs) at an acceptable level of risk. This goal can be achieved by developing and implementing effective investment and chartering strategies. Successful strategies require selecting the right mix of assets. A combination of owned tonnage, long term contracts (time chartered tonnage or contracts of affreightment), short term coverage (spot market, consecutive voyages), as well as positions in the paper (derivatives) markets constitute the mix of assets that the shipping market agent has to decide upon in designing a successful strategy.

As market volatility increases, flexibility to react becomes more important. The design and implementation of a robust strategy for investment management and risk control is a highly complicated task in a cyclical and volatile market, like bulk shipping. It requires detailed and continuous market and risk analysis to detect market trends early on, and to incorporate them in the appropriate strategy decisions. The key factors of any strategy in the shipping industry are: (a) Timing of making an investment; (b) Asset mix that is the split between short and long term contracts, as well as the distribution of assets across market segments; and (c) Management of the inherent volatility of shipping markets, and the uncertainty around market forecasts.

It is argued that because vessels are the main asset which ship-owners hold in order to provide their freight service to the market, and since the sums involved in holding these assets are the largest item in the ship-owner's cash-flow, changes in their values can make all the difference in terms of ending up with a profit or loss from their investments in the shipping sector. Often the contribution of asset play to the balance sheet is greater than operation of the vessel itself. The timing of the investment decisions is extremely important. Investors which have exercised successfully the "*buy low – sell high*" principle in the vessel's markets have ended up with hefty bank balances at the end of the day. A large number of ship-owners/companies rely on these (vessel) transactions to make a profit in the sector. Others make a loss, and fall substantially out of business, as the sums involved are large. For example, investors are only able to exploit correct anticipations of market upturns in the vessel value market. Thus, they would buy a vessel at a certain time period and wait until vessel prices increased to sell the vessel at a higher price. If prices fell they would make a loss.

The future development of second-hand tanker prices is investigated based on the assessment of their relationships to tanker freight rates and scrap values. The development of prediction models for future values of second hand prices based on freight rates and scrap values is the product of the project's investigation and the main intention of this study.

In detail, the thesis is divided into five chapters:

- The introduction that describes second hand market and defines the problem;
- The methodology chapter where pre-processing takes place along with the data mining technique, definition and implementation. The explanatory models are developed, trained, and tested;
- The results chapter where methodology output is presented and evaluated with various criteria.
- The Decision support tool and the case study chapter. In this chapter, the tool is described and presented through a case study.

The present document is an innovative research attempt to model the second-hand market and provide a useful tool to every party involved in tanker vessel brokerage. The innovation of this thesis, is that it is a first attempt at analyzing and predicting the second-hand tanker market using explanatory models and specifically data mining techniques.

1.2 Modelling Ship Prices and Characteristics of the Second-hand Tanker Market

The objective of the thesis is to analyze the second-hand tanker market and produce a decision support system. In order to achieve this, a sedulous market study is necessary. It aims to reveal all crucial interactions between the second-hand tanker prices and the shipping and global economic system.

The formulation mechanism for the second-hand tanker prices is not clearly known but depends on the global socioeconomic status and the shipping industry. Moreover, prices are the output of the equilibrium of supply and demand levels for sea transport tanker services, new building and steel prices. Second-hand tanker prices are formed under numerous excitations and the corresponding qualitative and quantitative impact in price formulation would be very difficult to be revealed.

Vessel prices fluctuate as wildly as freight rates. This is expected, as vessel prices of the expected cash-flows from operating the vessel over its lifetime plus the present value of the expected scrap value of the vessel at the end of its life. The largest contributor to the fluctuations in vessel values are expected freight rates. Expected discount rates (used to calculate the present values) and expected operating costs are relatively constant (with the exception of bunker prices). Strandenes (1984) investigates the price formation in the dry bulk and tanker sectors. She finds that prices are influenced more by changes in the long-term profits rather than changes in current operating profits. She also argues that such a relationship could be viewed as support for the validity of the rational expectations assumption in ship price formation. Beenstock and Vergottis (1989) show that second-hand vessel prices are positively related to expected discounted profits, to discounted newbuilding prices and to a wealth over the stock of the fleet variable; the latter two factors reflecting the state of the market for vessels as well as the wealth/income effect of investors.

Traditional approaches for modeling ship prices are mainly based on general and partial equilibrium models using structural relationships between a number of variables such as orderbook, newbuilding deliveries, scrapping rate, freight rates, bunker prices etc. (see Beenstock and Vergottis, 1989 and Tsolakis et al., 2003, among others). More recent studies have applied real options analysis for determining ship prices; this valuation framework takes explicitly into account the operational flexibility in ship management, in terms of choosing between spot and period time-charter contracts and switching between lay-up and trading modes (see Dixit and Pindyck, 1994, Tvedt, 1997 and Bendal and Stent, 2004, among others). Kavussanos (1996, 1997), by using GARCH type models, shows that the second moments (the variances) of vessel prices are time-varying and are affected by factors such as time-charter rates, interest rates and oil prices. Moreover, these variances, reflecting vessel price risks, are time-varying.

Another strand of research has examined whether markets for ships are efficient and whether prices are formed rationally. For example, Kavussanos and Alizadeh (2002), Hale and Vanags (1992) and Glen (1997), among others, test the validity of the Efficient Market Hypothesis (EMH) in the formation of second-hand dry bulk prices. These studies argue that the failure of the EMH may be attributed to either the existence of time-varying risk premia, or may reflect the existence of arbitrage opportunities in the market.

1.3 Problem Definition – Report Structure

All parties in vessel brokerage processes are using expert judgement to solve most of the aforementioned issues. The major problem, in my opinion, is to estimate the vessel price in an accurate, fast, and easy way. Moreover, this estimation has to be correlated with the current market status and trends. This means that experts should be continuously informed of current issues in shipping, freight rates and price values, in order to imprint this knowledge to a useful decision support tool.

This thesis aims to overcome these difficulties and develop a tool able to:

- Produce present second-hand vessel price estimations
- Produce future second-hand vessel price estimations
- Ensure high level of accuracy
- Adapt new second-hand market trends and innovations
- Adjust functionality according to user needs

The decision support tool will be the main product of this thesis. A database will be formed and used to explore market characteristics. Various statistical methods will be implemented in order to come up with solid results regarding the second-hand tanker market as well as the interactions with other markets and variables. A data mining technique will be applied in order to form explanatory models. Two models will be developed. The first one aims at producing estimations for present second-hand tanker values while the second one aims at producing future tanker values in six months. The model's dependent variable will be the second-hand tanker prices. The independent variables will consist of two main clusters. The first cluster includes vessel attributes

and the second shipping market and global economic variables. Numerous criteria will be used in order to evaluate the models and their goodness of fit. The overall output will be a decision support tool which will be demonstrated with a case study.

It should be noted that the proposed model, like many models, is not able to predict dramatic changes in market direction because it is based on historical data.

2 METHODOLOGY

In the context of this thesis, it was decided to use Data Mining Techniques in order to reveal relationships and patterns among data. Generally, Data Mining Techniques are used as a powerful operational research tool that enables researchers to form and seek rules of dependency among variables in a database. Data mining techniques have many areas of implementation. A similar research attempt was the one undertaken by Lyridis et al (2004b) where data mining models have been used to analyze and predict tanker new building prices and order book size. The method parcels out all of the possible multidimensional solution spaces seeking for clusters where a linear multi-parameter model can describe the relationship between the target variable (second-hand vessel price) and the informational variables.

This approach supports the initial statement that an explanatory model is more suitable to predict future and estimate present prices than a univariate model such as ARIMA or GARCH -Lyridis et al (2004a, b). The main advantage of an explanatory model is that by the use of an explanatory vector of informational variables, information is transferred to the target variable except for the information that is included in the precedent values of the target variable. Two specialized explanatory models will be constructed and used as “function approximation modules” for current and future values of tanker vessels second-hand prices.

The second-hand tanker vessel prices are examined in relation to their tonnage capacity, scrap values and tanker market freight rates, not only in their current levels but also in their past ones with a lag time of up to twelve months. The second-hand tanker prices are expressed in million \$. Conclusions from this approach will contribute to the development of predictive models.

2.1 Data Collection

Availability of data is basically the most crucial parameter when trying to solve a problem. The shipping sector, data and general information is valuable and difficult to collect and hence very expensive. Given that this is an academic attempt and there was no funding for purchase of the necessary information, the writer had to fill the database by transferring data from hard copy journals and magazines or by contacting large shipping companies and colleagues with access or subscriptions to data providers. Therefore, it is necessary to make a note on how difficult it is to find and collect data. Sometimes data from different sources differ substantially, other times categories in which data is organized (by various sources) are not steady in time. These problems are faced on a case by case basis, by reorganizing data in larger categories, by evaluating the reliability of each source etc.

In this case, data for the tanker second-hand prices, Aframax timecharter rates and Aframax scrap values were drawn from the Clarksons Research Studies the Drewry Shipping Statistics and Economics, the Lloyds' Shipping Economist, Mr. Sydney Levine of Shipping Intelligence, as well as from my advisor Henry S. Marcus.

Monthly values of the tanker second hand prices were collected from November 1986 to July 2005 mainly from the Clarksons Research Studies. These were then processed and filtered based on ship size in order to include vessels with tonnage from 60,000 to 100,000 dwt.

Freight rates in \$ per day for tankers were also collected from Clarksons Research Studies, the Drewry Shipping Statistics and the Lloyd's Shipping Economist on a monthly basis from November 1986 to July 2005 for the following time charter contract:

Vessel type: Aframax
Tonnage: 95,000 dwt
Age: early 90's
Hull: single
Duration: one year.

According to Clarksons, the one year tanker rates, expressed in \$/day, are collected on a weekly basis for average ships of the type specified above. It should be mentioned that this is an average index, and therefore Clarksons have included earlier charter contracts starting from 1986 with vessels built prior to 1986. This is actually explained in the Clarksons website under publications. The collection is done in the same way for spot market rates, by requesting brokers to fill in a weekly pro-forma with the latest rate for each ship type or by estimating the likely rate acceptable to an owner in the absence of any fixtures.

An important variable that describes the tanker second-hand market is the scrap values variable. Scrap values in million \$ were collected from the Lloyd's Shipping Economist on a monthly basis from November 1986 to July 2005.

It is important to explain the importance of each of the variable embedded in the database. Expert judgment is a common practice prior to pre-processing in order to form the appropriate explanatory model which contains most of the information without congestion and multi-colinearity effects. It is obvious that precedent prices will affect future ones. Market feeling is well described in precedent price values along with variables describing "second-hand market state". A variable that describes the Aframax and Panamax second-hand market and leads market progression is believed to be the freight rates variable. It is also important to note that by using a moving average of such a variable, one can obtain more than just a single value for the market state, which is a volatile variable.

The scrap values variable is the connection between the shipping market and the global industry state. For example, steel prices have reached historical highs due to China's enormous economic boom. This has pushed new building and scrap prices to extremely high levels. The second-hand market, which is located between the shipping and the global industry markets, has also shown an increase due to these virtual frontiers. Therefore, the inclusion of these variables was necessary for the formulation of the explanatory model.

The pre-processing procedure is what determines the exact form of the two explanatory models.

The available data has the following variables:

date	date variable denoting exact time of vessel transaction
Name	nominal variable denoting the name of the vessel
Year Built	ordinal variable denoting the year of vessel built
DWT	continuous variable denoting the vessel tonnage
Age	ordinal variable denoting the vessel age
TR	continuous variable denoting Time Charter Rate
TR(-1)	continuous variable denoting Time Charter Rate before 1 month
TR(-2)	continuous variable denoting Time Charter Rate before 2 months
TR(-3)	continuous variable denoting Time Charter Rate before 3 months
TR(-4)	continuous variable denoting Time Charter Rate before 4 months
TR(-5)	continuous variable denoting Time Charter Rate before 5 months
TR(-6)	continuous variable denoting Time Charter Rate before 6 months
TR(-7)	continuous variable denoting Time Charter Rate before 7 months
TR(-8)	continuous variable denoting Time Charter Rate before 8 months
TR(-9)	continuous variable denoting Time Charter Rate before 9 months
TR(-10)	continuous variable denoting Time Charter Rate before 10 months
TR(-11)	continuous variable denoting Time Charter Rate before 11 months
TR(-12)	continuous variable denoting Time Charter Rate before 12 months
MATR(6)	continuous variable denoting 6 months moving average of Time Charter Rate
MATR(6_12)	continuous variable denoting 12 to 6 prior months moving average of Time Charter Rate
SV 0	continuous variable denoting Scrap Value
SV -1	continuous variable denoting Scrap Value before 1 month
SV -2	continuous variable denoting Scrap Value before 2 months
SV -3	continuous variable denoting Scrap Value before 3 months
SV -4	continuous variable denoting Scrap Value before 4 months
SV -5	continuous variable denoting Scrap Value before 5 months
SV -6	continuous variable denoting Scrap Value before 6 months
SV -7	continuous variable denoting Scrap Value before 7 months
SV -8	continuous variable denoting Scrap Value before 8 months
SV -9	continuous variable denoting Scrap Value before 9 months
SV -10	continuous variable denoting Scrap Value before 10 months
SV -11	continuous variable denoting Scrap Value before 11 months
SV -12	continuous variable denoting Scrap Value before 12 months
MASV (6)	continuous variable denoting 6 months moving average of Scrap Value
MASV (6_12)	continuous variable denoting 12 to 6 prior months moving average of Scrap Value
Price0	continuous variable denoting Vessel Price
Price6	continuous variable denoting Vessel Price after six months

2.2 Data Preprocessing

In forecasting values for the tanker second-hand prices, prediction periods of zero and six months were selected. It was decided to develop two forecasting models dedicated to different time spans:

1. Zero time lead: This forecast model is very useful in order to have an accurate estimation of the price of a Panamax or an Afamax tanker vessel relative to the current state of the shipping market.
2. Six months time lead: In general, it can be understood that an increased predictive period provides more time in which ship-owners can make decisions based on future estimates, but it also leads to less reliable prediction values. A period of six months is considered sufficient for decision making, especially when the current value is provided for comparison, while it leads to the development of more reliable models.

Models are based on the previous values of the dependent variables, which are the second-hand tanker prices, and freight rates, as well as the previous values of the independent variables, which are in each case, the Aframax scrap values up to a year ago. It is expected that when the shipping market is in a continuous good state, prices will continue to increase and vice versa. Another consideration for the development of the models is that the historical data for a single hull 95,000 DWT Aframax vessel time charter freight rates for the six and twelve month moving averages, may better represent the continuous state of the shipping market versus a single monthly value.

The descriptive statistics of the vessels included in the database are shown in the table below:

	BUILT	DWT	PRICE	AGE
Mean	1983.68	87293.66	1.7E+07	13.95
Std. Error of Mean	.321	411.913	742754.642	.277
Median	1982.00	88034.00	14000000.00	15.00
Mode	1980	81283	4000000	19
Std. Deviation	7.167	9182.986	1.7E+07	6.165
Variance	51.366	8.4E+07	2.7E+14	38.004
Range	37	39607	200150000	28
Minimum	1967	60392	1850000	0
Maximum	2004	99999	2E+08	28

Table 1: Descriptive Statistics for Vessels Characteristics

The age profile of the vessels under examination is presented in figure 1. The age mean value of the second-hand vessels participating in the sale-purchase process is 14 years.

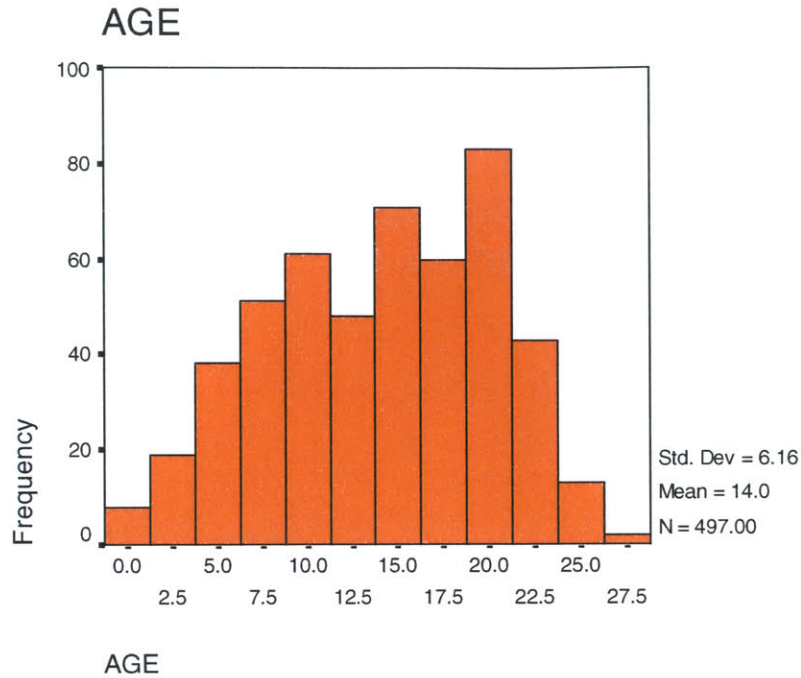


Figure 1: The Age Profile of the Tanker Vessels

The tonnage profile in DWT of the vessels under examination is presented in figure 2. The mean value of the second-hand vessels' DWT is 87,293.7

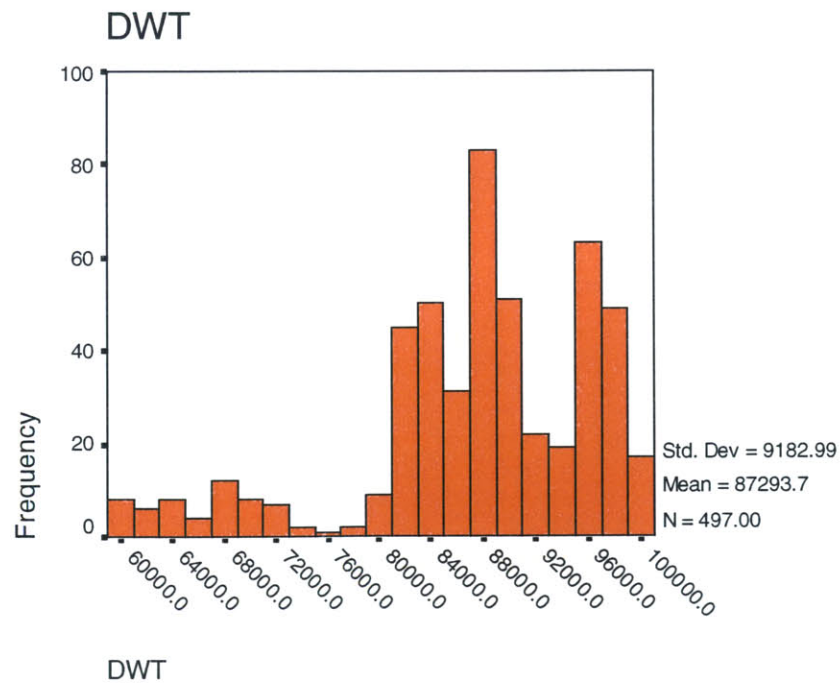


Figure 2: The Tonnage Profile of the Tanker Vessels

The values in \$ of the vessels under examination are presented in the histogram below. The mean value of the second-hand vessel prices is \$17.7 million.

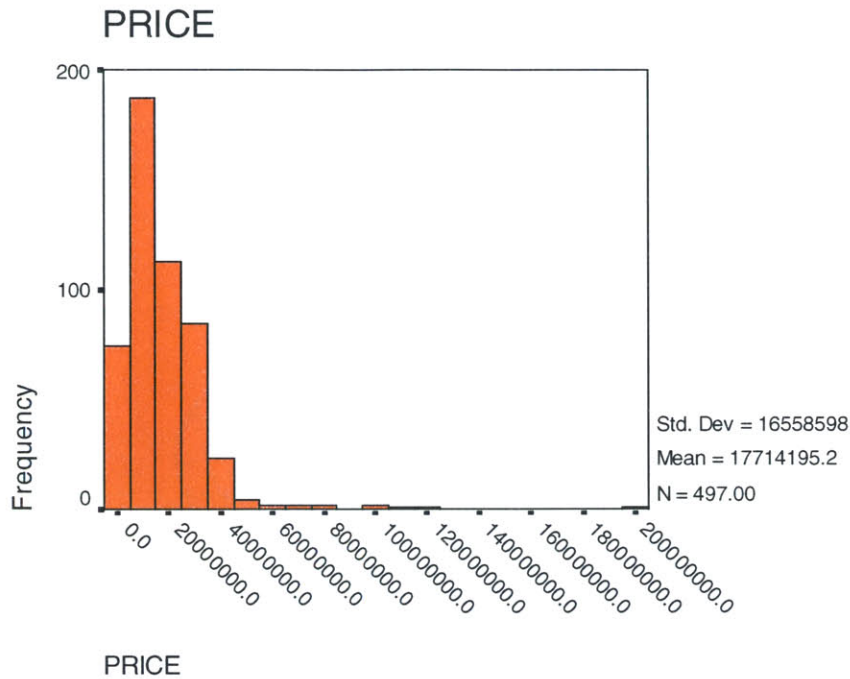


Figure 3: The Tonnage Profile of the Tanker Vessels

Figure 4, shows the variance of the: scrap values, second hand prices and the time-charter rates transformed. One can see the common variance and the high correlation. The figure also shows a short time lag between time charter rates and the other two attributes.

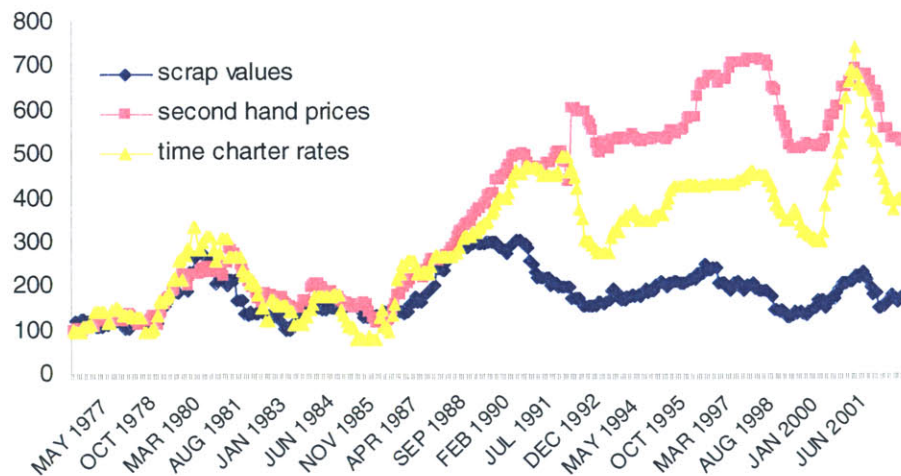


Figure 4: Scrap Value, Second Hand Prices and Time-Charter Rates diagram

The next figure shows the partial autocorrelation function for the 5 year old average tanker prices in \$ per DWT.

According to the partial autocorrelation chart, the second hand prices have one step dependence. The correlation factor at time lag 2 or higher is statistically insignificant and below the confidence limits.

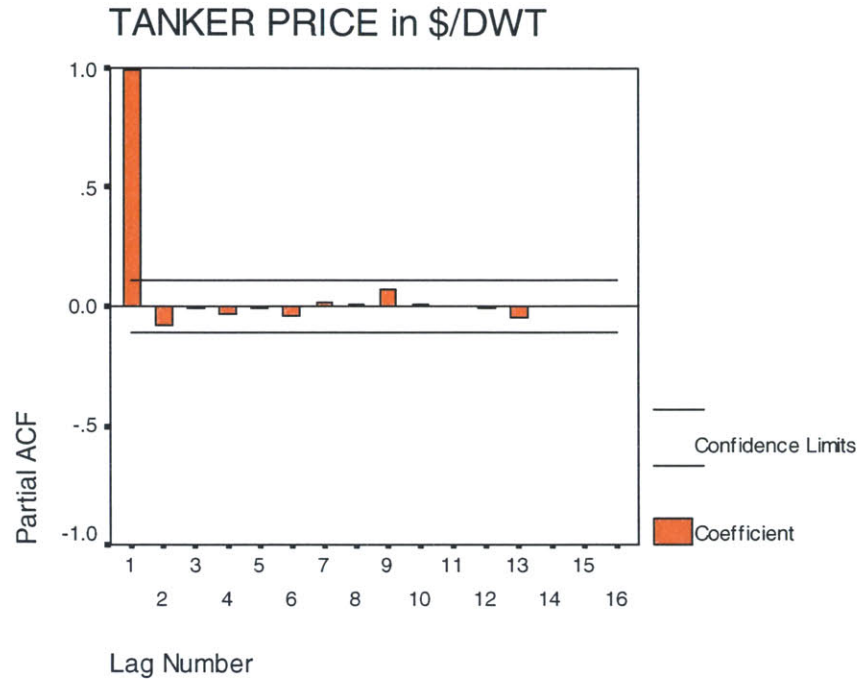


Figure 5: Partial Autocorrelation Function for Second Hand Prices

The descriptive statistics of second-hand prices are shown in the table below:

Mean	262.9438
Std. Error of Mean	7.56501
Median	297.8100
Mode	363.20
Std. Deviation	137.84108
Variance	19000.16249
Skewness	.025
Std. Error of Skewness	.134
Kurtosis	-1.551
Std. Error of Kurtosis	.267
Range	419.36
Minimum	66.30
Maximum	485.66

Table 2: Descriptive Statistics for Tanker 5 Years Old Average Price in \$/DWT

The following section discusses the criteria for the selection of the proper variables.

The main criteria that were used in selecting the appropriate variables are the following:

1. The correlation between independent and dependent variables measured by the correlation factor. It is necessary to mention that the autocorrelation factor of the dependent variable was calculated in order to determine its use as an input variable. Finally all the cross-correlation factors were calculated, thereby introducing the phenomenon of time delay often observed in the tanker market.
2. The low multi-colinearity between the independent variables. Multi-colinearity disorients the artificial neural networks and leads to poor performance by providing a piece of information multiple times. Multi-colinearity can be measured either by calculating the coefficient factors between each independent variable or by calculating the Variance Inflation Factor.

3. Supposing the existence of a set of k variables, the Variance Inflation Factor is

calculated by the equation
$$VIF = \frac{1}{1 - R^2}$$
 where R is the coefficient of determination between an independent variable and the k-1 residual variables. As the variance inflation factor increases, so does the variance of the regression coefficient, making it an unstable estimate. Large VIF values are an indicator of multi-collinearity.

4. Expert judgment is an asset when dealing with the shipping market as well as thorough knowledge and analysis of the events that have influenced the second-hand tanker market during the past two decades.

Co-linearity (or multi-colinearity) is an undesirable situation where the correlations among the independent variables are strong. The relationship between the dependent and independent variables as well as just between the independent variables is assessed by calculating Pearson's correlation coefficient [Edwards (1984), Kutner et al (2003), Draper and Smith (1982)]. The only variables chosen for the development of the prediction models, are ones with high correlation to the dependent variables and low correlation between themselves. Those that show low correlation to the dependent variables are immediately omitted from the training data. Pearson's correlation factor is given by the following equation:

$$\eta = \frac{(N - 1)^2 \sum_t (p_t^x - \overline{p^x})(p_t^y - \overline{p^y})}{N^2 \sigma_x^n \sigma_y^n} \quad (1)$$

where:

$p_t^x, p_t^y, t=1,2,\dots,N$ are two given time series

$\overline{p^x}, \overline{p^y}$ are the mean values of the X and Y time series respectively

σ_x, σ_y are the standard deviations of the X and Y time series respectively
 N is the number of data in each of the time series

The correlations among variables of the database are shown in the table below:

	AFRAMAX SCRAP VALUES in million \$	TANKER 5 YEARS OLD AVERAGE PRICE in \$/DWT	1 YEAR TIME CHARTER RATE AFRAMAX
AFRAMAX SCRAP VALUES in million \$	1	0.425	0.698
TANKER 5 YEARS OLD AVERAGE PRICE in \$/DWT	0.425	1	0.894
1 YEAR TIME CHARTER RATE AFRAMAX	0.698	0.894	1

Correlation is significant at the 0.01 level (2-tailed).

Table 3: Correlations

The bivariate correlations procedure computes Pearson’s correlation coefficient with its significance levels. Correlations measure how variables or rank orders are related. Pearson’s correlation coefficient is a measure of linear association. Pearson’s correlation coefficient is between -1 and 1. When the coefficient is close to 1 it means that this two variables are perfectly positively correlated. For example, when the first variable increases the second will also experience an increase. When the coefficient is close to -1, if the first variable increases the second will experience a decrease. If the coefficient is close to 0 or between the critical values of $\pm 1.96/\sqrt{n}$, where n is the number of time series cases, the variables are considered to be uncorrelated.

It is obvious that the average price of the second hand tankers is strongly positively correlated with the time charter rates and the scrap values. Therefore, these two variables can be included in the explanatory model. That leads to the conclusion that an increase in tanker freight rates or scrap values impels an increase in the second-hand values and vice versa.

It is generally accepted that scrap values are dependent on the global iron prices. Iron prices affect both the scrap and new-building value markets. Since the second-hand price market lies between the new-building and the global iron price markets, the second-hand market is forced to react, in a similar manner, to the move of those other two markets. The scrap value variable is not included in the model not because I chose to disregard it but because the model itself ignored the scrap value variable. This is shown in the name files in the Appendix. One can see that the variables initially considered but not chosen by the model have the statement “ignore” next to them.

It is crucial to check for multi-colinearity between database variables. An empirical rule is that variables with a bivariate correlation factor of more than 0.8 should not both be included in the model as independent variables. The correlation factor between time

charter rates and scrap values is 0.425, which is less than 0.8, and therefore both can be included as independent variables.

The development of models is done using a special software tool for developing rule-based predictive models from data. The tool is called Cubist and is an excellent data mining tool. The user determines the input data set, the test set, the target variables and the informational variables. All the above sets are located in individual files with formats specialized for cubist (Appendix A). The first essential file is the names file (e.g. now.names) which defines the attributes used to describe each case. The second essential file, the applications data file (e.g. now.data), provides information on the training cases that Cubist will use to construct a model. The entry for each case consists of one or more lines that give the values for all explicitly-defined attributes. Values are separated by commas and the entry for each case is optionally terminated by a period. The third kind of file used by Cubist is a test file of new cases (e.g. now.test) on which the model can be evaluated. This file has exactly the same format as the data file. In this application the cases have been split equally 50-50 into data and test files containing 200 and 200 cases respectively.

Generally, in order for both the training and the test dataset to be representative of all the possible (or as many as possible) market states in the shipping economy (from 1986-present), one must mix the data in a random manner and then split that into two sets. The train set and the test set. This is achieved by randomly changing the rows of the original database.

The models created are expressed as a collection of rules, where each rule has an associated multivariate linear model. The tool also incorporates a system that builds a piecewise linear model in the form of a model tree using recursive partitioning of the training data set by associating the leaves with the models [Breiman et al (1984),]. The partitioning process is guided by some heuristic function that chooses the best split of observations into subgroups [Quinlan J. R. (1992, 1993a, 1993b), Siciliano and Mola (1994)]. Some generalizations can be offered about what constitutes the right-number of subgroups. It should be sufficiently complex to account for the known facts, but at the same time it should be as simple as possible. It should exploit information that increases predictive accuracy and ignores information that does not. It should, if possible, lead to greater understanding of the phenomena which it describes.

Models are evaluated by assessing how reliable they are in the prediction of some training data cases and for a set of test cases by calculating the following parameters:

1. Average Error: calculated as the mean absolute difference of the predicted value and the actual value in each case.
2. Relative Error: its magnitude is the ratio of the average error magnitude to the magnitude of the error magnitude that would result if the mean value were steadily predicted; the models are useful if its value is less than 1.
3. Correlation Coefficient: this measures the agreement between the actual values and values predicted by the model.

It should be noted that the test cases are different from the set of data that are used to build the model. It is difficult to judge the accuracy of a model by measuring how well it does on the cases used in its construction; the performance of the model on new cases is much more informative.

2.3 Data Analysis and Model Development

The following variables are the final input vector and were analyzed as to their relationship to the tanker prices and then considered in the model development:

- i. Price0: continuous dependent variable representing the current price of the second-hand vessel
- ii. Price6: continuous dependent variable representing the future price of the second-hand vessel after six months.
- iii. DWT: continuous independent variable representing vessel DWT.
- iv. Age: continuous independent variable representing vessel age.
- v. Time Charter Rate0: continuous independent variable representing current Time Charter Rate.
- vi. Time Charter RateI: continuous independent variable representing precedent Time Charter Rate.
- vii. Six previous months Moving Average of Time Charter Rate: continuous independent variable representing six months moving average of Time Charter Rates.
- viii. Six to twelve previous months moving average of Time Charter Rate: continuous independent variable representing six to twelve months moving average of Time Charter Rate.
- ix. Scrap Value0: continuous independent variable representing current scrap values.
- x. Scrap ValueI: continuous independent variable representing precedent scrap values.
- xi. Six previous months Moving Average of Scrap Values: continuous independent variable representing six months moving average of scrap values .
- xii. Six to twelve previous months moving average of Scrap Values: continuous independent variable representing six to twelve months moving average of scrap values .

Where $I = 1, 2, \dots, 12$ is the numeric value representing how many months ago the variable refers to (e.g. Time Charter Rate₅ is the independent variable representing the value of the time charter rate 5 months before the current value). Variables with a lag time of up to 12 months were examined.

There are three steps in the model formulation:

- expert judgment for the preliminary form of the model. By using existing knowledge of pricing models from the ship finance field along with modeller

intuition, an initial revelation of what factors might be able to best explain the dependent variable takes place.

- pre-processing to build the final database. In pre-processing, correlation between the dependent variable and the independent ones (previously chosen by expert judgment) as well as the correlation of the independent variables with each other is checked. This way only the explanatory variables are kept.
- Finally, the method, which is data mining, performs the fine tuning of the model. Data mining disregards the variables that offer insignificant information to the model. By using error minimizing algorithms, the method tries all possible combinations and builds the final model that best describes the second-hand prices formulation mechanism. For example, in pre-processing the time charter rates prior 3 months were included but the method decided not to use it in the final form. The reason for not including it is that the variable did not offer statistically significant information to the model.

3 IMPLEMENTATION RESULTS

The implementation of the above described methodology provides two dedicated models. The first model can be used as a function approximation tool in order to have an accurate price for a second-hand tanker regarding market state and vessel characteristics in real time.

The second model is the six month model dedicated to providing an estimate of the possible future second-hand tanker price relative to the current vessel characteristics and the market state after six months.

3.1 Zero Month Model

The zero month model was constructed as a useful tool for investors, brokers and ship-owners. The main scope of this model is to provide real time estimates for vessels prices according to market states and vessel characteristics. This can be a significant help in a volatile system such as the second-hand market. It is not unusual to experience 100% difference in price of similar vessel cases in different environments of the shipping market and the global economic state. It is therefore a matter of experience to estimate a second-hand vessel price taking into account precedent and present realizations and future expectations.

3.1.1 Form of the Zero Month Model

According to the model's variable definitions, the target attribute was 'Price'. In the fitting process the tool reads 200 cases from the *now.data* file and 35 attributes from the *now.names* file.

The Zero Month Model form has two rules indicating that there are two subgroups where linear equations can be applied. The coefficient of every explanatory attribute is calculated by cubist trying to minimize error.

The model is shown below:

Model:

Rule 1: [applying to 82 cases of the training dataset]

If

Age > 16

Then:

Price =
14.8136

- 1.01 [Age]
+ 0.00051 [Time Charter Rate before one month]
+ 1 [Six to twelve previous months moving average of Scrap Value]

Rule 2: [applying to 118 cases of the training dataset]

If

Age <= 16

Then

Price =

19.8714
- 1.72 [Age]
+ 0.00109 [Six previous months Moving Average of Time Charter Rate]
+ 0.00011 [Time Charter Rate before one month]

The significant remarks from the model's form are the following:

- Age attribute has a negative coefficient as expected.
- Age attribute is the only vessel attribute that is applied to the model's form -e.g. DWT is not applicable.
- The market state is expressed by the attributes of "Time Charter Rate before one month" and the "Six previous months Moving Average of the Time Charter Rate". These issues depict two points: the second-hand market shows a time lag in relation to the freight market progression and that the market is dependent of the freight market trends under the expression of moving averages.
- The dependency with the steel market is set to be at Six to twelve previous months moving averages of the Scrap Values.

The results of the model are compatible with the correlation results. It is clear that the price at zero time lag is statistically positively correlated with the freight rates and negatively correlated with the age attribute. This is shown in the next table:

Correlations

		DWT	AGE	TCR	PRICE
DWT	Pearson Correlation	1	-.059	-.169**	.043
	Sig. (2-tailed)	.	.189	.000	.341
	N	489	489	489	489
AGE	Pearson Correlation	-.059	1	.191**	-.708**
	Sig. (2-tailed)	.189	.	.000	.000
	N	489	489	489	489
TCR	Pearson Correlation	-.169**	.191**	1	.259**
	Sig. (2-tailed)	.000	.000	.	.000
	N	489	489	489	489
PRICE	Pearson Correlation	.043	-.708**	.259**	1
	Sig. (2-tailed)	.341	.000	.000	.
	N	489	489	489	489

** . Correlation is significant at the 0.01 level (2-tailed).

Table 4: Correlations

3.1.2 Evaluation of the Zero Month Model

The Zero Month Model was evaluated by testing how reliable it is in the prediction of the 200 training data cases and in a set of 200 test cases by calculating the average error, the relative error and the correlation coefficient.

The test data have not been used in the model creation. These data are totally unknown to the model. The results of goodness of fit for both the train and the test datasets are shown. The model fits well to the train set, since it is created using that set, but that is for completeness. What is important, is the fit to the test set (also known as the out of sample dataset).

The evaluation results on the training data (200 cases) are shown below:

Average error	3.4142
Relative error	0.35
Correlation coefficient	0.84

To demonstrate goodness of fit, 60 training cases will be presented in three figures. All the results can be seen in Appendix B. It should be noted that the data listed in the Appendix are in random order.

The next figure shows the results for the first 20 cases of the training set. The actual (desired) value is compared with the model output. According to this figure the model results are adequately close to the desired values.

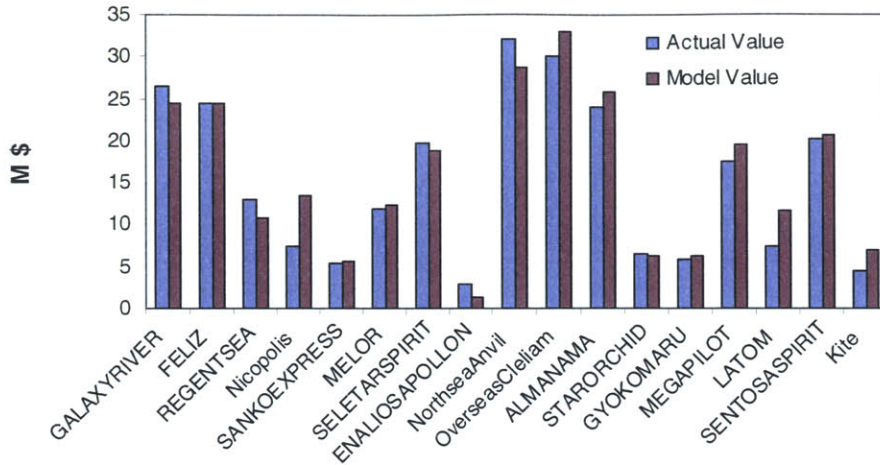


Figure 6: The Zero Month Model Fit on the first 20 Training Cases of Tanker Vessels

The next figure shows the results for the next 20 cases of the training set.

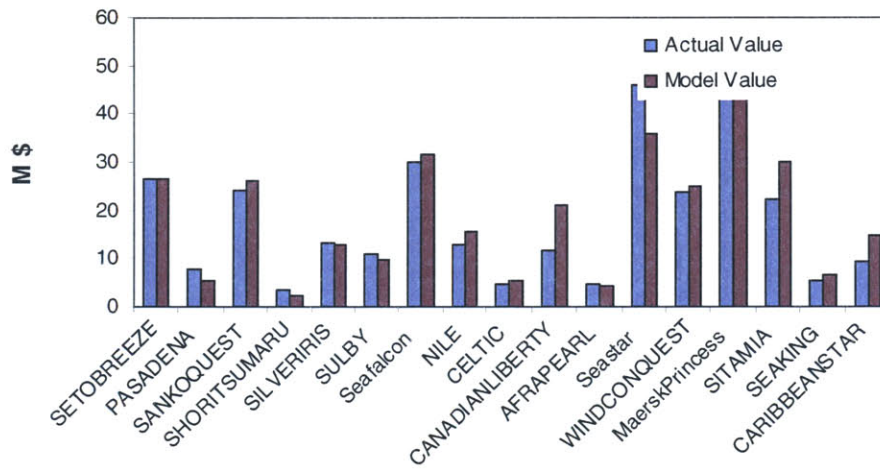


Figure 7: The Zero Month Model Fit on the next Training Cases of Tanker Vessels

The next figure shows the results for the next 20 cases of the training set.

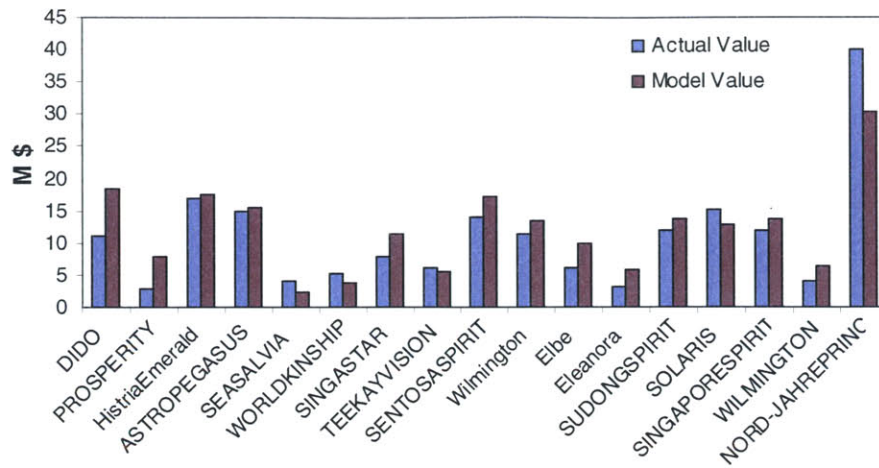


Figure 8: The Zero Month Model Fit on the next Training Cases of Tanker Vessels

Another way of assessing the accuracy of the predictions is through a visual inspection of a *scatter plot* that graphs the real target values of the new cases against the values predicted by the model. The scatter plot for training data is shown in figure 9:

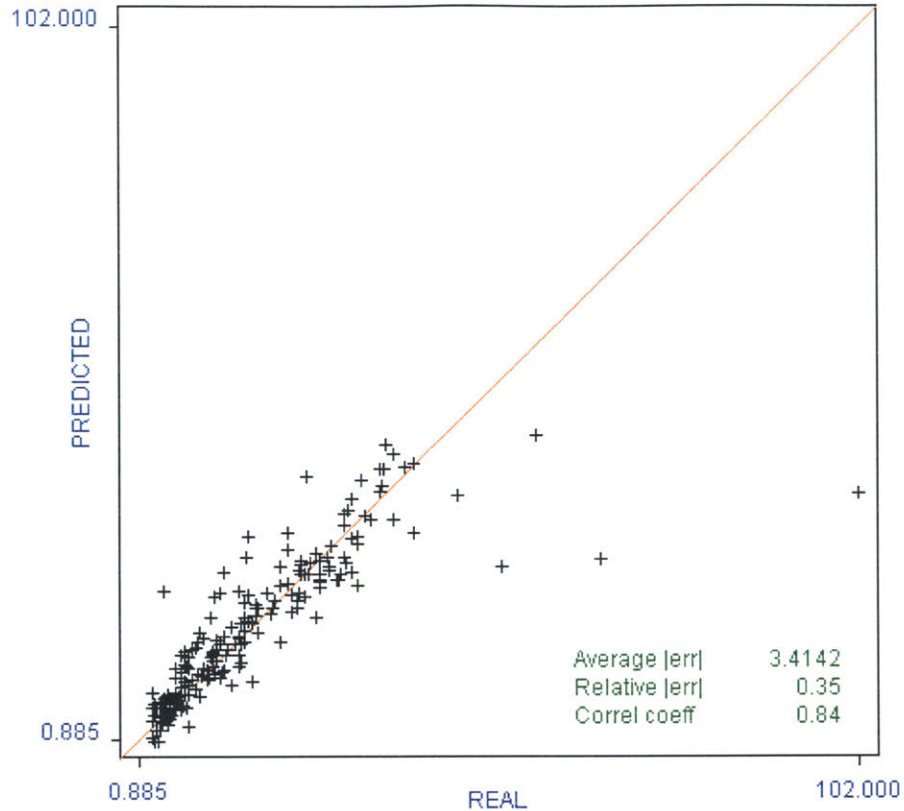


Figure 9: The Scatter Plot for Zero Month Model Fit on Training Cases of Tanker Vessels

According to the scatter plot the predicted and real numbers for the training process are crosses located around and close to the red line. The red line is the diagonal and shows where the crosses should be located in the non error model. The scope is to construct a model with the crosses of the scatter plot as close to the red line as possible.

The evaluation on test data (200 cases) is shown below:

Average error	3.8291
Relative error	0.38
Correlation coefficient	0.81

To demonstrate goodness of fit 60 testing cases will be presented in three figures. All the results can be seen in Appendix B.

Figure 10 shows the results for the first 20 cases of the testing set. The actual (desired) value is compared with the model output for the test data. According to this figure the results of the model are adequately close to the desired values and show the model's ability to generalize.

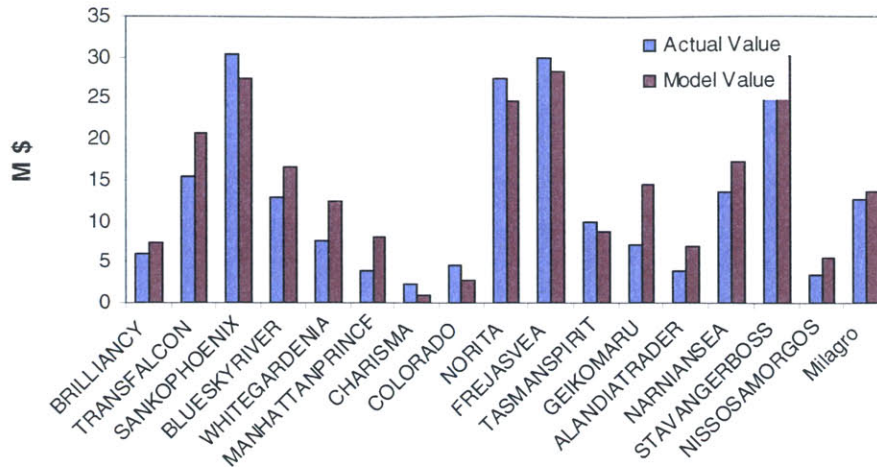


Figure 10: The Zero Month Model Fit on 20 First Testing Cases of Tanker Vessels

The figure below shows the results for the next 20 cases of the testing set.

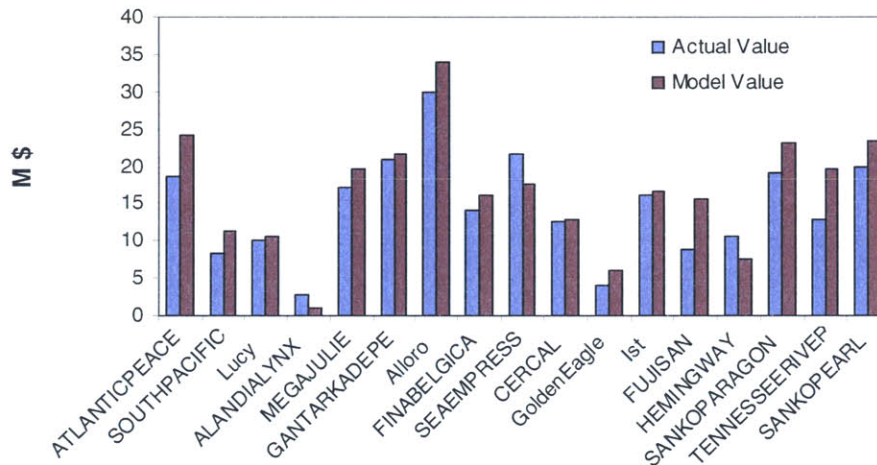


Figure 11: The Zero Month Model Fit on 20 NextTesting Cases of Tanker Vessels

Figure 12 shows the results for the next 20 cases of the testing set.

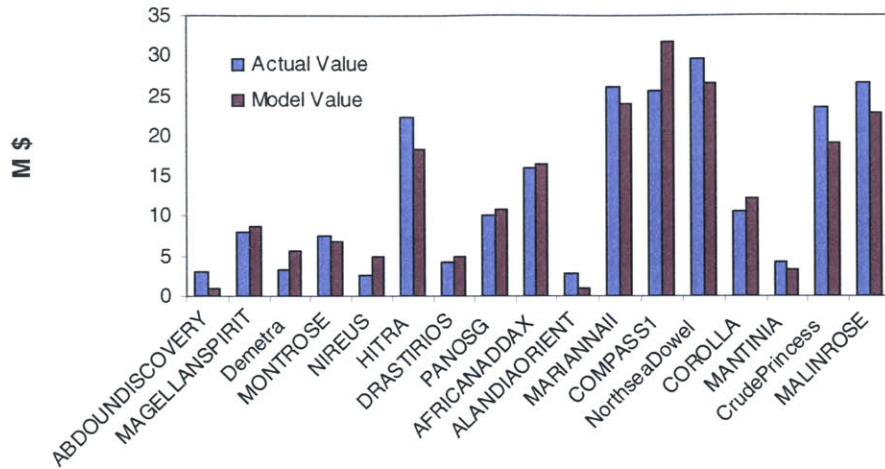


Figure 12: The Zero Month Model Fit on 20 NextTesting Cases of Tanker Vessels

The scatter plot for testing data is shown in figure 13:

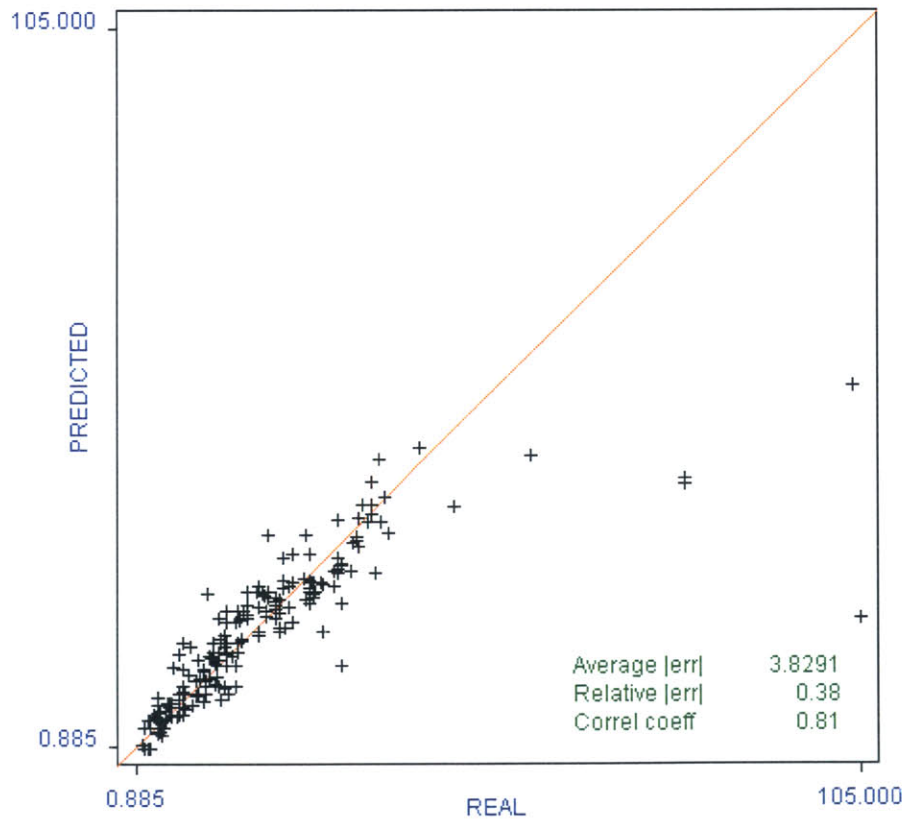


Figure 13: The Scatter Plot for Zero Month Model Fit on Testing Cases of Tanker Vessels

According to the scatter plot the vessel cases for the testing process are located around and close to the red line.

Analyzing the results of the Zero Month Model one can say they are adequately acceptable. The error terms are significantly low in all three categories. The Zero Month Model has excellent generalization ability. The error terms in the training (known) data are similar to those in the testing (unknown) data.

3.2 Six Month Model

The six month model is constructed as a useful tool for investors, brokers and ship-owners. The main scope of the model is to provide future estimates for vessel prices according to market states and vessel characteristics. Effort was given in order to model the mechanism that forms future second-hand vessel prices. The time span was set to six months which is a crucial time period when purchasing or selling a vessel. Such a model can be of significant help to a volatile system such as the second-hand market. By studying precedent realization, the six month model has the ability to generalize and predict future vessel prices according to historical records.

3.2.1 Form of the Six Months Model

According to the model's variable definitions, the target attribute was 'Price after six months' which refers to vessel prices after six months.

In the fitting process the tool reads 200 cases from the *plus6.data* file and 35 attributes from the *plus6.names* file.

The Six Months Model form has two rules indicating that there are two subgroups where linear equations can be applied. The model is shown below:

Model:

Rule 1: [applying to 82 cases of the training dataset]

If

Age > 16

Then

Price after six months = 16.1031
- 0.91 [Age]
+ 2.4 [Six previous months moving average of Scrap Value]
+ 0.0001 [Time Charter Rate]

Rule 2: [applying to 118 cases of the training dataset]

If

[Age] ≤ 16

Then

Price after six months = -5.1385 - 1.8 [Age]
 + 6.9 [Six previous months moving average of Scrap Value]
 - 3 [Scrap Value]
 + 0.00075 [Time Charter Rate]
 + 0.00024 [DWT]

The significant remarks from the model's form are the following:

- Age attribute has a negative coefficient as expected.
- Age attribute is not the only vessel attribute that is applied to the model's form. In the future second-hand vessel price model, DWT is also a significant attribute.
- Market state is expressed by the attributes of "Time Charter Rate" and the "Six previous months Moving Average of the Time Charter Rate". These issues depict two points: the Six Month Model needs the last available information and the future second-hand market is dependant of the freight market trends under the expression of moving averages.
- The dependency with the steel market is set to be at Six previous months moving average of the Scrap Values and the last available information of the Scrap Values.

The results of the model are compatible with the correlation results. It is clear that the price at time lag six is statistically positively correlated with the freight rates, and the DWT and negatively correlated with the age attribute. This is shown in the table below:

Correlations

		DWT	AGE	PRICE	TCRB6
DWT	Pearson Correlation	1	-.059	.043	-.156**
	Sig. (2-tailed)	.	.189	.341	.001
	N	489	489	489	489
AGE	Pearson Correlation	-.059	1	-.708**	.189**
	Sig. (2-tailed)	.189	.	.000	.000
	N	489	489	489	489
PRICE	Pearson Correlation	.043	-.708**	1	.208**
	Sig. (2-tailed)	.341	.000	.	.000
	N	489	489	489	489
TCRB6	Pearson Correlation	-.156**	.189**	.208**	1
	Sig. (2-tailed)	.001	.000	.000	.
	N	489	489	489	489

** . Correlation is significant at the 0.01 level (2-tailed).

Table 5: Correlations

3.2.2 Evaluation of the Six Months Model

The Six Month Model was also evaluated by testing how reliable it is in the prediction of the 200 training data cases and in a set of 200 test cases by calculating the average error, the relative error and the correlation coefficient.

The test data have not been used in the model creation. These data are totally unknown to the model. The results of goodness of fit for both the train and the test datasets are shown. The model fits well to the train set, since it is created using that set, and what is important is the fit to the test set (also known as the out of sample dataset).

The evaluations on the training data (200 cases) results are shown below:

Average error	3.5891
Relative error	0.37
Correlation coefficient	0.83

To demonstrate goodness of fit 60 training cases will be presented in three figures. All the results can be seen in Appendix B

The next figure shows the results for the first 20 cases of the training set. The actual (desired) value is compared with the model output. According to figure 14, the model results are adequately close to the desired values.

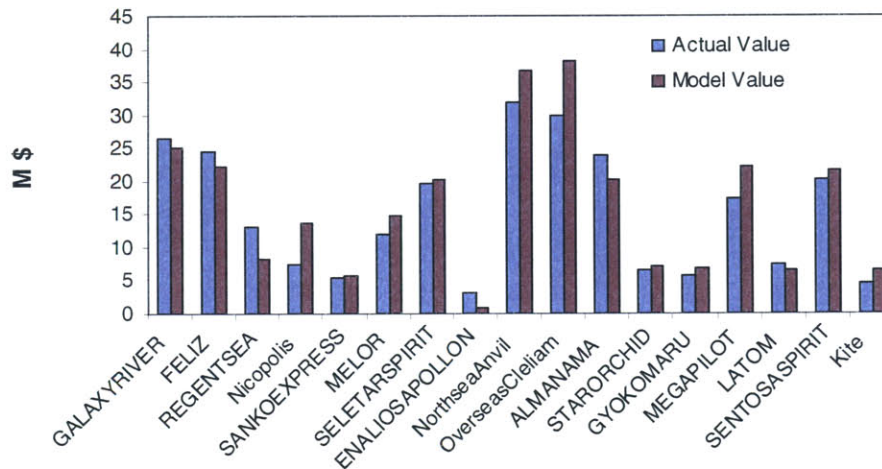


Figure 14: The Six Month Model Fit on 20 First Training Cases of Tanker Vessels

Figure 15 shows the results for the next 20 cases of the training set.

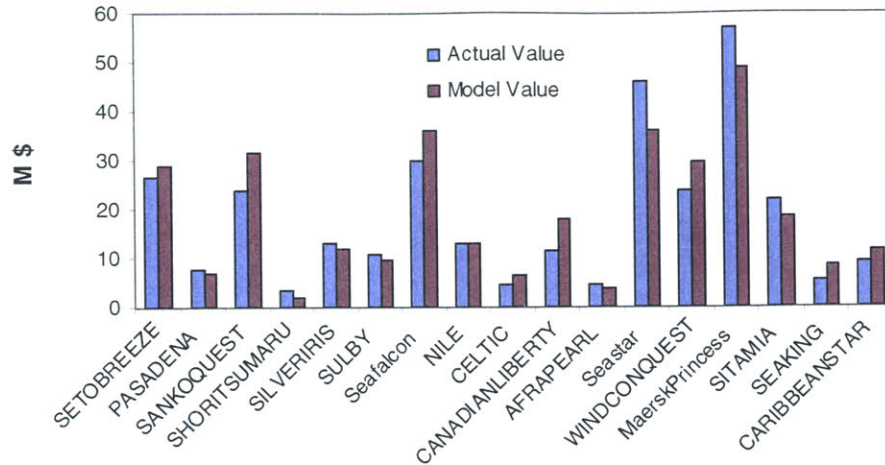


Figure 15: The Six Month Model Fit on 20 Next Training Cases of Tanker Vessels

Figure 16 shows the results for the next 20 cases of the training set.

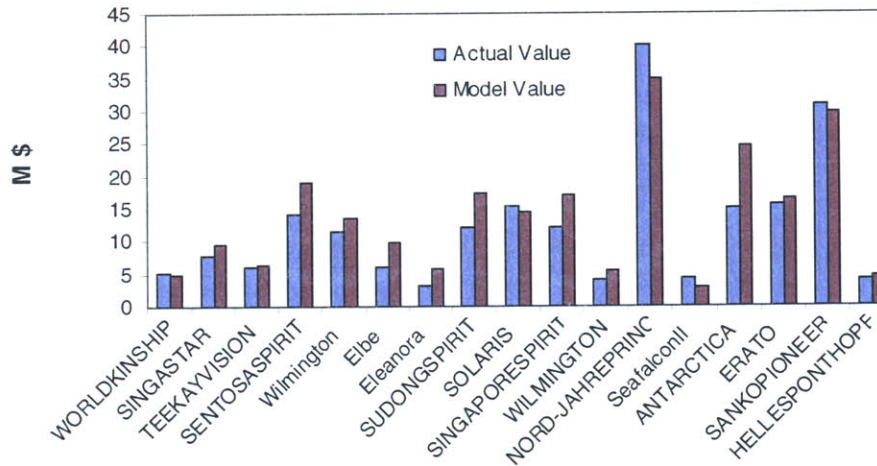


Figure 16: The Six Month Model Fit on 20 Next Training Cases of Tanker Vessels

The scatter plot for the training data is shown in figure 17:

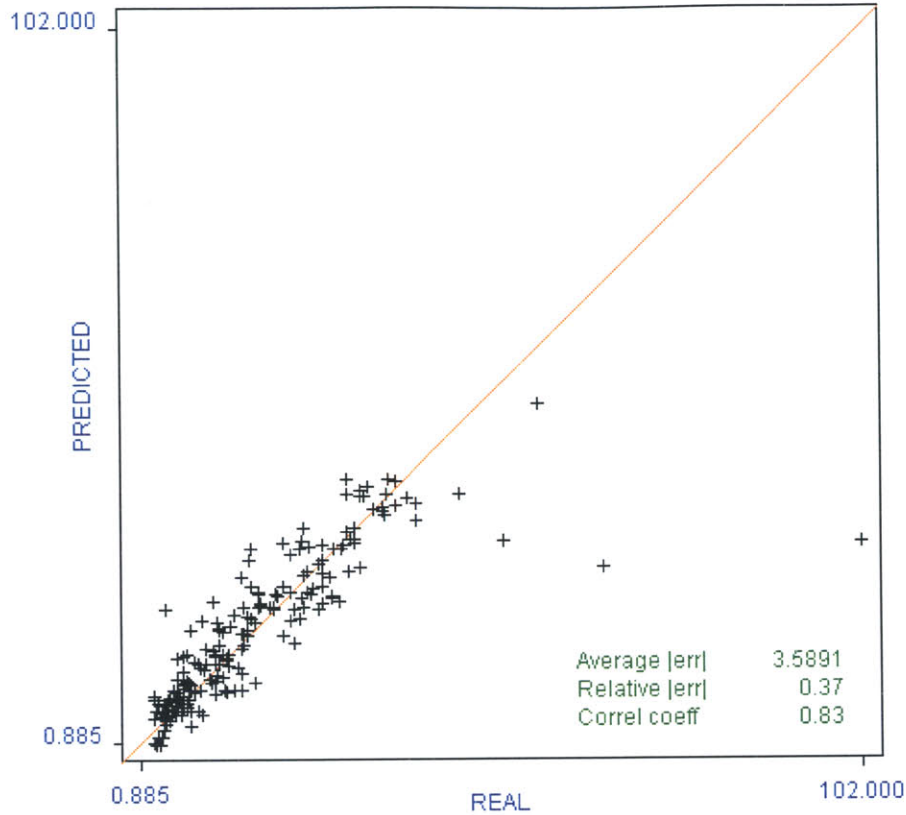


Figure 17: The Scatter Plot for Six Month Model Fit on Training Cases of Tanker Vessels

According to the scatter plot, the vessel cases for the training process are located around and close to the red line.

The evaluation on test data (200 cases) is shown below:

Average error	4.2198
Relative error	0.42
Correlation coefficient	0.79

To demonstrate goodness of fit 60 testing cases will be presented in three figures. All the results can be seen in Appendix B

Figure 18 shows the results for the first 20 cases of the testing set. The actual (desired) value is compared with the model output for the test data. According to this figure, the results of the model are adequately close to the desired values and show the model's ability to generalize.

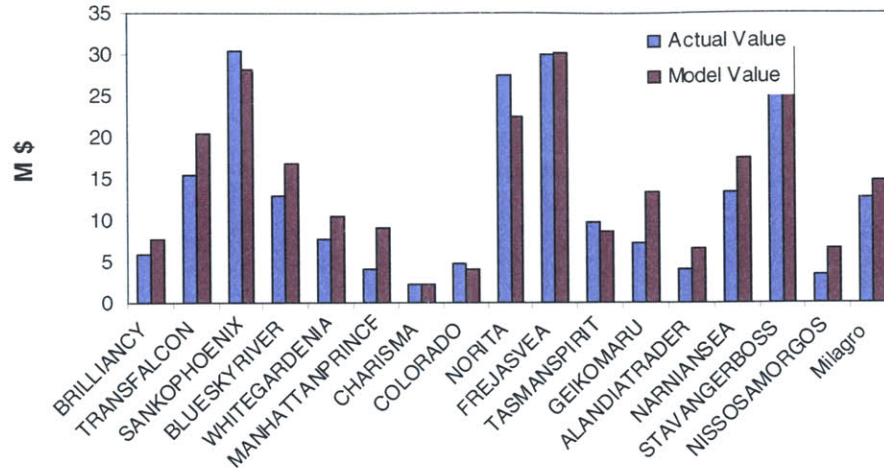


Figure 18: The Six Month Model Fit on 20 First Testing Cases of Tanker Vessels

Figure 19 shows the results for the next 20 cases of the testing set.

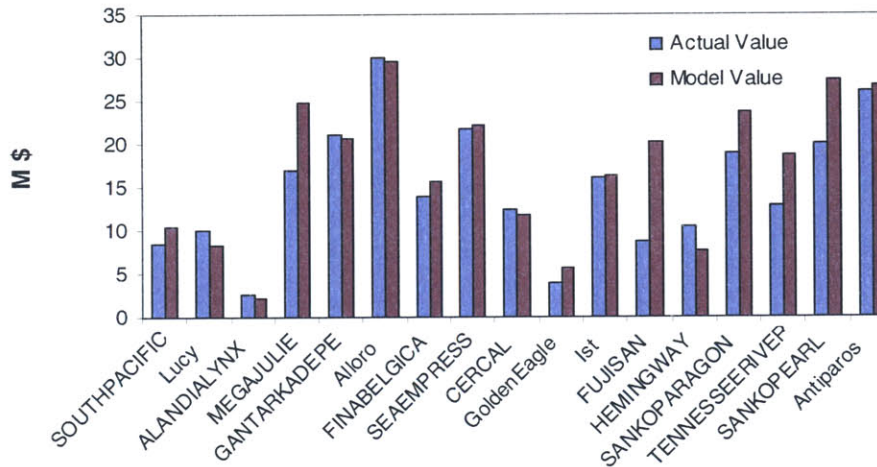


Figure 19: The Six Month Model Fit on 20 Next Testing Cases of Tanker Vessels

Figure 20 shows the results for the next 20 cases of the testing set.

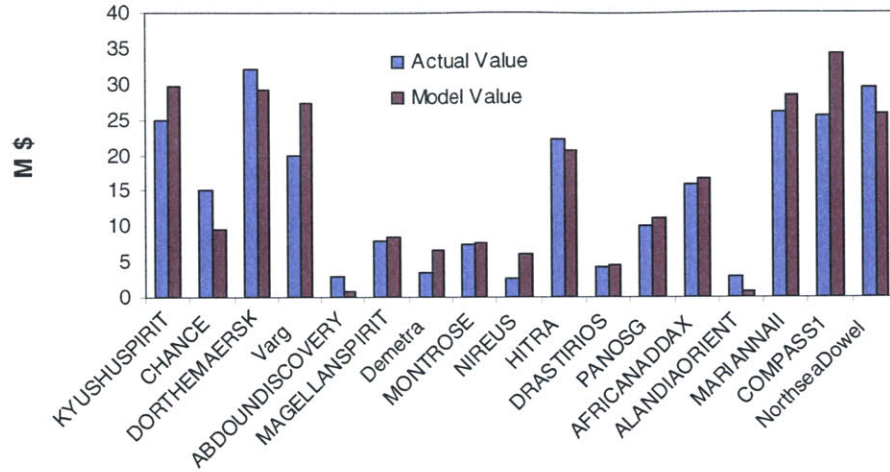


Figure 20: The Six Month Model Fit on 20 Next Testing Cases of Tanker Vessels

The scatter plot for the testing data is shown in the figure below:

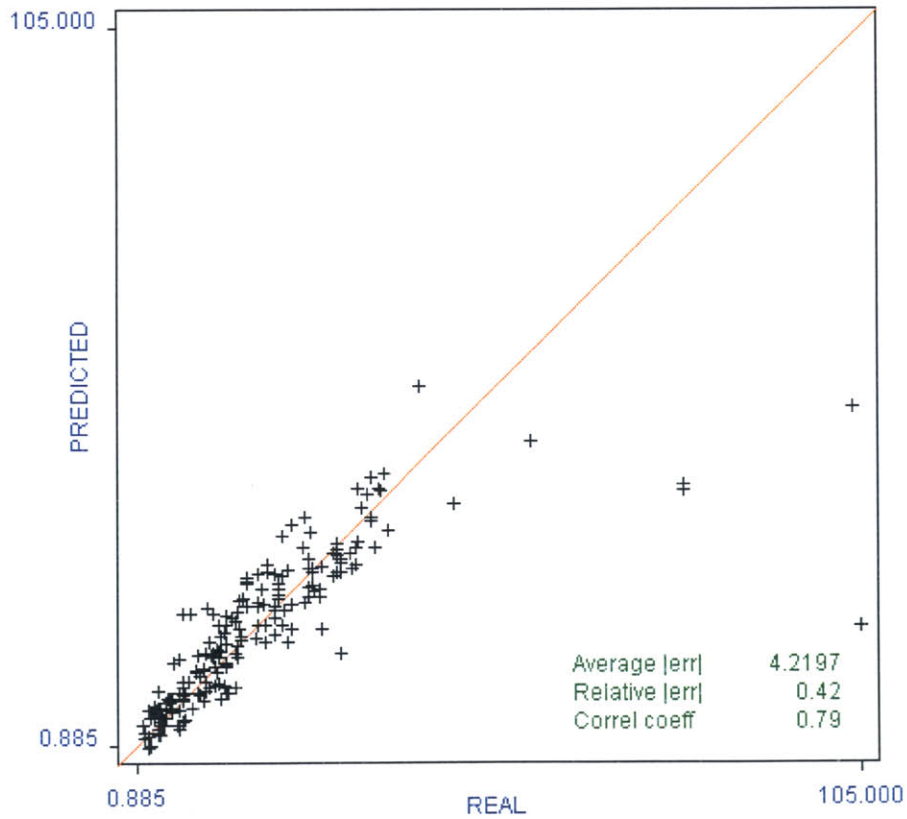


Figure 21: The Scatter Plot for Six Months Model Fit on Testing Cases of Tanker Vessels

According to the scatter plot, the vessel cases for the testing process are located around and close to the red line.

Analyzing the results of the Six Month Model, one can say that they are adequately acceptable. The error terms are significantly low in all three categories. The Six Month Model has excellent generalization ability. The fact is that the error terms in the training (known) data are similar to those in the testing (unknown) data.

By comparing the two models, one can conclude that: the zero month model has a better goodness of fit in both the training and the testing data. This is easily explained by the fact that the future shipping market is dependent on a number of parameters that cannot all be included in the model. Also note that many of them are of stochastic nature with an unpredictable progression in time. Therefore, it is extremely difficult to predict future second-hand prices with the same error as the estimates on present second-hand tanker prices.

4 DECISION SUPPORT TOOL - A CASE STUDY

In order to evaluate the proposed methodology as a decision support tool a case study will be examined. The main scope of this thesis is to provide an econometric tool to possible investors, ship-owners, ship-brokers and shipyards in trading second hand tanker vessels. This approach would require some specifications in order to meet the user's needs and standards.

These specifications are the following:

- Accurate tool output. It is obvious that the decision support tool should be adequately accurate. This is ensured by the low error terms on the train and test data according to the evaluation of the zero month and the six month model.
- Easy to use. The use of the models is easy but requires continuous data collection and a kind of preparatory process to extract moving averages from time series. In a subsequent software form, this could be automatically updated with real time data and the calculations could be performed by the software.
- Adaptation is essential to ensure continuous enhancement of performance. The data covers the period from 1986 to present and hence encloses many different second-hand market states. In addition, the data were randomized during train and testing to insure more representative samples. Data mining techniques provide the ability to retrain and fit the model to the new situations of the non-stationary system.
- Customization. The proposed tool can easily be adapted to the customers' needs. For example, this technique could be constructed using an appropriate data set specific to ship-owners who own and trade VLCC tanker vessels.
- Modeling and product forming. This methodology could easily be embedded in a software tool to form a viable, marketable and profit making product.

4.1 Decision Support Tool Definition

The decision support tool consists of two different modules aiming to a wider area of implementation. According to the methodology results, two different models were constructed, trained, tested and evaluated.

The first module is designed to provide real time estimates for tanker vessel second-hand prices. As mentioned in previous chapters the zero month model can be used towards this scope. The user should provide all necessary input data to the model according to the partitioning of the solution space (rule 1 or 2). The input data are divided into two clusters. The first cluster refers to the second-hand vessel characteristics such as Age and the second one refers to market status such as the time charter rate attribute. The decision support tool result is a value which is an estimate of a realistic price of a vessel. It should be noted that, vessel special particularities cannot be addressed with the corresponding model. For example, it is out of the model's scope to include attributes like whether the vessel has successfully passed a special survey. This initial estimate of the vessel price can be the starting point of a negotiation of the final

price among the vessel's particulars. It is obvious that this tool can provide valuable help to all parties participating in the purchase-sale process. For example, the similar vessels sold in different market states cannot have the same price. It is evident, that a vessel sold in a high market state will achieve a higher price than one sold in a low state. The decision support system can provide a realistic approach of a vessel's pricing by taking into account timing and other special circumstances in shipping and global economic systems. The multi-parameter explanatory rule-based model can be a reference for every party involved in second-hand tanker vessel purchase-sale process.

The second module aims to play a considerable role in decision making. For the first time, a forecasting model is applied to the tanker second-hand market. It is a new approach in tanker vessel pricing. The six month model has been constructed with this main scope and evaluated as a successful model for future vessel pricing. It should be noted that the proposed model is able to make an estimate of future vessel prices, based on present and precedent information. The user again should provide all necessary input data to the model according to the partitioning of the solution space (rule 1 or 2). The input data are divided into two clusters. The first cluster refers to the second-hand vessel characteristics. Apart from Age, DWT should also be included. The second cluster refers to the market status such as the time charter rate attribute. The six month model output is a value indicating a possible tanker vessel price after six months. A possible user can exploit this by collecting information for the future.

The decision support tool can work separately, either by using the models independently or by using them jointly. The first operation provides valuable answers to the question "at what price should I sell or purchase a specific vessel?". The advantage of using the modules jointly is that one can be assisted in the decision making of when and at what price to purchase or sell a particular vessel. For example, let us assume a particular market state, and by the implementation of the zero and six month models a second-hand AFRAMAX price is expected to rise. Then, from a seller's point of view, one must wait for an increase of the vessel's price in the future before selling. It is obvious that all parties involved in the second-hand tanker vessel purchase-sale process can obtain significant help in their decision making by using the proposed tool.

At the following sections the case study parameters will be defined. The aim is to examine the usage and the necessity of the tool given it meets the above specifications.

4.2 Case Study

In order to present the decision support tool, a case study will be assessed. The numbers and values of the case are fictitious but within reason. Suppose that a 75,000 DWT 20 year old tanker is to be sold at \$7 million. This is a generic case where the ship has no particularities.

The ship-owner asks for help regarding the following issues:

- Which is the right price for this vessel?
- When is the right time to sell this vessel?

The key point is to provide the best strategy according to expert judgment and model output support.

Suppose a ship-owner's initial estimate of the vessel is \$7 million but is considering the revaluation of the price according to an expert judgment. In order to estimate the vessel price, the decision support tool user will apply the models mentioned throughout the paper in order to obtain valuable information.

To answer the first question, the expert will use the zero month model. There are some input data necessary to apply the model. The first step is to seek information for the zero month model. Due to the fact that the vessel age is 20 years, the first rule will be applied. Hence, the necessary model attributes describing the particular market state are the following:

- The Time Charter Rate before one month is 17500 \$ per day
- The six to twelve previous months moving average of Scrap Values, which is \$2.25 per ton

The zero month model for this case is :

Rule 1:

If

Age > 16

Then:

Price =

$$\begin{aligned} & 14.8136 \\ & - 1.01 [\text{Age}=20] \\ & + 0.00051 [\text{Time Charter Rate before one month}=17500] \\ & + 1 [\text{Six to twelve previous months moving average of Scrap Value}=2.25] \end{aligned}$$

By performing the above calculations, the suggested vessel price under the specific market state is \$5.8 million. This value is \$1.2 million lower than the ship-owner's initial estimate. According to the decision support model, the ship owner has overvalued the vessel and should revalue according to the recommendations of the decision support tool.

In order to answer the second question, the expert will need to apply the six month model. This will give him a future estimate of the vessel price. The vessel age will direct the ship-owner to the first rule. For the first rule application, the decision support user would need the following information for the six month model.

The market state attributes required for the model are the following:

- The Time Charter Rate, which is \$18,600 per day
- The six previous months moving average of the Scrap Values, which is \$2.25 per ton

The six month model for this case is:

Rule 1:

If

Age > 16

Then

Price after six months = 16.1031
 - 0.91 [Age=20]
 + 2.4 [Six previous months moving average of Scrap Value=
 2.25]
 + 0.0001 [Time Charter Rate= 18600]

By performing the above calculations, the price of the vessel in six months for the specific market state will be \$5.1 million.

The next table summarizes the case study results:

	Ship – owner estimation	Decision Support Tool	
		Zero month model	Six months model
Vessel price in million \$	7	5.8	5.1
Recommended price	5.8 million \$ now or 5.1 million \$ after six months		
Recommended timing	Sell without no further delay		
Best Strategy	Reconsider initial vessel price and sell according to decision support tool recommended price and time		

Table 6: Case Study Results

The model estimates that after six months there will be a decrease of \$0.7 million in the vessel price. That gives a short preference to the sale of the vessel without further delay.

According to the case study results and the aforementioned user requirements and needs, the decision support tool can be a useful tool to all parties involved in the sale-purchase process. It produces accurate outputs, is easy to use, and can be customized and adapted into a profitable product. The market has to test it several times in order to achieve the necessary trust and confidence. It would be a matter of time before the market returns feedback and reconstructs the tool in order to best fit users' needs.

5 CONCLUSIONS

In this section, the conclusions of the analysis are presented. The main scope of the project was the prediction of the second-hand tanker market. The attempt was difficult for many reasons:

- The sources of information are not many contrary to the need for data.
- Data mining techniques and generally explanatory models that need superior data in terms of quality and quantity
- Second-hand markets like the shipping market, are generally subject to numerous interactions and feedbacks. Therefore, every modeling attempt was extremely difficult.

The use of every possible source of the database decreases the deficiency of the data. The sources were the Drewry Shipping Consultants, the Lloyd's Shipping Economist, the Clarksons Research Studies, my advisor Henry S. Marcus and colleagues of mine. This implies that every available source of information should be considered in developing a multivariate model. Also note that the final database was formed by an adequate number of qualitative and quantitative time series.

Based on the results, the use of multivariate models was successful. The goodness of fit and the ability of generalization was good. Generally, multivariate explanatory models can simulate complex systems in a better manner than univariate ones.

The second-hand prices prediction models that were developed in this project can be used to give accurate predictions in the two different time spans. This was feasible with the use of data mining techniques. Data mining techniques proved to be useful in their ability to reveal data interactions and connections. This applies both to the zero month and the six month models. The zero month model experienced better performance because of the shorter time span.

It is true that the proposed model like every model will never predict dramatic changes in market direction because it is based on history. It is also fair to state that no model can predict market states/events that haven't been taken into consideration during the model creation. The model was trained to predict situations of market states similar to those in the database. To the writer's knowledge there is no such model that can predict values outside of the training set. Maybe a stochastic model along with the use of probability theory can do better, but this was not the purpose of this project.

The decision support tool, via the use of a case study, demonstrated its usefulness. The decision support tool addresses all parties of tanker vessel brokerage. Possible users are ship owners, brokers, banks and generally investors wishing to purchase or sell vessels.

5.1 Suggestions for Further Research

The developed methodology framework, the decision support tool, and its results, is the first attempt to model and produce a tool dedicated to tanker vessels. This attempt can be expanded to other sectors in the shipping industry. For example, the implementation of the above methodology could be incorporated to all tanker sizes. The present attempt applies to Panamax and Aframax tanker vessels. VLCC, Suezmax and ULCC should also be include for an integrated and complete tool.

The decision support tool should also be applied and tested on the dry sector. It should be mentioned that the dry sector has many differences relative to the tanker sector. This is due to the fact that there are more commodities, and therefore there will be more interactions.

Finally, further research on alternative methods should be considered. For example, Artificial Neural Networks have proved their ability in the tanker and bulk market simulation. During the last couple of years, there have been enormous attempts to use such methods in freight rate forecasting. Other methods that could improve model accuracy are the generic algorithms. The generic algorithms are used as an optimization technique in reducing method errors. For example a modeller could experiment on data mining and generic algorithm composite models. A possible field of application of generic algorithms in data mining techniques could be the optimization of rule splitting, coefficient determination, training method, etc.

APPENDICES

APPENDIX A: NAME FILES

1 ZERO MONTH MODEL

This appendix provides the formal input file for the zero month model

```
Price.
Name:      label.
Year of Built:  ignore.
DWT:      continuous.
Age:      continuous.
Time Charter Rate: ignore.
Time Charter Rate before one month: continuous.
Time Charter Rate before two months: ignore.
Time Charter Rate before three months: ignore.
Time Charter Rate before four months: ignore.
Time Charter Rate before five months: ignore.
Time Charter Rate before six months: ignore.
Time Charter Rate before seven months: ignore.
Time Charter Rate before eight months: ignore.
Time Charter Rate before nine months: ignore.
Time Charter Rate before ten months: ignore.
Time Charter Rate before eleven months: ignore.
Time Charter Rate before twelve months: ignore.
Six previous months Moving Average of Time Charter Rate:
    continuous.
Six to twelve previous months moving average of Time
Charter Rate:      continuous.
Scrap Value:      ignore.
Scrap Value before one month:      continuous.
Scrap Value before two months:      ignore.
Scrap Value before three months:      ignore.
Scrap Value before four months:      ignore.
Scrap Value before five months:      ignore.
Scrap Value before six months:      ignore.
Scrap Value before seven months:      ignore.
Scrap Value before eight months:      ignore.
Scrap Value before nine months:      ignore.
Scrap Value before ten months:      ignore.
Scrap Value before eleven months:      ignore.
Scrap Value before twelve months:      ignore.
Six previous months Moving Average of Scrap Value:
    continuous.
Six to twelve previous months moving average of Scrap
Value:      continuous.
Price:      continuous.
```

2 SIX MONTH MODEL

This appendix provides the formal input file for the six month model

```
Price after six months.
Name:      label.
Year of Built:  ignore.
DWT:       continuous.
Age:       continuous.
Time Charter Rate(unknown): ignore.
Time Charter Rate before one month(unknown): ignore.
Time Charter Rate before two months(unknown): ignore.
Time Charter Rate before three months(unknown):
ignore.
Time Charter Rate before four months(unknown):
ignore.
Time Charter Rate before five months(unknown):
ignore.
Time Charter Rate: continuous.
Time Charter Rate before one month: ignore.
Time Charter Rate before two months: ignore.
Time Charter Rate before three months: ignore.
Time Charter Rate before four months: ignore.
Time Charter Rate before five months: ignore.
Time Charter Rate before six months: ignore.
Six previous months Moving Average of Time Charter
Rate(unknown): ignore.
Six previous months moving average of Time Charter Rate:
continuous.
Scrap Value(unknown): ignore.
Scrap Value before one month(unknown): ignore.
Scrap Value before two months(unknown): ignore.
Scrap Value before three months(unknown): ignore.
Scrap Value before four months(unknown): ignore.
Scrap Value before five months(unknown): ignore.
Scrap Value: continuous.
Scrap Value before one month: ignore.
Scrap Value before two months: ignore.
Scrap Value before three months: ignore.
Scrap Value before four months: ignore.
Scrap Value before five months: ignore.
Scrap Value before six months: ignore.
Six previous months Moving Average of Scrap Value(unknown):
ignore.
Six previous months moving average of Scrap Value:
continuous.
Price after six months: continuous.
```

APPENDIX B: RESULT FILES

1 ZERO MONTH MODEL

This section provides the results file for the zero month model for the train file.

Rule 1: [82 cases, mean 7.6013, range 2.85 to 22.5, est err 1.9630]

```
if
  Age > 16
then
  Price = 14.8136 - 1.01 Age + 0.00051 Time Charter Rate before one month
        + 1 Six to twelve previous months moving average of Scrap Value
```

Rule 2: [118 cases, mean 22.7970, range 4.5 to 102, est err 4.8097]

```
if
  Age <= 16
then
  Price = 19.8714 - 1.72 Age
        + 0.00109 Six previous months Moving Average of Time Charter Rate
        + 0.00011 Time Charter Rate before one month
```

Case	Actual Value	Model Value
DUKE	13.5	13.7616
MAGNOLIA	11.5	13.3616
THORSHAMMER	16.5	21.4626
ARETUSA	10	11.2443
TENRYUSANMARU	12.5	14.4986
SabineSpirit	66	26.4692
GALAXYRIVER	26.5	24.5302
FELIZ	24.5	24.4756
REGENTSEA	13	10.7581
Nicopolis	7.5	13.5353
SANKOEXPRESS	5.4	5.5769
MELOR	12	12.2534
SELETARSPIRIT	19.75	18.8635
ENALIOSAPOLLON	3	1.2519
NorthseaAnvil	32	28.6352
OverseasCleliam	30	33.0681
ALMANAMA	24	25.7373
STARORCHID	6.45	6.3636
GYOKOMARU	5.8	6.2803
MEGAPILOT	17.5	19.6053
LATOM	7.5	11.7195
SENTOSASPIRIT	20.25	20.5835
Kite	4.5	6.9529
SETOBREEZE	26.5	26.3968
PASADENA	7.75	5.4332
SANKOQUEST	24	26.1901
SHORITSUMARU	3.5	2.2903
SILVERIRIS	13.25	12.897

SULBY	10.75	9.7786
Seafalcon	30	31.3998
NILE	13	15.6827
CELTIC	4.5	5.5903
CANADIANLIBERTY	11.7	21.2274
AFRAPEARL	4.5	4.3103
Seastar	46	35.7212
WINDCONQUEST	23.75	24.9806
MaerskPrincess	57	44.1845
SITAMIA	22.1	30.1594
SEAKING	5.45	6.7429
CARIBBEANSTAR	9.2	14.7752
FREJASVEA	29.95	26.8568
GITAYU	12.7	10.5572
SANKOETERNAL	21	25.5488
KIHO	7.85	12.8152
MARINEREUNION	16.3	26.8234
TARIMRIVER	24.5	21.3627
Margara	102	35.8358
LMZCHRISTIANA	7.5	7.3569
EAGLELYRA	37	32.1774
GOLDENTIGER	6	11.1541
BroSelma	21	14.9469
ALDEBARAN	22.5	21.6214
TormMargrethe	52	25.3672
DIDO	11	18.3829
PROSPERITY	2.97	7.7774
HistriaEmerald	17	17.6453
ASTROPEGASUS	15	15.5854
SEASALVIA	4	2.2619
WORLDKINSHIP	5.2	3.8407
SINGASTAR	7.8	11.3434
TEEKAYVISION	6.05	5.5903
SENTOSASPIRIT	14	17.1001
Wilmington	11.5	13.5353
Elbe	6.06	9.7996
Eleanora	3.2	5.9429
SUDONGSPIRIT	12	13.7135
SOLARIS	15.2	12.9269
SINGAPORESPIRIT	12	13.7135
WILMINGTON	4	6.3019
NORD-JAHREPRINC	40	30.2514
SeafalconII	4.2	3.3003
ANTARCTICA	15	22.0665
ERATO	15.5	11.9129
SANKOPIONEER	31	29.4796
HELLESPONTHOPE	4.125	3.7546
SEASONG	4.2	3.7015
GLORY	2.85	5.5386
Diane	15.9	14.9469
TOSCA	4.5	4.5382
FINAAMERICA	11.5	11.3165
NISSOSTHERASSIA	7.35	9.3936
WINDCONQUEST	29.5	24.5285
MARINEREGENT	26.5	23.5429
BAYOVAR	5.7	6.6253

SEAROYAL	9.7	10.0311
MAJESTICPRIDE	9.25	10.3939
JAPANSTORK	9.5	16.2552
ANELLA	31	35.1567
ANGELOD'AMATO	24.7	38.2395
FULLMOONRIVER	25	24.3157
WILLIAME.MUSSMA	5	3.2403
SEMEKAUSPIRIT	19.75	18.8635
SIBEIA	6	7.3569
SEAFLACON	31	24.8027
IDEAL	5.5	4.5719
ARABIANADDAX	4.25	5.5194
GOLDENGATESUN	4.3	5.5194
CANADIANLIBERTY	12.5	9.7994
CSKVALIANT	17.5	18.5803
IRONGIPPSLAND	28.2	28.4678
KOS	7	8.4678
SEACHARM	30.3	26.0321
NPTATINA	5	7.2753
BANDASEA	40	40.0215
PRIMO	29	23.6476
JAHREPROSPECT	13.3	13.0514
VICTORY	6	7.6386
LOUCAS	13	24.6647
SERENO	16	18.3007
DIRCHMAERSK	26	18.1965
PALMMONARCH	29.25	23.5914
TAKAMINEMARU	33.8	32.1774
WINDSOR	14	8.7686
Silba	16	16.5653
GOLDENFLEECE	20	19.6611
IRENE	26	27.2358
DOLVIKEN	9.5	7.1757
Latgale	35	39.3553
SaintVassilios	3.25	4.5719
GANTAKADEPE	22	23.217
BAGE	8	11.2403
ESSOORIENT	4.1	4.3236
ASTROPERSEUS	24	24.358
SUNNYPROGRESS	8.5	13.6588
CYPRESS	19	21.8828
CaboTamar	12.5	21.8245
CATHAYSPIRIT	4.9	7.0089
NEPTUNELEO	15.5	17.5187
OCEANVICTOR	14.5	14.6843
ANJA	30.5	33.4367
RASLANUF	4	4.4518
ClareSpirit	15	11.3661
Afraparl	4.9	4.0809
VESTALEGIA	17.75	16.2129
BERNORA	4.5	6.0828
AMERSHAM	11.5	13.0514
ATLANTIS	3.5	5.5194
MANHATTANPRINCE	6.8	12.8626
ORCHID	3.25	0.885
SERICATA	11.6	10.2046

STARCHERRY	6.8	7.4578
Berthea	7	10.4669
ASTROPEGASUS	3.6	0.885
LAURA	35.45	36.8767
Vukovar	17	9.1946
EmeraldRay	35	36.0735
PEARLPACIFIC	17.7	19.6053
GLADYS	11.3	12.2104
EDOARDOD'ALESIO	8.6	9.4986
Metaxata	15.5	14.5069
Aruba	3	3.5619
ALLIANCE	11.2	12.7253
FourBrig	38.5	39.5035
Sealion	8	2.9873
FourKetch	36	42.7953
NEWTATINA	6.8	5.9161
STENACONCERT	21	22.7981
UnitedWill	25.3	26.1454
MagellanSpirit	8	8.7619
Berana	22.5	18.9794
JUDITHPROSPERIT	4.7	6.6286
RICHDUCHESS	23.6	21.6968
PRIMO	27.8	25.5486
StenaVenture	35.5	39.4601
KRITI	7.1	5.8686
GElephant	16.5	17.6869
KENYOMARU	4.5	21.9881
CORCOVADO	32	22.7054
KANTANJAYAEKSPR	23.5	19.5397
HOPE	16.5	29.8385
TEMPERA	27.7	26.9007
SILVERIRIS	9	8.3079
EmeraldSky	15	15.3801
Nidia	37	41.5596
SEASKY	8	7.4229
SILVERVENUS	17.5	20.1924
HELLESPONTPROSP	5.4	4.9409
UNITEDSELMA	28	25.0614
SEASALVIA	10.5	9.6578
NEWIDEAL	7	5.2603
NORDSYMPHONY	32.5	37.8425
BORNES	15.8	20.4353
Athina	4	4.5719
GOLDENSUNRAY	10.7	10.9044
OverseasPolys	30	33.0681
R.HalDean	10	15.4335
TOMISLIBERTY	11.8	15.2286
REBECCA	32	29.6885
HAPPYSPRITE	23.5	20.6416
JAHREPRINCE	26.5	23.3532
YUHSEIMARU	22	27.932
NEPTUMEOTOME	26.5	22.5957
SERIFOS	6	5.9941
ZEPHYROS	4.75	5.2243
STELLATA	11.6	10.2046
STALEGIA	9	14.1003

SKAUFAST	6.5	7.1757
Lanner	6.9	9.7719
OSCOBEDUIN	33	32.6816
NOLPAVO	5.7	5.5482

This section provides the results file for the zero month model for the test file.

Case	Actual Value	Model Value
METSOVON	13	7.7753
MARINA	12.75	9.8146
TOURAINÉ	14.8	14.2085
Kliomar	16.85	20.2412
OREMBAE	6	5.4561
SETOBREEZE	28	24.5259
BRILLIANCY	6	7.4068
TRANSFALCON	15.5	20.703
SANKOPHOENIX	30.5	27.3299
BLUESKYRIVER	13	16.5454
WHITEGARDENIA	7.7	12.3803
MANHATTANPRINCE	4	8.0629
CHARISMA	2.25	0.885
COLORADO	4.7	2.7836
NORITA	27.5	24.7369
FREJASVEA	30	28.4133
TASMANSPIRIT	9.8	8.8296
GEIKOMARU	7.175	14.4199
ALANDIATRADER	4	6.9344
NARNIANSEA	13.5	17.2696
STAVANGERBOSS	33	30.0626
NISSOSAMORGOS	3.5	5.5328
Milagro	12.7	13.6469
ATLANTICPEACE	18.65	24.2504
SOUTHPACIFIC	8.4	11.4204
Lucy	10	10.6569
ALANDIALYNX	2.7	0.885
MEGAJULIE	17	19.6224
GANTARKADEPE	21	21.5538
Alloro	30	34.0012
FINABELGICA	14	16.0394
SEAEMPRESS	21.7	17.6485
CERCAL	12.5	12.9333
GoldenEagle	4	5.9429
Ist	16	16.5653
FUJISAN	8.75	15.4889
HEMINGWAY	10.5	7.4786
SANKOPARAGON	19	23.2243
TENNESSEERIVER	12.8	19.5979
SANKOPEARL	20	23.4428
Antiparos	26	28.9465
TEEKAYVIGOUR	6	5.5903
SEAEAGLE	18.5	17.2016

Zemgale	35	39.3553
PACIFICLIBRA	33.5	35.9926
HELLESPONTTENAC	4.5	3.6332
FORTUNE	26.75	23.4607
Odin	80	39.7921
KritiRock	9.5	10.5753
CARIBBEANSTAR	20	22.6842
FLORESSEA	5.1	4.7453
OSCOBELLONA	33	34.2729
SPONSALIS	14	12.9336
CANOPUS	26.5	23.1555
SEASTAR	47	35.7212
MAERSKPRIDE	58	43.2491
CORALSEA	23	21.3729
ANGELRIVER	17	23.4254
YUYOMARU	11.35	10.8794
SaraViking	105	19.7013
KYUSHUSPIRIT	25	25.5065
CHANCE	15.2	9.7819
DORTHEMAERSK	32	26.6226
Varg	20	31.6292
ABDOUNDISCOVERY	2.95	0.885
MAGELLANSPIRIT	8	8.7619
Demetra	3.4	5.7215
MONTROSE	7.5	6.8736
NIREUS	2.6	4.9153
HITRA	22.3	18.2114
DRASTIROS	4.25	4.8444
PANOSG	10	10.9053
AFRICANADDAX	16	16.3399
ALANDIAORIENT	2.8	0.885
MARIANNAI	26	23.9529
COMPASS1	25.5	31.6292
NorthseaDowel	29.5	26.4692
COROLLA	10.6	12.2104
MANTINIA	4.25	3.2719
CrudePrincess	23.5	19.0511
MALINROSE	26.5	22.6967
AriadneJacob	104	53.2491
OSHIMASPIRIT	5.6	7.3119
FULLMOONRIVER	27.5	24.9135
NISSOSAMORGOS	30	26.6591
EnaliosHellas	4.1	4.7757
BERYL	18.6	21.3811
TORUNGEN	32.75	31.3533
CADDIE	11.25	23.2608
SANKOPAGEANT	22	25.1389
GLEFI1	34.5	33.7305
VERONIQE	10.5	12.1096
GLOBTIKBRITAIN	15.25	18.9939
ODIN	80	39.0828
AGIPLOMBARDIA	7.1	7.7903
MerseySpirit	7.5	9.7719
ALANDIAFOX	4.2	4.5382
BUNGAKERANJI	3.5	5.5482
Cerigo	6.65	5.3369

MENDANASPIRIT	4.7	4.5382
GATEWAYNORTH	12.25	12.9643
BONARAINBOW	14.25	8.7636
GreenValley	11.75	13.9343
HELENE	11	10.6779
SPECTRUM	15.2	12.9269
BONAIRE	11.5	14.097
NORTHSEA	4	3.3003
URSAMAJOR	5.75	6.6686
YUHSEIMARU	22	28.5029
NISSOSSERIFOS	9	6.9841
SEACONFIDENCE	17	21.6229
PANADA	37	37.2614
SPYROS	37.5	31.9654
YAMATOPACIFIC	16.5	20.8104
PacificFalcon	19.75	19.9894
FLYINGCLIPPER	5	5.2559
Riga	35	39.3553
ALFAAMERICA	2.9	3.8544
ClydeSpirit	7	8.7619
HANDYSONATA	12.75	14.617
Serifos	6.35	12.4869
SANKODYNASTY	42	44.2872
MaryAnn	15.5	15.9553
Solaris	30.5	12.9269
SANKOPROTECTOR	23.5	28.9888
PACIFICMERCURY	30	26.1264
JAHREPROSPECT	12	16.1369
SAINTANDREW	9.6	8.4426
EAGLEORION	30	28.4678
ODYSSEY	13.75	15.6504
AMBRABLUE	29.5	24.3737
HELLESPONTSEREN	5.5	7.4068
KAKUKOMARU	5.2	6.3436
Suzanne	10	10.6569
ELOUNDA	7.5	16.2027
OLYMPICSUNII	12.5	11.1643
HELLESPONTCOURA	2	3.8033
CORALSEA	26.6	22.6967
DENEK	7.7	8.9729
GELIBOCU	13.8	14.3944
SEAGRACE	21.5	18.1589
Panda	28	17.6453
BTSTREAM	8	6.4129
NIKKOMARU	21	22.1086
SEALOYALTY	21.5	20.3465
POPPY	14	20.7139
PARISII	3.9	2.9873
PERNASDUYONG	15.5	14.7714
Grigoroussa	21	20.9994
INTERMARALLIANC	19.6	20.7458
VICBILH	26.2	24.9806
JAHREPROSPECT	14	14.5935
ELIANE	19.5	23.0057
ANTARES	23.5	24.8607
MELOR	21	19.5397

TAGASAN	12	14.617
EmeraldSun	35	36.0735
COOKSPIRIT	9.7	13.6601
AFRAGOLD	3.9	3.2719
SIBREGHEL	3.75	5.2559
FourClipper	36	42.7953
THISEAS	12	14.0842
NORTHERNBELL	32.25	30.6757
EPIC	5.6	7.2469
TAMYRA	10.75	8.7896
SKAUFJORD	15.7	19.777
VICTOIRE	14	19.0241
UMMSAID	22	24.0173
AKADEMIKLUYANEN	30.5	21.8714
FULLMOONRIVER	26	25.0614
CHANNELDRAGON	21	22.7054
JILLJACOB	21.5	22.2601
SOLENA	7.6	5.7869
JAHREPRINCESS	35	34.7367
CHEVRONFRANKFUR	1.85	1.3906
VENDEMIAIRE	15.9	19.4568
PANDA	26	23.4168
ERA	26.5	24.8755
COLBY	36.5	33.7368
PALMMONARCH	13.5	9.4986
Piemonte	18.5	17.6869
FOURLAKES	32.75	30.8421
NEVA	14	14.7414
CLOUDSDALE	3.8	5.2703
EUOPRIDE	4.2	5.9989
SAIKOMARU	5.2	6.3436
Venetikos	18.25	23.3552
GRACECENTURY	23	24.3332
ASTROPEGASUS	4.8	3.7219
PACIFICJUPITER	30.5	27.5658
LAURA	35.5	26.1454
MISSOURI	7	5.5444
OCEANMAID	12.25	9.9269
ALDEBARAN	7.5	8.8236
PRETTYLADY	25.9	21.8192
GORBEIA	13	16.1369
ZORAS	11	9.9036
Raven	4	6.9529
BALTICSEA	25.5	22.4911
BTSTREAM	13.5	9.7694

2 SIX MONTH MODEL

This section provides the results file for the six month model for the train file

Model:

Rule 1: [82 cases, mean 7.6013, range 2.85 to 22.5, est err 2.1817]

```

if
  Age > 16
then
  Price after six months = 16.1031 - 0.91 Age
                        + 2.4 Six previous months moving average of Scrap Value
                        + 0.0001 Time Charter Rate
    
```

Rule 2: [118 cases, mean 22.7970, range 4.5 to 102, est err 5.2035]

```

if
  Age <= 16
then
  Price after six months = -5.1385 - 1.8 Age
                        + 6.9 Six previous months moving average of Scrap Value
                        - 3 Scrap Value + 0.00075 Time Charter Rate
                        + 0.00024 DWT
    
```

Case	Actual Value	Model Value
DUKE	13.5	17.6149
MAGNOLIA	11.5	7.8494
THORSHAMMER	16.5	23.0828
ARETUSA	10	12.2641
TENRYUSANMARU	12.5	13.5499
SabineSpirit	66	25.8623
GALAXYRIVER	26.5	25.0691
FELIZ	24.5	22.2205
REGENTSEA	13	8.1391
Nicopolis	7.5	13.5871
SANKOEXPRESS	5.4	5.8036
MELOR	12	14.7301
SELETARSPIRIT	19.75	20.1931
ENALIOSAPOLLON	3	0.9731
NorthseaAnvil	32	36.7581
OverseasCleliam	30	38.2206
ALMANAMA	24	20.304
STARORCHID	6.45	7.0201
GYOKOMARU	5.8	6.8421
MEGAPILOT	17.5	22.1772
LATOM	7.5	6.6371
SENTOSASPIRIT	20.25	21.7226
Kite	4.5	6.5511
SETOBREEZE	26.5	28.9769
PASADENA	7.75	7.0591
SANKOQUEST	24	31.3911
SHORITSUMARU	3.5	1.9411
SILVERIRIS	13.25	11.8163
SULBY	10.75	9.5064
Seafalcon	30	36.0754
NILE	13	13.0831

CELTIC	4.5	6.4071
CANADIANLIBERTY	11.7	18.0231
AFRAPEARL	4.5	3.7611
Seastar	46	36.1518
WINDCONQUEST	23.75	29.4419
MaerskPrincess	57	48.9993
SITAMIA	22.1	18.3831
SEAKING	5.45	8.5771
CARIBBEANSTAR	9.2	11.7089
FREJASVEA	29.95	30.8088
GITAAYU	12.7	8.5997
SANKOETERNAL	21	29.3436
KIHO	7.85	17.0376
MARINEREUNION	16.3	26.9585
TARIMRIVER	24.5	25.2786
Margara	102	29.1778
LMZCHRISTIANA	7.5	5.9851
EAGLELYRA	37	34.452
GOLDENTIGER	6	12.8679
BroSelma	21	16.1691
ALDEBARAN	22.5	19.9346
TormMargrethe	52	29.5402
DIDO	11	20.8773
PROSPERITY	2.97	7.6481
HistriaEmerald	17	18.0801
ASTROPEGASUS	15	16.556
SEASALVIA	4	1.8831
WORLDKINSHIP	5.2	4.9931
SINGASTAR	7.8	9.4464
TEEKAYVISION	6.05	6.4071
SENTOSASPIRIT	14	19.0875
Wilmington	11.5	13.5871
Elbe	6.06	9.9361
Eleanora	3.2	5.6411
SUDONGSPIRIT	12	17.2236
SOLARIS	15.2	14.3491
SINGAPORESPIRIT	12	16.9241
WILMINGTON	4	5.5231
NORD-JAHREPRINC	40	34.9396
SeafalconII	4.2	2.8511
ANTARCTICA	15	24.4555
ERATO	15.5	16.3499
SANKOPIONEER	31	29.7186
HELLESPONTHOPE	4.125	4.5661
SEASONG	4.2	4.8391
GLORY	2.85	7.2471
Diane	15.9	16.1691
TOSCA	4.5	4.1344
FINAAMERICA	11.5	9.7788
NISSOSTHERASSIA	7.35	9.7501
WINDCONQUEST	29.5	28.9519
MARINEREGENT	26.5	26.916
BAYOVAR	5.7	7.3771
SEAROYAL	9.7	11.321
MAJESTICPRIDE	9.25	8.5555
JAPANSTORK	9.5	18.3437

ANELLA	31	31.411
ANGELOD'AMATO	24.7	28.673
FULLMOONRIVER	25	22.0515
WILLIAME.MUSSMA	5	4.1701
SEMEKAUSPIRIT	19.75	19.9253
SIBEIA	6	5.9851
SEAFLACON	31	29.1812
IDEAL	5.5	5.4611
ARABIANADDAX	4.25	6.5211
GOLDENGATESUN	4.3	6.5211
CANADIANLIBERTY	12.5	10.4181
CSKVALIANT	17.5	21.9542
IRONGIPPSLAND	28.2	28.3563
KOS	7	8.7111
SEACHARM	30.3	25.2749
NPTATINA	5	7.5191
BANDASEA	40	32.5095
PRIMO	29	20.88
JAHREPROSPECT	13.3	13.5043
VICTORY	6	8.1731
LOUCAS	13	12.6908
SERENO	16	16.867
DIRCHMAERSK	26	19.9625
PALMMONARCH	29.25	28.5468
TAKAMINEMARU	33.8	33.9485
WINDSOR	14	8.5964
Silba	16	16.3171
GOLDENFLEECE	20	22.0974
IRENE	26	26.1706
DOLVIKEN	9.5	5.0326
Latgale	35	33.6932
SaintVassilios	3.25	5.4611
GANTAKADEPE	22	22.2271
BAGE	8	9.2791
ESSOORIENT	4.1	5.5211
ASTROPERSEUS	24	24.6157
SUNNYPROGRESS	8.5	12.408
CYPRESS	19	20.1954
CaboTamar	12.5	16.5952
CATHAYSPIRIT	4.9	7.1471
NEPTUNELEO	15.5	20.2882
OCEANVICTOR	14.5	11.6214
ANJA	30.5	29.6374
RASLANUF	4	5.2761
ClareSpirit	15	8.4576
Afrapearl	4.9	4.2671
VESTALEGIA	17.75	20.311
BERNORA	4.5	5.0999
AMERSHAM	11.5	13.2234
ATLANTIS	3.5	6.5211
MANHATTANPRINCE	6.8	13.2862
ORCHID	3.25	0.885
SERICATA	11.6	10.4851
STARCHERRY	6.8	7.8011
Berthea	7	11.2591
ASTROPEGASUS	3.6	0.885

LAURA	35.45	33.1527
Vukovar	17	9.5751
EmeraldRay	35	34.2449
PEARLPACIFIC	17.7	20.7329
GLADYS	11.3	12.2894
EDOARDOD'ALESIO	8.6	8.2126
Metaxata	15.5	14.8991
Aruba	3	4.5511
ALLIANCE	11.2	14.0568
FourBrig	38.5	35.743
Sealion	8	3.4031
FourKetch	36	38.365
NEWTATINA	6.8	7.1541
STENACONCERT	21	23.0452
UnitedWill	25.3	22.8293
MagellanSpirit	8	8.5991
Berana	22.5	15.2451
JUDITHPROSPERIT	4.7	7.2631
RICHDUCHESS	23.6	21.5885
PRIMO	27.8	21.6465
StenaVenture	35.5	36.0555
KRITI	7.1	9.1951
GElephant	16.5	18.4871
KENYOMARU	4.5	19.9234
CORCOVADO	32	25.8953
KANTANJAYAEKSPR	23.5	18.6737
HOPE	16.5	28.4931
TEMPERA	27.7	24.4632
SILVERIRIS	9	5.4691
EmeraldSky	15	10.8073
Nidia	37	37.9159
SEASKY	8	5.6651
SILVERVENUS	17.5	20.2723
HELLESPONTPROSP	5.4	4.9551
UNITEDSELMA	28	21.5622
SEASALVIA	10.5	10.0531
NEWIDEAL	7	5.9901
NORDSYMPHONY	32.5	35.8526
BORNES	15.8	18.793
Athina	4	5.4611
GOLDENSUNRAY	10.7	10.0851
OverseasPolys	30	38.2175
R.HalDean	10	14.3294
TOMISLIBERTY	11.8	12.1569
REBECCA	32	35.8735
HAPPYSPRITE	23.5	28.3916
JAHREPRINCE	26.5	23.071
YUHSEIMARU	22	27.7282
NEPTUMEOTOME	26.5	20.5798
SERIFOS	6	7.1753
ZEPHYROS	4.75	5.6821
STELLATA	11.6	10.4851
STALEGIA	9	12.3002
SKAUFAST	6.5	5.0326
Lanner	6.9	9.5091
OSCOBEDUIN	33	37.2082

FORTUNE	26.75	23.5275
Odin	80	38.8145
KritiRock	9.5	11.7101
CARIBBEANSTAR	20	26.2274
FLORESSEA	5.1	5.0251
OSCOBELLONA	33	38.2887
SPONSALIS	14	13.0411
CANOPUS	26.5	24.3133
SEASTAR	47	36.1518
MAERSKPRIDE	58	45.0013
CORALSEA	23	26.55
ANGELRIVER	17	25.3807
YUYOMARU	11.35	9.5333
SaraViking	105	18.3841
KYUSHUSPIRIT	25	29.6724
CHANCE	15.2	9.5706
DORTHEMAERSK	32	29.0473
Varg	20	27.2582
ABDOUNDISCOVERY	2.95	0.9051
MAGELLANSPIRIT	8	8.5991
Demetra	3.4	6.6591
MONTROSE	7.5	7.5811
NIREUS	2.6	6.1071
HITRA	22.3	20.6491
DRASTIROS	4.25	4.6251
PANOSG	10	11.0621
AFRICANADDAX	16	16.8199
ALANDIAORIENT	2.8	0.885
MARIANNAI	26	28.2601
COMPASS1	25.5	34.1992
NorthseaDowel	29.5	25.6701
COROLLA	10.6	12.2894
MANTINIA	4.25	2.7931
CrudePrincess	23.5	18.0526
MALINROSE	26.5	26.881
AriadneJacob	104	50.1925
OSHIMASPIRIT	5.6	7.6571
FULLMOONRIVER	27.5	23.6435
NISSOSAMORGOS	30	28.5583
EnaliosHellas	4.1	5.3691
BERYL	18.6	21.4254
TORUNGEN	32.75	27.4215
CADDIE	11.25	20.9896
SANKOPAGEANT	22	25.7759
GLEFI1	34.5	37.5421
VERONIQUE	10.5	11.9362
GLOBTIKBRITAIN	15.25	19.0776
ODIN	80	37.935
AGIPLOMBARDIA	7.1	3.589
MerseySpirit	7.5	9.5091
ALANDIAFOX	4.2	4.1344
BUNGAKERANJI	3.5	5.0444
Cerigo	6.65	4.1651
MENDANASPIRIT	4.7	4.1344
GATEWAYNORTH	12.25	9.7941
BONARAINBOW	14.25	8.6431

GreenValley	11.75	14.2881
HELENE	11	14.3834
SPECTRUM	15.2	14.3491
BONAIRE	11.5	16.0937
NORTHSEA	4	2.8511
URSAMAJOR	5.75	7.4591
YUHSEIMARU	22	31.4562
NISSOSSERIFOS	9	6.3904
SEACONFIDENCE	17	24.4991
PANADA	37	40.3827
SPYROS	37.5	32.2815
YAMATOPACIFIC	16.5	22.2974
PacificFalcon	19.75	16.1551
FLYINGCLIPPER	5	6.3391
Riga	35	33.6771
ALFAAMERICA	2.9	5.1971
ClydeSpirit	7	8.5991
HANDYSONATA	12.75	13.8753
Serifos	6.35	13.0791
SANKODYNASTY	42	53.1905
MaryAnn	15.5	15.6121
Solaris	30.5	14.3491
SANKOPROTECTOR	23.5	32.9443
PACIFICMERCURY	30	26.138
JAHREPROSPECT	12	14.0193
SAINTANDREW	9.6	12.0831
EAGLEORION	30	29.4306
ODYSSEY	13.75	17.5756
AMBRABLU	29.5	28.9855
HELLESPONTSEREN	5.5	7.8011
KAKUKOMARU	5.2	7.3411
Suzanne	10	8.3356
ELOUNDA	7.5	20.2892
OLYMPICSUNII	12.5	14.8892
HELLESPONTCOURA	2	2.8861
CORALSEA	26.6	26.8812
DENEB	7.7	8.3711
GELIBOCU	13.8	8.7132
SEAGRACE	21.5	22.8887
Panda	28	18.0801
BTSTREAM	8	4.7551
NIKKOMARU	21	21.3242
SEALOYALTY	21.5	24.5097
POPPY	14	20.0354
PARISII	3.9	3.4031
PERNASDUYONG	15.5	13.8615
Grigoroussa	21	17.0651
INTERMARALLIANC	19.6	18.5171
VICBILH	26.2	32.007
JAHREPROSPECT	14	12.7288
ELIANE	19.5	21.5887
ANTARES	23.5	21.5455
MELOR	21	19.5948
TAGASAN	12	14.5461
EmeraldSun	35	34.254
COOKSPIRIT	9.7	14.1766

AFRAGOLD	3.9	2.7931
SIBREGHEL	3.75	6.3391
FourClipper	36	38.3429
THISEAS	12	20.0738
NORTHERNBELL	32.25	26.8597
EPIC	5.6	7.7851
TAMYRA	10.75	9.0261
SKAUFJORD	15.7	18.0119
VICTOIRE	14	18.5164
UMMSAID	22	18.5328
AKADEMIKLUYANEN	30.5	26.1235
FULLMOONRIVER	26	22.774
CHANNELDRAGON	21	25.914
JILLJACOB	21.5	23.7675
SOLENA	7.6	4.4991
JAHREPRINCESS	35	40.0215
CHEVRONFRANKFUR	1.85	3.9346
VENDEMIAIRE	15.9	22.0774
PANDA	26	23.9577
ERA	26.5	26.0989
COLBY	36.5	37.9723
PALMMONARCH	13.5	9.4714
Piemonte	18.5	18.4871
FOURLAKES	32.75	29.7358
NEVA	14	12.4204
CLOUDSDALE	3.8	5.9321
EUROPRIDE	4.2	6.2371
SAIKOMARU	5.2	7.3411
Venetikos	18.25	16.639
GRACECENTURY	23	16.2248
ASTROPEGASUS	4.8	4.1106
PACIFICJUPITER	30.5	27.4763
LAURA	35.5	29.6962
MISSOURI	7	6.2426
OCEANMAID	12.25	12.5161
ALDEBARAN	7.5	7.8901
PRETTYLADY	25.9	22.6854
GORBEIA	13	14.596
ZORAS	11	10.3111
Raven	4	6.5511
BALTICSEA	25.5	21.7198
BTSTREAM	13.5	9.7341

APPENDIX C: STATISTICAL ANALYSIS RESULTS

1 DESCRIPTIVE STATISTICS

This section provides the descriptive statistics.

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Error	Std. Deviation	Variance	Skewness	Std. Error	Kurtosis	Std. Error
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
AFRAMAX SCRAP VALUES in million \$	354	5.97	1.43	7.40	2.9318	.0596	1.12229	1.260	1.619	.130	3.162	.259
TANKER YEARS OLD AVERAGE PRICE in \$/DWT	5332	419.36	66.30	485.66	262.9438	7.5650	137.84108	19000.162	.025	.134	-1.551	.267
1 YEAR TIME CHARTER RATE AFRAMAX	354	31225	3025	34250	13153.46	332.85	6262.442	39218176.260	.384	.130	-.129	.259
Valid N (listwise)	332											

2 CORRELATIONS

This section provides the correlation outputs.

Correlations

		AFRAMAX SCRAP VALUES in million \$	TANKER 5 YEARS OLD AVERAGE PRICE in \$/DWT	1 YEAR TIME CHARTER RATE AFRAMAX
AFRAMAX SCRAP VALUES in million \$	Pearson Correlation	1	.425	.698
	Sig. (2-tailed)	.	.000	.000
	N	354	332	354
TANKER 5 YEARS OLD AVERAGE PRICE in \$/DWT	Pearson Correlation	.425	1	.894
	Sig. (2-tailed)	.000	.	.000
	N	332	332	332
1 YEAR TIME CHARTER RATE AFRAMAX	Pearson Correlation	.698	.894	1
	Sig. (2-tailed)	.000	.000	.
	N	354	332	354

** Correlation is significant at the 0.01 level (2-tailed).

Non-parametric Correlations

		AFRAMAX SCRAP VALUES in million \$	TANKER 5 YEARS OLD AVERAGE PRICE in \$/DWT	1 YEAR TIME CHARTER RATE AFRAMAX
Kendall's tau_b	AFRAMAX SCRAP VALUES in million \$	Correlation Coefficient	1.000	.380
		Sig. (2-tailed)	.	.000
		N	354	332
Spearman's rho	TANKER 5 YEARS OLD AVERAGE PRICE in \$/DWT	Correlation Coefficient	.380	1.000
		Sig. (2-tailed)	.000	.
		N	332	332
Kendall's tau_b	1 YEAR TIME CHARTER RATE AFRAMAX	Correlation Coefficient	.527	.724
		Sig. (2-tailed)	.000	.000
		N	354	332
Spearman's rho	AFRAMAX SCRAP VALUES in million \$	Correlation Coefficient	1.000	.542
		Sig. (2-tailed)	.	.000
		N	354	332
Spearman's rho	TANKER 5	Correlation Coefficient	.542	1.000
		Sig. (2-tailed)	.000	.000
		N	354	332

YEARS OLD AVERAGE PRICE in \$/DWT	Coefficient			
	Sig. (2-tailed)	.000	.	.000
	N	332	332	332
1 YEAR TIME CHARTER RATE AFRAMAX	Correlation Coefficient	.718	.885	1.000
	Sig. (2-tailed)	.000	.000	.
	N	354	332	354

** Correlation is significant at the .01 level (2-tailed).

Correlations

		DWT	AGE	TCR	PRICE
DWT	Pearson Correlation	1	-.059	-.169	.043
	Sig. (2-tailed)	.	.189	.000	.341
	N	489	489	489	489
AGE	Pearson Correlation	-.059	1	.191	-.708
	Sig. (2-tailed)	.189	.	.000	.000
	N	489	489	489	489
TCR	Pearson Correlation	-.169	.191	1	.259
	Sig. (2-tailed)	.000	.000	.	.000
	N	489	489	489	489
PRICE	Pearson Correlation	.043	-.708	.259	1
	Sig. (2-tailed)	.341	.000	.000	.
	N	489	489	489	489

** Correlation is significant at the 0.01 level (2-tailed).

Correlations

		DWT	AGE	PRICE	TCRB6
DWT	Pearson Correlation	1	-.059	.043	-.156
	Sig. (2-tailed)	.	.189	.341	.001
	N	489	489	489	489
AGE	Pearson Correlation	-.059	1	-.708	.189
	Sig. (2-tailed)	.189	.	.000	.000
	N	489	489	489	489
PRICE	Pearson Correlation	.043	-.708	1	.208
	Sig. (2-tailed)	.341	.000	.	.000
	N	489	489	489	489
TCRB6	Pearson Correlation	-.156	.189	.208	1
	Sig. (2-tailed)	.001	.000	.000	.
	N	489	489	489	489

** Correlation is significant at the 0.01 level (2-tailed).

REFERENCES

- M Azoff (1994): *Neural Network Time Series Forecasting of Financial Markets* (Wiley)
- M. Beenstock, A. Vergottis (1993) : *Econometric Modelling of World Shipping* (Chapman & Hall)
- M Beenstock,, A Vergottis (1989): "An Econometric Model of the World Market for Dry Cargo Freight and Shipping," *Applied Economics*, 21: 339-359
- Bendall, H B and Stent, A (2004): "Ship Investment under Uncertainty: A Real Option Approach," *Working Paper*, University of Technology, Sydney, Australia
- Breiman L, Friedman, J H , Olshen, R A , Stone, C J (1984), *Classification and Regression Trees*. Wadsworth, Belmont, CA
- Campbell, J Y and Shiller, R J (1987), "Cointegration and tests of present value models," *Journal of Political Economy*, 95 (5): 1062-1088
- Campbell, J Y and Shiller, R J (1988), "Stock prices, earnings, and expected dividends," *Journal of Finance*, 43 (3): 661-676
- Dixit, A. K. and Pindyck, R. S. (1994): "Investment under Uncertainty", Princeton University Press
- Draper N.R., & Smith H. (1982), *Applied Regression Analysis*. John Wiley & Sons
- Drewry Shipping Consultants Ltd.: *The Drewry Monthly*
- Allen L. Edwards (1984), *An Introduction to Linear Regression and Correlation*, 2nd edition. W. H. Freeman & Co
- Enders, W., *Applied Econometric Time Series*, John Wiley & Sons, 1995

- Engle, R.F. (1995), "ARCH Selected Readings", Advanced Texts in Econometrics, Oxford University Press
- Fama E F and French, K R (1988b), "Dividend yields and expected stock returns," *Journal of financial Economics*, 22: 3-25
- Glen, D. R. (1997): "The Market for Second-Hand Ships: Further Results on Efficiency using Cointegration Analysis," *Maritime Policy & Management*, 24(3): 245-260
- K. M. Gwilliam (1993), *Current Issues in Maritime Economics*. Kluwer Academic Publishers 1993
- Hale, C. and Vanags, A. (1989): "Spot and Period Rates in the Dry Bulk Market," *Journal of Transport Economics and Policy*, September: 281-291.
- Kavussanos, M. G. (1996): "Price Risk Modelling of Different Size Vessels in the Tanker Industry using Autoregressive Conditional Heteroskedasticity (ARCH) Models," *Logistics and Transportation Review*, 32(2): 161-176.
- Kavussanos, M. G. (1997): "The Dynamics of Time-Varying Volatilities in Different Size Second-Hand Ship Prices of the Dry-Cargo Sector," *Applied Economics*, 29: 433-443.
- Kavussanos, M. G. and Alizadeh, A. (2002): "The Expectations Hypothesis of the Term Structure and Risk Premia in Dry Bulk Shipping Freight Markets; An EGARCH-M Approach," *Journal of Transport Economics and Policy*, 36(2): 267-304.
- Koopmans, T.C. (1939): *Tanker Freight Rates and Tankship Building*, Haarlem, The Netherlands.
- Kutner, Nachtsheim, Wasserman (2003), *Applied Linear Regression Models*, 4th Edition. Irwin Professional Pub.

Lloyd's: Shipping Economist, Clare Longley (publisher)

Lyridis D.V., Zacharioudakis P.G., Mitrou, P., and Mylonas (2004a), A., "Forecasting Tanker Market Using Artificial Neural Networks", *Maritime Economics and Logistics*, 6 (2), June 2004: 93-108.

Lyridis, D. V., Zacharioudakis, P. G., and Paschos, C. (2004b), "Prediction of the Tanker Shipbuilding Market in Relation to the Tanker Shipping Market", *Proceeding of the Annual Conference of the International Association of Maritime Economists*, IAME 2004, Izmir, Turkey, 2: 797-811.

James McConville (1999), *Economics of Maritime Transport, Theory and Practice*. First Edition, Witherby Publishers.

R. Pindyck, D.Rubinfeld (1998): *Econometric Models and Economic Forecasts* (McGraw-Hill)

Quinlan J. R. (1992), "Learning with Continuous Classes". In *Proceedings AI'92*, Adams & Sterling (Eds.), World Scientific

Quinlan, J.R. (1993a), *Programs for Machine Learning*. Morgan Kaufmann, San Mateo CA.

Quinlan J.R. (1993b), "Combining Instance-Based and Model-Based Learning". In *Proceedings ML'93* (Utgoff, Ed), Morgan Kaufmann, San Mateo, CA.

T. Shimojo (1979): *Economic Analysis of Shipping Freights* (Kobe University)

Shipping Economist. Lloyd's (ed).Clare Longley.

Siciliano R., & Mola F. (1994), "Modelling for recursive partitioning in variable selection". In *COMPSTAT™ 94*, Dutter R., & Grossman W. (Eds.), Physica-Verlag: 172-177.

Martin Stopford (1997), *Maritime Economics*, Second Edition. Routledge, London.

Strandenes, S P (1984), "Price determination in the time charter and second hand markets," Centre for Applied Research, Norwegian School of Economics

Svendsen, A.S. (1958): *Sea Transport and Shipping Economics*, Bremen

Timbergen, J. (1931): Ein Schiffbauzyclus? *Weltwirtschaftliches Archiv*, 34: 152-64.

Timbergen, J. (1939): *Selected Papers*, L.H. Klaasen et al. Editors, North Holland Publishing Company, Amsterdam, The Netherlands.

Tsolakis, S. D., Cridland, C. and Haralambides H. E. (2003): "Econometric Modelling of Second-Hand Ship Prices," *Maritime Economics and Logistics*, 5: 347-377.

Tvedt, J. (1997): "Valuation of VLCCs under Income Uncertainty," *Maritime Policy and Management*, 24: 159-174.

A.W. Veenstra (1999): *Quantitative Analysis of Shipping Markets* (Delft University Press Postbus)

Vergottis, A R (1989), "An econometric model of the world shipping markets," City University Business School, London

Z.Zannetos (1966): *The theory of oil tankship rates* (MIT press)

