Leading indicators for the Port of Rotterdam

Identifying and forecasting economic indicators to improve the process of making short-term forecasts for dry bulk throughput in the Port of Rotterdam.

Govert Le Fever

MSc thesis

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Delft University of Technology

Port of Rotterdam

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PREFACE

This report outlines the work done on the identification of leading indicators for dry bulk goods in the Port of Rotterdam, forecasting them and provides an information dashboard that can be used to support the forecasting process. It is the deliverable of the Master Thesis Project of the Systems Engineering, Policy Analysis and Management master programme at Delft University of Technology. This project was commission by the Port of Rotterdam Authority and provides insight into scientific and societal aspects that can be used for forecasting and other business activities.

I would like to thank the Port of Rotterdam Authority for giving me the opportunity to perform this work within the company. Being able to work in and around the port itself and learning from people at the company that perform various important activities, has enriched my experience and allowed me to develop myself. In particular, I would like to thank Frank for providing me with interesting insights, knowledge and valuable feedback concerning the work. I would also like to thank Aernoud, Karin, Anneke and Roy from the BAI department for their contributions.

A special thanks goes to Jan for taking the time to help me with setting up the research and developing the VAR model. The journey to Groningen was well worth it!

Furthermore, I would like to thank Lori, Ron, Sander and Ronald from the TU Delft for supervising the project. In various meetings, they have provided me with challenges, shown me new insights into scientific work and have 'kept me on track' to scope the project and finish it on time.

Lastly, thanks must go out to my family and friends who have spent time to review my work and help me out with any questions or difficulties. Your support has been very valuable for this research!

Govert Le Fever
December 2012

SUMMARY

Over the last couple of years the economic climate has not be favourable for businesses and companies worldwide. The economic crisis of 2008 has left a major impact on trade and production and many companies have been forced to close due to this. Uncertainty among businesses and consumers is high, making the future difficult to predict. The Port of Rotterdam Authority (PoR) uses various forecasting methods to deal with market uncertainty, one of these focusing on the short-term period ahead (3 months). At the moment, the forecasting process is mainly of a qualitative character were commodity expert make decisions based on their experience. This research investigates the possibilities to improve the forecasting process at the PoR by focusing on the following design objectives for a Forecasting Support System (FSS) that can be added to support the forecasting process. By determining leading economic indicators that have a significant effect on the throughput of dry bulk goods in the Port of Rotterdam, the FSS aims to:

1. Provide information on the direction of the trend;
2. Provide extra information on market developments and trends so that a more substantiated forecast can be made;
3. Further improve the accuracy of the forecast for dry bulk goods;
4. Be able to be implemented alongside qualitative forecasting.

The FSS has been designed to be implemented into the current process and must provide users with information concerning market developments. Designing the FSS is done according to the framework by Herder & Stikkelman – a generic framework that delineates important design aspects. Thereby, this research provides a contribution to science as well as a deliverable to be implemented at the PoR. The research question that guides this research is formulated as follows:

Adding a quantitative element to the process of making short-term forecasts at the Port of Rotterdam Authority by determining leading indicators and showing them as an information dashboard.

Before identifying the leading indicators, an IDEF0 diagram, a network diagram and survey amongst forecasters have analysed the current system. This was done to identify the design space that is best suitable for implementing the FSS. It has shown that a quantitative element is most effective in supporting the decision that users make concerning the market developments, information that is later used to test if the forecasts are accurate enough. This way, forecasters can base their decisions on both qualitative information (experience, market information and trends, closures and opening of companies) and a quantitative element with statistics about the leading indicators that have an influence on dry bulk goods.

In this research, four main categories of dry bulk goods have been analysed and market variables are tested on whether or not they can be determines a leading indicator for one of these category of goods or not.

- Agribulk
- Iron Ore & Scrap
- Coal
- Other dry bulk goods

In order to identify leading indicators, several market statistics have been collected and prepared for statistical analysis. Decision rules concerning availability of data, statistical properties and sample size have ensured that all data was usable. Some variables initially selected were removed and a final list of variables was deemed usable for building a Vector Autoregressive (VAR) Model. The VAR model proved to be a good model for identification of leading indicators, but also providing coefficients that have been used for making forecasts of the leading indicators. These forecast are the basis for the information dashboard – the spreadsheet based model that is implemented into the forecasting process at the PoR. The leading indicators that have been identified are shown in yellow in Figure A.

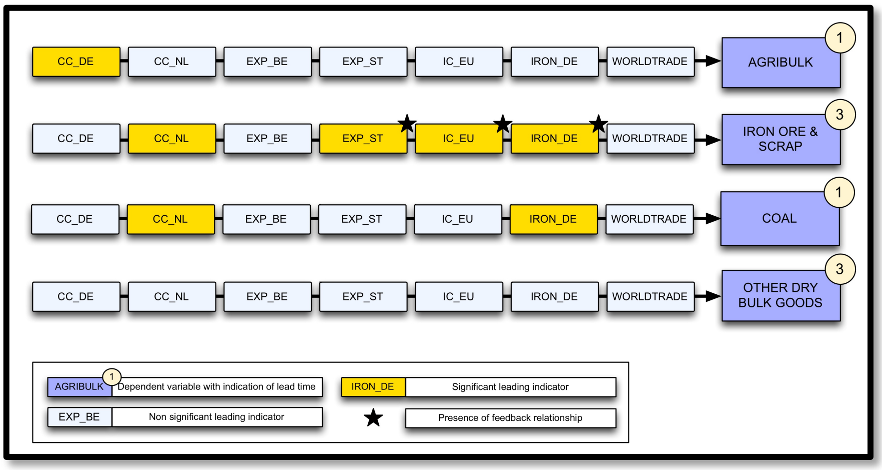

Figure A: Leading indicators per throughput good

The forecasts of the VAR model have been verified and validated using forecasting statistics as well as being compared to other forecasts. Furthermore, the forecasts were evaluated against the exponential smoothing method and the Mean Square Error (MAE) and the Mean Relative Square Error (MRAE) show the VAR model forecasts are better predictors for the variables included. Generally, the forecasts give good indication of the trend of leading indicator but sudden peaks and troughs are still not forecasted accurately. The advantage of combining a qualitative and quantitative tool is that forecasters can adapt the forecast based on their knowledge and experience.

The information dashboard was designed according to several design guidelines and design requirements. These have been set up according to the framework by Sage & Armstrong and the requirements have been established in cooperation with users of the forecasting tool. It is important to involve users as they will be working with the model and need the tool to fit their expectations and demands. An evaluation of the implementation has shown the users feel the information dashboard will provide them with a 'second opinion' for making forecasting decisions. However, full evaluation can only be done once the tool has been used several times.

This research provides some important conclusions and recommendation concerning forecasting and the forecasting process at the PoR. A literature review has concluded that the combination of qualitative and quantitative elements is very beneficial to the accuracy of the forecast. Analysis has shown that adding a quantitative element can be best done in the support of the process, where the information is provided to the dry bulk experts. Furthermore, the VAR model has shown to be able to identify leading indicators and make a forecast using the coefficients. The accuracy is good compared to the exponential smoothing method. The use of requirements for the design of the dashboard has proved to be beneficial for user participation. Users have been involved since the beginning and the use of spreadsheet has ensured that changes and updates can be easily made. Furthermore, a manual is provided for estimating a new VAR model as well as making new forecasts within the information dashboard.

This research also proposes several amendments to the framework of Herder & Stikkelman, the most important one being the transformation into a step based framework as supposed to only describing important elements of design. The new framework, shown in figure B, allows future researchers to gain a grip on designing a FSS for supporting a decision making process. A limitation of this framework is that it requires testing, validation and verification. When used in for other commodities, such as designing a FSS for container throughput, researchers might feel the need to improve or make changes to the model.

Recommendations are aimed at using the VAR model and framework for identifying and forecasting leading indicators for other goods in the port. As this was a pilot project and a small budget was only available, a recommendation is aimed at purchasing statistics to be used for further analysis. Also, splitting out the categories into more specific goods can yield more determined leading indicators. Another recommendation is to reflect on the implementation success of the information dashboard after a certain period of time. This can pose new desires for information in the model that can be easily added due to the fact that the model is a spreadsheet-based tool.

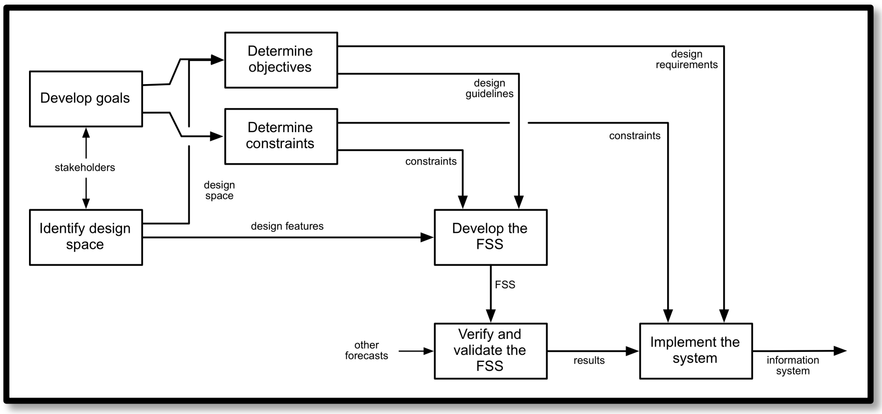

Figure B: New proposed framework for FSS design

As was explained, this research provides a societal and scientific contribution. By using the FSS, forecast decisions can be substantiated. Experts have indicated that the model can serve as a good 'second opinion' tool for making a forecast. Involving the users from the beginning of the research has provided transparency for the design and allows users of the model to make changes to the dashboard if they require doing so. The practical aim has been fulfilled; the Forecasting Support System is ready to be implemented into the forecasting process at the PoR. The scientific contribution of this research has focused on the framework. Because the generic framework is based on another sector, amendments have been proposed for a new framework that is applicable for FSS design.


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1. INTRODUCTION

The global economy has changed significantly over the last couple of years. Due to the collapse of the financial system in 2008 and a following loss in market confidence by producers and consumers, companies have been severely affected or have been forced to close. In 2008, as much as 120 businesses were closing every week and international trade to and from the European Union decreased by 23% (FSB, 2009) (WTO, 2012).

Today, in 2012, industrial production is recovering from its second sudden decline in 2011, bringing back imports and exports to normal levels after a balance of payments deficit which occurred in most EU countries (IMF, 2012). Even though markets are recovering from the financial collapse, market uncertainty for various goods and services is still high and producers and consumers are aware of the risks involved when entering a market or making an investment. The responsive state and confidence of market players are key factors that influence recovery; this makes it even harder to determine an exact recovery point for the economy (Azis, 2010). Therefore, companies need to be able to deal with levels of uncertainty in the market and creating insight into product developments and trends are valuable for making decisions on a strategic level. Slovik states that the balance between ‘known information sets’ and ‘unknown information sets’ determines market instability. He shows that market uncertainty is directly related to this and it is therefore clear that at the moment, the ‘unknown information set’ is larger than the ‘known information set’, as is reflected by the current economic situation in Europe (Slovik, 2011). In order to deal with uncertainty and to ensure as much support for making a decision, managers often rely upon ‘decision support systems’ (DSS). Generally speaking, a DSS is a model or interface of any format or size that can help non-technical specialists, such as managers, to create a more substantiated decision. A DSS can have one of five information backgrounds, for example a document-driven, knowledge-driven or data-driven background (Power & Sharda, 2007). One of the most commonly used data-driven DSS is forecasting, defined as *“a planning tool that helps management in its attempts to cope with the uncertainty of the future, relying mainly on data from the past and present and analysis of trends”* (WebFinance Inc., 2012). For the support of forecasting processes, a Forecasting Support System (FSS) is often implemented. A FSS is a system comprising of a database of multiple time series, a quantitative forecasting tool and a facility that allows managerial judgement to be made and can be considered a derivative from a DSS (Fildes, Goodwin, & Lawrence, 2006). The combination of these elements forms a strong and effective tool for supporting a forecasting system and the system acts as a decision support tool for managerial decisions.

The Port of Rotterdam Authority (PoR), responsible for port development, vessel movement and safety and regulation in the largest port in Europe, has recovered well from the economic crisis that hit Europe and the world in 2008. Total throughput in the port grew by 11% in 2010 to 430 million tonnes of goods after a decline of 8% from 2008 to 2009 (Havenbedrijf Rotterdam N.V., 2010). This has mostly been due to increases in trade with China and a growing German economy (Z24, 2010), two important markets for goods travelling to and from the port. Despite the growth of goods throughput, the PoR needs to be aware of market uncertainty for the various types of goods passing through the port. To realise the desired situation of the port in 2030, depicted in the ‘Port Visie 2030’, trends and developments of the port and industries must be known. Being able to make accurate long and short-term forecasts is crucial for investments in the port so that the Port of Rotterdam becomes Europe’s most important port and industrial complex (Havenbedrijf Rotterdam N.V., 2011). At the moment, however, the process of making a short-term forecast is not as efficient as desired. Because the short-term forecasts cover periods from 3 to 15 months, various organisational units have different needs from the forecast. For example, top management would need insight into total sales, sales breakdowns and pricing and the finance department would use the forecasts for cash flows, short-term borrowing and pricing strategies. Forecasts are made for throughput volumes and price per tonne for goods transported through the port, two important statistics for calculating port dues for the Port of Rotterdam. It is important to keep the port dues as accurately priced as possible as this is a deciding factor for ships and companies to transport goods through the port or not. For the Port of Rotterdam, port dues are the main source of income; 50% of total income is generated by vessels using the port (Havenbedrijf Rotterdam N.V., 2011); (Makridakis & Wheelwright, 1989). Income from the port dues can then be used to further improvement of facilities in the port, creating better facilities to attract and keep attracting companies to use the port. For Rotterdam, in order to remain the largest port in Europe, investments are essential to keep in front of many other competing ports. Forecasting is a vital element in the business that has its effects, sometimes only visible after several years, on the development of the Port of Rotterdam.

Making a forecast based solely on human judgement has its limitations according to Hogarth and Makridakis. The "illusion of control", the accumulation of redundant information and the overconfidence in judgement of information creates problems for the accuracy of the forecast and planning effectiveness (Hogarth & Makridakis, 1981). To deal with this dilemma it is often argued in the literature that adding a quantitative element to the forecast making process can reduce uncertainty with regard to trends and developments and improves the accuracy of the forecast made (Guerts & Reinmuth, 1972); (Diamantopoulos & Mathews, 1989). Therefore, the aim of this research is to add a quantitative element to the forecasting process by identifying relations between market data and throughput in the port. Relationships that incorporate a delay between the data, shows that certain data can be defined as a 'leading indicator'. A leading indicator is a pattern in the form of a time series of a product or statistic that gives an advanced indication of changes in trends and developments (Atan & Wu, 2010); (The Economist, 2006). By presenting these leading indicators in an information dashboard, managers at the PoR can not only base their decisions on qualitative input from the experts but also on quantitative information. According to Few (2004), a dashboard is *"a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance"*. The aim of using this dashboard is therefore to show important market information that has a causal influence on the throughput data of commodities being transported through the port, so that forecasts for these goods can be substantiated and the process of making a forecast becomes more effective.

1.1 Problem statement and research objective

The fact that many experts are involved in the process of making a forecast defines the process as a complex multi-actor environment. The experts that represent the departments have different views towards the forecast and could behave in contradictory ways when changes are proposed. Besides the uncertainty in the market for goods and the reliability of information used for the forecast, dealing with this multi-actor setting also has to be taken into account. The forecasts are made by segment specialists, in this report referred to as forecasters or experts, and a manager from the BAI department at the PoR. Because there are multiple actors involved with the forecast, attention needs to be given to their expectations and demands for design of the Forecasting Support System. Further analysis of the forecasting process and its environment and users is provided in Chapter 3. In general, the following statement addresses the overall problem concerning the current forecasting process that provokes this project.

The process of making short-term forecasts at the PoR is not as effective as desired and, according to the people who make forecasts, can be improved by adding a quantitative element to support the process.

This means that the aim of this research is to add an element to the process of making a forecast at PoR. A decision support tool has been designed and implemented into the process of making a short-term forecast. The tool provides quantitative information of the market and allows decision makers at the PoR to base their forecasts on qualitative (from the experts) and quantitative information (from the Forecasting Support System). A research objective has been set to determine what should be the result of this research:

Adding a quantitative element to the process of making short-term forecasts at the Port of Rotterdam Authority by determining leading indicators and showing them as an information dashboard.

The aim of the FSS and the information dashboard is to give a quick overview of the leading indicators and show, by means of gauges and graphs, how the leading indicators are developing and what their trend is moving towards. This information can then be used to forecast the throughput goods. The dashboard has been designed to support the forecasting process and should:

1. Provide information on the direction of the trend;
2. Provide extra information on market developments and trends so that a more substantiated forecast can be made;
3. Further improve the accuracy of the forecast for dry bulk goods;
4. Be able to be implemented alongside qualitative forecasting.

1.1.1 Relevance of the research

Besides the technical part of this research, societal value is added and a contribution to science is made. The focus of this research is on the (1) technical part where the leading indicators are determined by statistical analysis. Figure 1-1 shows the focus points of this project. The use of leading indicators helps to establish a broader forecasting process at the PoR, whereby the quantitative tool is supporting the mainly qualitative process that is performed at the moment. The forecasts made are important for predicting throughput in the port and based on this information, analysis can be done on whether or not port dues and price per tonne of good transported through the port are still up to date with the expected figures that are forecasted for the coming year. The financial department of the PoR uses this information for developing expected income figures for the Port of Rotterdam. The forecasts are set out in the workplan, which is developed every year and provides expectations for the coming year. As has been discussed in the literature, the involvement of users and evaluating the interactions that the model has with users is also important to consider when designing the FSS. The forecasts that are made, together with the dashboard that has been developed in cooperation with the users, is considered as the (2) societal value that is contributed to by the research. This must take place within the boundaries that have been set by the objectives. The PoR has established certain goals and aims for the FSS and the societal interaction must comply with these guidelines. These include general aims such as the goal to determine the leading indicators and design a quantitative element.

The last aspect of this research concerns the (3) contribution to science. The scientific objective of this research is to contribute to the use of leading indicators as a support tool for a forecasting process. This research sets out preliminary analysis on the use of leading indicators for forecasting throughput of dry bulk goods in seaports. Existing literature seems to be focused on the leading indicators and Forecasting Support Systems individually, but lacks work on design methods for this type of work. By proposing a framework for the design, implementation and evaluation of a FSS, this research makes a contribution to scientific knowledge about Forecasting Support Systems. This research tests the frameworks ability to serve as design framework for designing a FSS and provides an evaluation of the framework. Once successfully implemented, the framework can be applied when determining and presenting leading indicators for other throughput goods in Rotterdam or in other seaports.

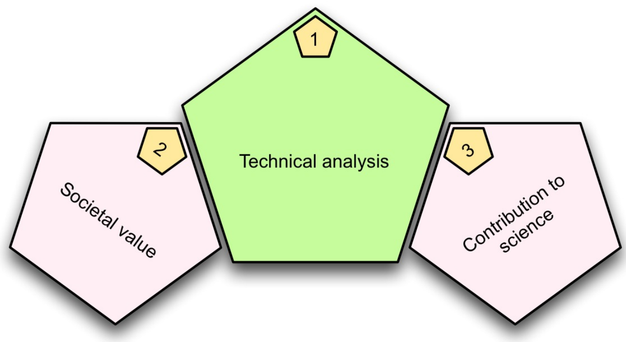


Figure 1-1: Contributing areas of the research

The problem statement and the research objectives form the basis of this research project. A set of research questions, derived from the research objective, is presented below and set out the research approach.

1.2 Research questions

For this research the following research question has been formulated:

What should the design of a Forecasting Support System with leading indicators entail to support short-term forecasting processes for dry bulk goods throughput in seaports?

In order to answer this main research question, several sub questions have been formulated. These address various methods for carrying out the research and also form the structure of this report.

1. *What are strengths and weaknesses of short-term forecasting methods and what guidelines for the design of a FSS can be identified?*
2. *What components of the current forecasting process indicate that a quantitative element can be added to improve the process?*
3. *Which economic drivers can be identified as 'leading indicators'?*
4. *Is the quantitative forecasting tool a reliable and accurate source of information to support the forecasting process?*
5. *How does the Forecasting Support System need to represent information, be implemented and be maintained to effectively support the forecasting process?*

1.3 Methodology of the research

This Chapter elaborates on the methods used for providing answers to the research questions posed in Chapter 1.2. A design framework is introduced after which the research methods and project outline are explained.

1.3.1 Design framework

The goal of this research is to develop a Forecasting Support System that can help to improve the current forecasting process at the PoR. Subsequently a design phase to develop a quantitative forecasting element that is added to the forecasting process forecast at PoR is included in this research. This is illustrated in Figure 1-2, where the red dotted frame indicates the element that is added to the process in order to support it. The figure shows that current forecasts are based on market developments and that PoR experts use the forecasts to provide also provide information on new developments. A Forecasting Support System with leading indicators, shown in an information dashboard, adds a quantitative element to the forecasting process.

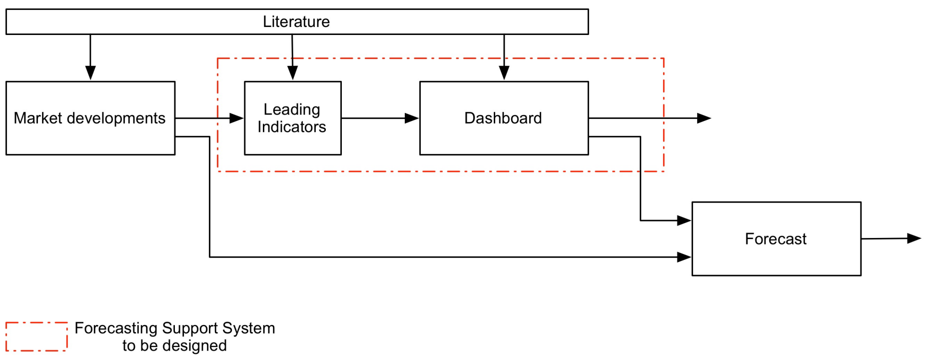


Figure 1-2: Conceptual outline of the research

The design of the Forecasting Support System is based on the generic conceptual design framework developed by Herder & Stikkelman (2004). The framework includes various aspects of design and, although it was originally developed for the design of a methanol cluster in the Port of Rotterdam, it is argued that the framework is very suitable for use in this research for the following reasons:

- The design framework takes into account the users of the system and involves them from the start of the design phase. User involvement and incorporating user demands from the beginning of the design phase is considered to be a decisive factor for creating and implementing a successful FSS (Sauter, 1997). The model is appropriate here because we aim to include users from the beginning of the design phase. Users of the system have been consulted for validation of variables, model validation, the dashboard design and testing the information dashboard.
- The design process incorporates developing objectives and constraints for the design and the development of the model. The selection of a suitable visual output of the information dashboard is also influenced by the objectives and constraints.

The framework in Figure 1-3 has been slightly adapted to show the research questions in various phases of the design process. Although the elements of this framework are not completely in line with the design of an FSS, an evaluation of the framework is provided in

Chapter 10.2. For example, the framework develops and executes a test and eventually selects one of the alternatives created. As was described, the model was not made for FSS design and therefore will not perfectly align at this moment. By performing the design process for FSS design leads to evaluation and recommendations concerning changes and improvements to the framework. The design process that is proposed here is outlined in Figure 1-4 in Chapter 1.3.2 and the corresponding elements are illustrated in the outline. The research questions in Figure 1-3 have been assigned to one of the elements in the framework and belong to one of the three main parts that this structure this research report (Figure 1-4)

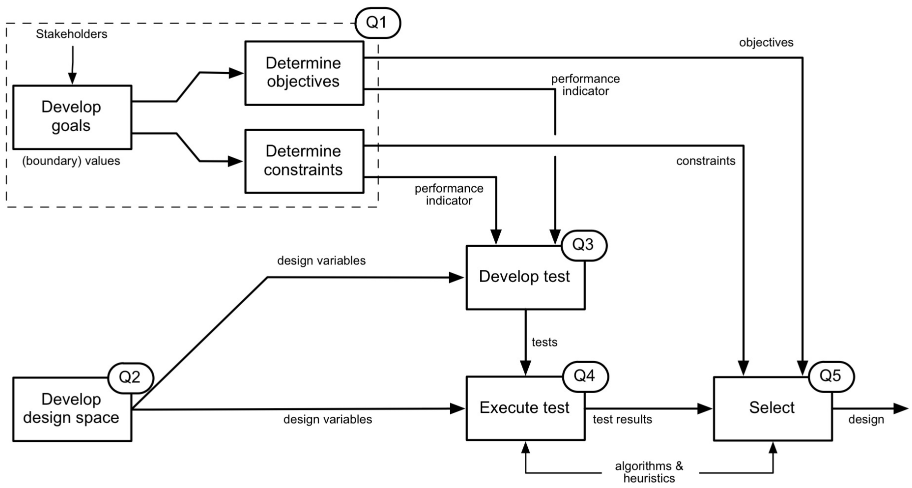


Figure 1-3: Generic conceptual design framework (based on (Herder & Stikkelman, 2004))

1.3.2 Research methods and outline

The following figure graphically represents the structure of this research and the research questions have been assigned to some of the Chapters. When implementing a FSS, it is important to get insight into current mechanisms and their strengths and weaknesses. A desk study has resulted in more detailed insights and information concerning forecasting practises. Consulting scientific articles, newspapers and business reviews, has retrieved this material. Chapter 2 describes the method and results.

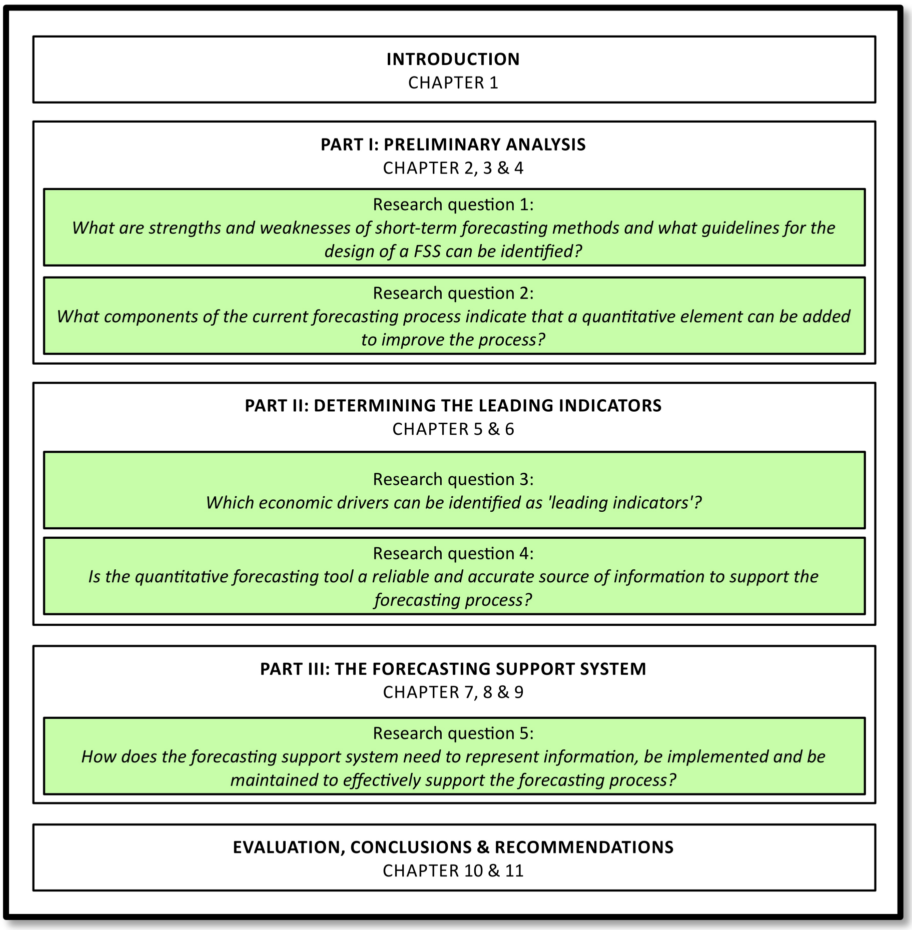


Figure 1-4: Outline of research

The first part of this research is focused on forecasting methods and practises in general as well as the forecasting process as it is currently being performed at the PoR. Chapter 2 explores forecasting in general and on a more detailed level and determines the **objectives** and **constraints** for developing a quantitative forecasting tool. This Chapter provides an answer to research question 1. Chapter 3 describes the forecasting process currently being performed. By mapping the process, a clear overview is created and in- and outputs of the system can be analysed. It is important that this step recognises where in the process the accuracy of the forecast is created and to analyse if modifications can decrease the overall error of the forecast. Research question 2 is answered in this Chapter and concentrates on identifying a possible **design space** for the tool to be implemented into. Attending a forecasting session and speaking with experts who make the forecasts provides information for this step of the research. Chapter 4 elaborates on work that has been performed to set up the research. This is focused on the theoretical knowledge that needs to be gained before performing statistical analysis.

The second part of this research focuses on the determination of the leading indicators and answers research question 3 and 4. Determining the economic indicators for various goods requires quantitative data analysis of data from various sources providing information about the market. The analysis determines which goods have a significant effect on throughput in the Port of Rotterdam. Databases provided by the Centraal Bureau voor de Statistiek (CBS), Centraal Planbureau (CPB), International Monetary Fund (IMF) and others have been consulted. The data that has been collected was analysed by means of statistical modelling using the software package SPSS. This software is used at TU Delft and is applicable for performing various statistical tests. The user-friendliness and the fact that user of the system at the PoR have experience with SPSS makes this a wholesome package for use in this research. Data concerning throughput volumes of the dry bulk goods is available from PoR databases. Market developments that have a strong relationship with throughput data, including the delay in trend, are characterised as 'leading indicators' and are represented in the dashboard. Statistical modelling **develops** an equation to describe the trend of a leading indicator. The coefficients that are delivered as output of the statistical model are used to make forecasts for the leading indicators. These are needed for building the information dashboard.

To determine whether the quantitative forecasting tool is a reliable and accurate information source for the forecasting process, the build up of the model and the results need to be verified and validated. Research question 4 has been developed to cover this important part of the research. The tests are done according to well-established methods for verification and validation of statistical analysis and forecasts. Algorithms and heuristics provide a basis for **executing** the verification and validation. The results of these tests provide input for the final selection of the information dashboard.

Part III of the research is focused on **selecting** appropriate visual representations of the information and translating these into an information dashboard. The design options for representing the dashboard have been based on objectives and constraints determined in the first part of this research. Research question 5, which is covered in Chapters 7,8 & 9, also covers the implementation and evaluation of the dashboard into the system. Furthermore, some recommendations for the maintenance of the model are provided.

To round up the research, conclusions and recommendations are provided for the PoR and for further research. A reflection Chapter provides an evaluation of the project as a whole.

1.4 Scope of the project

Providing the correct information on the dashboard means that a wide variety of indicators have to be investigated and the determination of which economic statistics can be defined as 'leading indicators' for the throughput in Rotterdam is based on a causality method. Because leading indicators are statistics that describe only a part of the economy, for example a specific branch or sector, trends and fluctuations in the economy can therefore only be predicted partly. This entails that leading indicators give a general sector indication but is refrained from detailed analysis of all factors influence the changes in the economy (Rekowski, 2003).

The data required for this research comes from various sources, including OECD, IMF and CBS databases that are publically accessible or accessible with Port of Rotterdam Authority licences. In order to get a realistic view on the effect on throughput in Rotterdam, several levels of aggregation have been chosen. The Netherlands and Germany are the most important hinterland areas for Rotterdam and are therefore included in the research. Germany is an important economy for the Netherlands; roughly 24% of Dutch exports are destined for Germany, thereby being the most important import country for Germany in 2011. A total of €82,1billion was transported from the Netherlands to Germany, accounting for 9,10% of German imports (ABN AMRO, 2012). The European Union as a whole is also important to consider, as Germany is not the only country that relies heavily on activity in

the Port of Rotterdam. Many other European countries, including the Czech Republic, Poland and Austria depend on the Port of Rotterdam for their imports.
Market data from China is relevant to include because of the amount of goods being transported to and from Asia. Especially China is interesting to consider and include in the research as 8 out of 10 of the worlds' biggest ports are in China (Havenbedrijf Rotterdam N.V., 2012). Furthermore, the world economic data also be considered to be able to consider global economic changes and their effect on the throughput of goods in Rotterdam.

This research is a pilot project for the PoR and the results and evaluation determines whether or not to extend the research to other goods in the port so that leading indicators can be determined. Once approval for extension has been given, budget and resources are made available for the project. The implication for this research is that only publically accessible and freely available data can be used. As many institutions, such as the OECD, CBS, UN etc., publish data on online databases that are publically accessible, this does not seem to be a problem. However, finding more detailed information concerning market trends and company information might be more difficult or impossible due to confidentially, late publication or simply having to purchase the data.

1.5 Deliverables of the project

This research is set up to answer the research questions from Chapter 1.2, but also have some clear deliverables that can already be determined beforehand. This research aims to create insight for the reader into the methods and results from forecasting with leading indicators in the dry bulk shipping market. This also provides awareness of relevant market changes and developments that influence dry bulk throughput in Rotterdam. Although considered as a 'nice to have' model, an information dashboard is a useful tool for translating model output into an organised and manageable interface. The dashboard that has been created provides statistics on the trend of the leading indicators, the forecast for the coming period and other information that is considered relevant for making a short-term forecast for dry bulk goods.

Another deliverable of this research is to provide analysis on the combination of qualitative and quantitative information as a forecasting method. The implementation of such a model into the current process also be evaluated and assessed. Besides the physical creation of the dashboard, this analysis provides an important intangible contribution to the research project as a whole. A scientific contribution is delivered by this research, as was explained in Chapter 1.1.1.

PART I: PRELIMININARY ANALYSIS

INTRODUCTION
CHAPTER 1

PART I: PRELIMINARY ANALYSIS
CHAPTER 2, 3 & 4

Research question 1:
What are strengths and weaknesses of short-term forecasting methods and what guidelines for the design of a FSS can be identified?

Research question 2:
What components of the current forecasting process indicate that a quantitative element can be added to improve the process?

PART II: DETERMINING THE LEADING INDICATORS
CHAPTER 5 & 6

Research question 3:
Which economic drivers can be identified as 'leading indicators'?

Research question 4:
Is the quantitative forecasting tool a reliable and accurate source of information to support the forecasting process?

PART III: THE FORECASTING SUPPORT SYSTEM
CHAPTER 7, 8 & 9

Research question 5:
How does the forecasting support system need to represent information, be implemented and be maintained to effectively support the forecasting process?

EVALUATION, CONCLUSIONS & RECOMMENDATIONS
CHAPTER 10 & 11

2. PRELIMINARY ANALYSIS OF FORECASTING

The preliminary analysis of this research is aimed at providing background information about forecasting and its use in the maritime sector. An evaluation is given to provide an answer to the first part of research question 1. Chapter 4 focuses on the second part and sets out several guidelines for designing a FSS. Research question one was defined as:

What are strengths and weaknesses of short-term forecasting methods and what guidelines for the design of a FSS can be identified?

This Chapter first sets out a brief description of forecasting, the characteristics and practises in the business environment. An introduction to the concept of forecasting is given and the use of forecasts in general is explained. Secondly, various qualitative and quantitative methods are analysed and their strengths and weaknesses are presented. Thirdly, this Chapter focuses on forecasting in the maritime industry and the use of leading indicators for making a forecast. Finally, a knowledge gap, to be found in the literature, sets out the further research into the use leading indicators for making short-term forecasts for the Port of Rotterdam Authority.

2.1 Forecasting characteristics

Having knowledge about the future is vital for many people and companies, for example when they concern the weather forecast for an outdoor activity, taking place in a few days, or an anticipated increase in demand for t-shirts produced by the clothing company. This information is important because it can reduce 'uncertainty' in the future, thereby giving people the chance to change something today which affects their situation from that point onwards. Predicting the exact events that might occur in the future is not always possible and accuracy also plays a role, but people can prepare themselves well to cope with the anticipated situations. A Yiddish proverb states: *"You can't control the wind, but you can adjust your sails"*, thereby referring to the fact that people do not always know what will happen and what events will take place and therefore can only change elements within their own environment. For the situations described above, setting up shelter so that the activity can take place indoor or ordering more raw materials to cope with the increased demand for t-shirts are examples of how people prepare for uncertainty in the future.

Predicting the future can be done using various tools and models. Most common are forecasting tools, used to determine trends and developments based on market information. Scenario building is another popular tool used to predict future events, whereas models can simulate the expected growth of the variables involved. All methods are closely linked and the decision to choose one of these models depends on various factors, such as the time period, nature of underlying data, accuracy and intended goals. This research focuses on forecasting as this allows for flexibility with regard to the various requirements. Scenario building and modelling are mainly focused on long-term predictions of future events and often cannot deal with the short-term period of 3 months. These methods are therefore not applicable for this research. Below, various factors for making a forecast are discussed according to findings of a literature review.

2.1.1 Short-term and long term forecasting

The goal of the forecast determines the time period that the forecast concerns, being immediate term (less than 1 month), short-term (1 to 3 months), medium term (3 months to 2 years) or long term (2 years or more) (Makridakis & Wheelwright, 1989, pp. 20-21). For example, the construction of a new container terminal requires a long-term forecast to predict demand for the coming decades for container throughput in the port. This requires a different approach when making a forecast about whether or not to hire extra personnel to cope with extra demand for products in the high season.

Because forecasts can be used for many different time periods and provide (limited) insight into future demand they have proven to be a valuable tool for many companies. The interest in forecasting can be summarised in several points, as Waddell and Sohal (1994) point out:

- *"Because organisations and their environments are becoming more and more complex, decision makers find it more difficult to weight all the factors in a given situation without some explicit, systematic aids.*
- *As organisations have grown larger, the magnitude and importance of individual decisions have grown. Many decisions warrant special forecasting studies and more thorough analysis.*
- *The circumstances of most organisations have been changing at an accelerating rate. With key relationships no longer stable, forecasting has proved to be one of the best tools for quickly identifying and understanding new relationships.*
- *Many organisations have moved towards more systematic decision-making, requiring explicit justification of individual actions. Formal forecasting methods are one way to support and evaluate such actions.*
- *And perhaps most important, forecasting methods (and cumulative experience concerning their application) have been developed which can be applied directly by practitioners rather than by technical experts only."*

2.1.2 Qualitative vs. quantitative forecasting

Depending on the type of information available, forecasters can choose to apply one of many qualitative or quantitative forecasting methods. Qualitative forecasts are based on the judgement from experts and their knowledge about the market, whereas quantitative forecasts are made using historical data and concern a time series of the specific variable of interest (Advameg, Inc., 2012). Although there are two main categories of forecasts, qualitative and quantitative methods, research into literature has revealed three main forecasting models that can be identified. These are judgemental, causal and time-series models. Judgemental models produce a forecast based on the knowledge of experts and their expectation for future demand for a product or service. Causal models analyse data and test for causality between data series. A strong causality indicates that events are not completely random because they are associated with the changes in other variables. Time series models are based on correlations between the data and time. Often, decomposition of data helps to better understand the relations between multiple related components (Whiteside, 2008). Within the three models identified, there are several methods that can be applied. The choice for one of these models depends on the type of data available, the time horizon and expected results of the forecast.

2.1.3 Accuracy of forecasts

Many companies spent a lot of time on creating accurate forecasts and they can be used for any type of business aspect such as finance, marketing and management (Makridakis &

Wheelwright, 1989, pp. 20-21). Wadell and Sohal (1994) state that forecasting is an essential part of efficient and effective management and it is therefore a crucial modelling tool for strategic and tactical decision-making. The accuracy of the forecast is therefore of vital importance for managers who make these decisions and can often be interpreted as the “goodness of fit” of forecasted data compared with actual data of the corresponding time period (Makridakis & Wheelwright, 1989, p. 56). Measuring the accuracy of a forecast can be done using various measures. Hyndman and Koehler provide an evaluation of these methods and their paper is used to determine an accuracy method for this research (Hyndman & Koehler, 2005). What can be stated is that accuracy of forecasts has improved enormously over the last 50 years, mainly due to the fact that computers have the ability to store large amounts of data and can perform complex mathematical calculations (Stopford, 2009, p. 701). Managers have since been able to produce more accurate forecasts, but reducing the error to zero is still a challenge to forecasters.

Besides ensuring that a forecast is accurate, decision makers need to ensure that the forecast contributes towards a general plan. A plan is dependent on the forecasts and is only as good as the forecast on which it is based, argue Wadell and Sohal (1994). Others agree that forecasting is meaningless without a plan and state that planning, regardless of other aspects, relies heavily on forecasts being generated and helping to assess the alternatives and the prediction of future states of the environment (Hogarth & Makridakis, 1981). In the case of the PoR, forecasts contribute to a general plan known as the workplan. Current forecasts can depict whether or not the expected throughput, made by the workplan, is accurate or not. Furthermore, because the forecast output is used for financial analysis, ensuring a high level of accuracy is vital.

2.2 Combining qualitative and quantitative forecasting methods

Because choice for a certain type of forecasting method depends on various factors, many methods and models have been developed and used for determining future values of statistics. Makridakis and Wheelwright (1989, pp. 14-15) find 23 methods that are currently being used and divide them into three categories as defined earlier. The quantitative, judgemental and technological categories are further decomposed into 11 subgroups, from time series to expert based groups. All methods are analysed and Table 2-1 shows each methods’ field and area of business application. Distinction has also been made between short-, medium- and long-term application for each of the methods. This overview gives a good indication of the various methods that are that are available for forecasting use, but Bunn and Wright (1991) state that research on combined model is still a long way behind the knowledge of separate models. They discuss the need to further develop the research as several researchers have shown that combined forecasts can deliver more accurate output than single, independent models.

			Major areas of business application																
		Forecasting method	Production planning	Production scheduling	Inventories	Material requirements	Personnel scheduling	Personnel planning	Pricing	Advertising and promotion	yearly budgeting	New products	R&D projects	Capital budgeting	Conjecture analysis	Strategy	**Short-term**	**Medium term**	**Long term**
Quantitative	Time Series	Naïve			X				X										
		Smoothing	X	X	X	X	X	X											
		Autoregressive moving average	X	X			X	X									X		
	Explanatory	Vector autoregressive							X	X	X						X	X	
		Regression							X	X	X						X	X	
		Econometrics							X	X	X						X	X	
	Monitoring approaches			X	X	X	X												
Judgemental	New products forecasting								X	X	X	X	X		X	X	X	X	X
	Individual	Individual judgement	X				X		X	X	X	X	X	X	X	X	X	X	X
	Group	Decision rules		X	X	X	X												
		Sales force estimates									X								
		Juries of executive opinion							X	X	X	X	X	X	X	X		X	
		Role playing													X				
	Aggregate	Anticipatory surveys									X							X	
		Market research							X	X		X	X						
		Pilot programs and pre-market tests							X	X		X							
Technological	Extrapolative	Growth curves											X	X	X	X			
		Time-independent comparisons											X	X	X	X			
		Historical and other analogies											X	X	X	X			
	Expert-based	Delphi										X	X	X	X				
		Futurists										X	X	X	X				
		Cross-impact matrices										X	X	X	X				

Table 2-1: forecasting methods, adapted from (Makridakis & Wheelwright, 1989)

Over the last 50 years, the combination of at least two forecasting methods from Table 2-1, has become an important focus of research and articles published, as is explored by Clemen (1990). From the 1960's, the number of articles published that discuss the combination of forecasts has grown exponentially to over 200 in 1990; a quick search on online literature databases indicates that over 350 papers are available today. Many organisations have already been working with forecasts and the combination of forecasting has become regular practise in decision-making processes. Combining forecasts can entail two methods, the combination of information (CI) or the combination of forecast (CF) as Huang and Lee (2007) conclude. Engle, Granger and Kraft state the following that shows researchers are leaning towards CI: *"The best forecast is obtained by combining information sets, not forecasts from information sets. If both models are known, one should combine the information that goes into the models, not the forecasts that come out of the models"* (Engle, Granger, & Kraft, 1984). This shows that the combination of forecasts can be value adding when the information (CI) is combined, not the method (CF). Huang and Lee (2007) test several situations with CI and CF and conclude that actually, CF prefers an advantage over CI in real time forecasting. This general conclusion, based on several research papers, is analysed on the basis of a literature review. The findings and arguments are described below.

Two major methods for combining forecasts are proposed by Granger and Bates (1969) and Granger and Ramanathan (1984). Sir Clive Granger is regarded as one of the pioneers of forecasting and his work on stationary and non-stationary time series has revolutionised forecasting as a whole and still forms the basis of many research papers today[1]. Together with Bates he proposed to add weights, based on out-of-sample forecast variance, to the quantitative models and found that a combination of methods is able to provide a smaller Mean Square Error than either of the individual forecasts. The results are positive but the method is based on uncorrelated forecasts and the researchers use two forecasts from one type of data to determine a single forecast, namely airline passenger data (Granger & Bates, 1969). This is a clear example of combining information (CI) and thereby merging the information input to make a single forecast. In Granger's paper, written together with Ramanathan in 1984, three approaches for obtaining linear combinations between forecasts are proposed and tested. Their regression method shows that linear methods can be combined and that the combination reduces the forecasting error significantly (Granger & Ramanathan, 1984). Opposed to Grangers' other paper (together with Bates, (1969)), this research focuses on combing the outcomes of two forecasts and using regression to make the combination, thereby indicating a clear combination of forecasting method (CF).

Because expert opinions and judgements are proven to be useful forecasting methods, researchers have been investigating the combination of various methods. Aiolfi et al. (2010) and Ashton and Ashton (1985) have done research into the combination of subjective forecasting methods and conclude that an aggregate model can be more useful than individual forecasting methods separately. However, their arguments include the weighting of methods, as this is an important aspect of providing an accurate combined forecast. In their research, Ahston and Ashton apply one combination method with equal weights and four differential weighting methods. The equal weights method is simple but lacks the accuracy when only a small number of forecasts are combined. The other methods, using the Mean Absolute Error (MAE) and correlations as determinants of accuracy, share this conclusion but the effect is much stronger. Ashton and Ashton therefore propose that when combining subjective forecasts, differential weighting produces better aggregate forecasts than individuals' forecasts of the aggregates. They show this by calculating the Mean Absolute Percentage Error (MAPE) and graphing this against the number of forecasts that are combined. By combining more forecasts, a smaller MAPE value can be achieved. However, there exists doubt with the result of this research as no indication is given concerning a potential biased opinion of experts and their influence on their individual forecast. This might lead to problems when evaluating the credibility of the forecast, as many other physiological aspects can play a role when making a forecast. Hogarth and Makridakis state two key findings from cognitive psycology relating to human judgement:

[1] Sir Clive Granger (1934-2009) was a British econometric and Professor at the University of California. His work changed forecasting as we know it and concentrated on the concept of co-integration – methods to analyse time series of economic data at regular intervals. In 2003, together with Robert Engle, he received the Nobel Prize for economics. Alongside research, Granger also published 12 books, of which *'Forecasting Economic Time Series'* has become standard reference work on time series forecasting (The Telegraph, 2009).

"People's ability to process information is limited and people are adaptive" (Hogarth & Makridakis, 1981). This means that people could provide wrong forecasts because they are influenced from outside when making a decision, a statement that Franses (2008) also concludes from one of his propositions that he investigates. He finds that experts are often influenced and therefore adjust the forecast that has been made.

A model between an expert opinion or judgement and a forecasting model makes a third combination of methods discussed in the literature. Here, a clear combination between a qualitative and a quantitative method is present. The strength of this combination is the fact that, as Blattberg and Hoch (1990) state, *"Models and experts have shared but also unique forecasting aptitudes; models are too consistent and experts are too flexible. By integrating these decision inputs, we can exploit strengths and compensate for weaknesses"*. The authors give much credit to the 'database model', any model that uses historical data for analysis and use in a statistical model, but urge that human intuition is vital for making a forecast. The 'gut-feel' and 'tacit' knowledge that people have are strong elements that alone often fails to make an accurate forecast but combined with a quantitative element, provides a substantiated forecast, based on different types of information. This makes the combined forecast a very useful tool for any business decision maker. In the literature concerning this combination, Bunn and Wright (1991), among others, conclude from their literature review a difference between combining with a single model or with several models. Most combinations concern the single model type and therefore variable selection and data analysis are important aspects to keep forecasting using the judgemental method. When using multiple models, the authors argue that structure of the decomposition is more important and should be determined in a judgemental way. They recommend using a 'framework' or 'system representation' in order to provide a much more structured adjustment to the forecast, based on human judgements (Bunn & Wright, 1991).

Among the literature, much has been investigated on the role of experts and their adjustments of the forecasting process. Fildes et al. (2009) show that based on their research on macroeconomic data used for forecasting, allowing experts to adjust a forecast can substantially reduce the MAPE value. They also argue that the 50% model – 50% manager model, proposed by Blattberg and Hoch (1990) is limited to positive adjustments and therefore they also look into negative adjustments made by forecasters. They analysed over 12.000 judgementally adjusted forecasts, and found that three out of four investigated companies achieve a higher accuracy when adjusting their forecast. Overall, the negatively adjusted values where experts would estimate lower than normal in order to account for uncertainty in the market, turned out to create a higher level of accuracy. A conclusion that is also drawn concerns the motive of the forecaster. When this is clearly aimed at increasing accuracy and thereby eliminating a potential biased expert opinion, higher levels of accuracy are achieved. This can be achieved by *"more effective codification and incorporation of available data – such as market intelligence, the basis of most adjustments"* (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009). This suggests that even higher levels of accuracy can be obtained by providing information directly from the market, such as macro- and microeconomic data that is directly influenced by the market for a certain product.

The literature research into forecasting in general has provided many methods for determining future values of the data concerned. The individual use of methods has proved to be successful but combining forecasts is still developing and much research concludes that there is room for improvement in order to make the forecasts more accurate. Especially when it comes to expert-model methods, covered by Blattberg and Hoch (1990), Fildes et al. (2009), Bunn and Wright (1991) and others, clearly more accuracy can be achieved by making this combination as opposed to expert-expert or model-model combinations. This research continues on the expert-model track by adding a quantitative element to the forecasting process at the Port of Rotterdam Authority, thereby allowing the experts to make adjustments, but providing them with market intelligence so that a more substantiated forecast can be made. As stated by Fildes et al. (2009), the combination models can be improved by providing more market intelligence to the experts. The literature researches that continues looks into 'leading indicators' and then focuses on recent developments in forecasting in the maritime industry.

2.3 Forecasting using leading indicators

As mentioned earlier, leading indicators are variables whose outcome influences other variables in the economy, thereby giving an early warning for changes in the trend of that dependent statistic. The use of leading indicators is useful for use in the forecasting process, as uncertainty about statistics that need to be forecasted can be anticipated by analysing the trend of the leading indicator. Thereby, the accuracy of forecasts can be improved.

A search among databases and libraries has shown that a lot of research has been done on the identification and use of leading indicators. Much is focused on forecasting general economic indicators such as Gross Domestic Product (GDP) (OECD, 2006) or Industrial Production (Heij, van Dijk, & Groenen, 2011), as these are two key statistics that give a general indication of a country's economic performance. Heij et al. (2011) use leading indicators for predicting industrial production growth rates in the Netherlands between 1989 and 2009, using real time data to determine rates at horizons from one to six months ahead. The statistically significant relation between the leading indicators and industrial growth rate has resulted in a reduction in the Mean Square Error (MSE) of between 8% and 15% relative to benchmark figures[2]. This shows that using leading indicators can be very useful for determining a trend of a certain commodity, but also for identifying cyclical revivals and coincident indexes, as can be seen in Figure 2-1 where the red leading indicator gives a short-term indication of the trend of world equities that is likely to come. Mitchell and Burns have performed some pioneering work on leading indicators and Marcellino (2006) provides a structured guidebook to determining, using and evaluating leading indicators. This is of use when the leading indicators for this research are identified.

[2] The Mean Square Error is one of many statistics used to determine the accuracy of forecasts. Some good research by Lawrence, O'Connor & Edmundson (2000) provides nice information on the accuracy of forecasts.

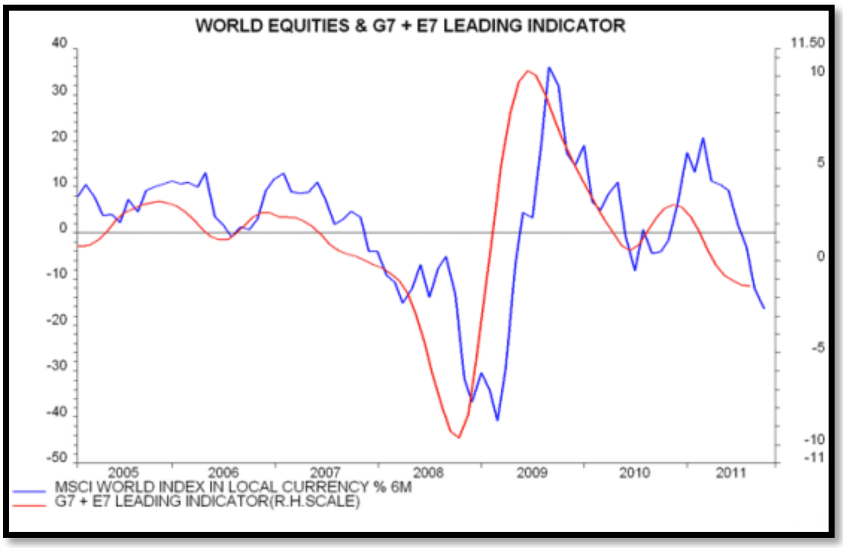


Figure 2-1: Leading indicator for world equities (Thomson Reuters, 2012)

Forecasting economic performance using leading indicators has led to some research on leading indicators being able to predict economic crises and vulnerability of country's financial system. Frankel and Saravelos (2010) conclude two implications from their research. First, they show that the levels of financial reserves of a country (as percentage of GDP and external debt, in months of imports and others) are significant indicators and showed leading changes in the currency market, equity market and in Industrial Production before the global economy collapse in 2008. Secondly, they conclude that their findings from the literature review can indeed be determined as leading indicators. By investigation with historic data they show that coefficients on the current account/national savings, credit growth, GDP and total and short-term external debt can be used for calculating crisis indices (Frankel & Saravelos, 2010).

Because leading indicators are determined on the basis of historical data and can therefore be categorised a 'quantitative model' they are interesting for further research into economic changes and behaviour that has a significant effect on throughput of goods in the Port of Rotterdam. Therefore, to get a complete picture of the literature available, attention is given to what has been published concerning the use of leading indicators to make short-term forecasts in the maritime industry.

2.4 Using leading indicators for short-term forecasting in the maritime industry

Contrary to the amount of literature that is available on the use of leading indicators for forecasting in general, not a lot can be found on forecasting port throughput using leading indicators. Many researchers have focused on developing or using a model for trend extrapolation and base forecasts on this information. Using leading indicators in another form in order to make a forecast has not been identified from the literature review. The OECD develops a set of composite leading indicators and updates these on a monthly basis. The method used by the OECD for constructing the leading indicators, the NEFTCI method, is able to predict economic turning points and assess economic behaviour in general. However, the focus of these indicators is on global and nationwide economic performance, not on a company-based level, and therefore not directly applicable when forecasting port throughput (OECD, 2012).

Articles that concern forecasts in the maritime sector involve the long-term future and often focus on trade routes development or changes in freight rates (van Dorsser, Wolters, & van Wee, 2012); (Veenstra & Franses, 1997). De Langen, van Meijeren and Tavasszy (2012) develop a long-term vision for the Port of Rotterdam that has been used to develop the 'Port Vision 2030' – A strategic plan for the Port of Rotterdam that sets out expected developments of the port in the coming decades (Havenbedrijf Rotterdam N.V., 2011). In their research, the authors combine model generated long-term projections with expert judgement about the future. The results concern long-term projections but the combination of both forecasts is concluded to be very effective. This research aims to provide such a combination for the PoR by developing the quantitative short-term forecasting tool.

Other research only focuses on the import of containers into a single country and use extensive computer models for their research (Chou, Chu, & Liang, 2008). These models tend to be more successful as long-term forecasts because they incorporate a larger amount of uncertainty, which is acceptable in for the long-term but not for the short-term. In the maritime sector many developments can only be modelled by a long-term method, for example the growth of the shipping market because ships tend to be in service for approximately 20 - 30 years. Building a new cargo terminal is another example that requires a (very) long-term forecast. This is very different from, for example, forecasting market developments due to a recent oil embargo in Iran. Stopford states that it is difficult not to agree with the statement made by Drucker: *"If anyone suffers from the delusion that a human being is able to forecast beyond a very short-term time span, look at the headlines in yesterday's paper, and ask which of them anyone could have possibly predicted a decade ago… we must start out with the premise that forecasting is not a respectable human activity and not worthwhile beyond the shortest of periods"* (Stopford, 2009).

Considering that no literature has been found on the exact combination of using leading indicators for short-term port throughput forecasting, this last section of the literature review focuses on various methods that can be used in the process of building a decision support system for forecasters at the PoR. The focus is on short-term model and the PoR must be considered as a company where in- and output go through a certain process (the Port of Rotterdam). Application of one of these methods, which one depends on the data available, contributes towards scientific research. Conclusions and recommendations concerning the application of one of these methods serves as input for the contribution to scientific knowledge about forecasting throughput goods using statistical analysis.

2.5 Methods for identification of trends and short-term forecasting

On the basis of literature research, several applicable models have been identified and are analysed below. The models can be used for making short-term forecasts in the maritime sector and the selection of models is based on a list of models touched upon by Makridakis and Wheelwright (1989). All models discussed are based upon quantitative data because of the benefits of combining forecasts of different nature's explained earlier. Depending on the data and current forecasting process at the PoR, a choice for one of these models is made in Chapter 4.

	Description	Strengths	Weaknesses	Sources
Trend analysis models				
Naïve	Simple rule e.g. 'no change', or 'if earnings are more than twice OPEX they will fall'	- No exogenous variables to forecast - Useful in stock markets, certain commodity future markets and currency exchange markets	- Forecast often over-adjusted due to use of last known value only - Cannot indicate changing trend	(Lawrence, O'Connor, & Edmundson, 2000) (Stopford, 2009) (Makridakis & Wheelwright, 1989)
Autoregressive Integrated Moving Average (ARIMA)	Popular model that identifies components of time series	- Can represent stationary and non-stationary processes - Identifies time series according to autoregressive form, differencing passes and seasonal parameter	- Has specific requirements for data that is analysed - Is based on linear approach	(Arsham, 2012) (Makridakis & Wheelwright, 1989, p. 135)
Auto Regressive Moving Average (ARMA)	Forecasts expressed as a linear combination of past values	- Can deal with time-lagged variables - Identification of any data pattern	- Autocorrelation is highly influenced by seasonal or cyclical patterns	(Makridakis & Wheelwright, 1989, p. 127)
Exponential smoothing	Weighted moving average method that assigns higher weights to more recent data	- Quick, easy to use method - Uses interval averages to determine trend - Forecast changes with added variables	- Assumes that a underlying pattern is available in the data - Makes no attempt to identify individual components of trend	(Makridakis & Wheelwright, 1989, pp. 72,94-95)
Mathematical models				
Simple regression	Estimated equation with one explanatory variable to predict target variable	- Strong predictor of dependent variable, once relationship has been determined - It uses a statistical model to discover and measure the relationship between an independent and dependent variable	- Estimates only a linear relationship between an independent and dependent variable - Cannot deal with changes in trends or periodic changes - Accuracy depends on sample size	(Makridakis & Wheelwright, 1989, p. 159)
Multiple regression	Estimated equation with more than one independent variable to predict target variable	- Is able to determine linear and non-linear relationships between variables - Can easily deal with seasonality or qualitative effects - Alternative methods provide improved results	- Requires estimates for the independent variables before a forecast can be made - A minimum of cases is essential for providing a reliable and accurate result.	(Hair, Black, Babin, & Anderson, 2009)
Econometric models	System of regression equations to predict target variable	- These models can deal with an unlimited amount of interdependent relationships between variables - Useful when testing and evaluating alternative policies and determining influence on critical variables	- Econometric models are not by definition more accurate than time-series models - Highly dependent of specific situation - Requires skilled and experienced econometricians to constantly run and update the model	(Makridakis & Wheelwright, 1989, p. 212&218)
Neural Networks	Nonlinear forecast based interconnection between layers of neurons	- Is applicable to any time series - Nonlinerity means higher accuracy for changing trends - Easy to use method with high accuracy	- Can be hard to interpret results - Overfitting is possible due to adding to much weights - Too much 'Black Box'	(Aburto & Weber, 2007)

Table 2-2: Forecasting methods analysed

2.5.1 Trend analysis models

Naïve

The naïve method comprises of making a forecast based on simple rules, often involving the outcome of the forecast for the current period and making slight changes to that. It can also involve a rule concerning the level of a certain statistic; when this reached a certain point, the forecast is adjusted according to the rule. Because of it heavy reliance on the last couple of data, the naïve method is very suitable for making short-term forecasts. Often, the forecasted figure is equal to the last observation so the accuracy of the forecast is not very accurate for sudden changing time series (de Gooijer & Hyndman, 2006). Makridakis and Wheelwright (1989) evaluate the naïve method and conclude that it can be useful in stock markets, certain commodity future markets and currency exchange markets.

Auto Regressive Integrated Moving Average (ARIMA)

The ARIMA model is a general class model widely used in statistical analysis. The aim of this model is to find the best fit of a time series to past values of that same series so that the forecasting error is as small as possible and contains no pattern. Applying this underlying trend to current data, a forecast for the coming time period can be made (Box, Jenkins, & Reinsel, 1994). One of the reasons for using ARIMA is its ability to deal with transformations such as logging and differencing, thereby being applicable to many different time series. Box and Jenkins have depicted a methodology to properly define an ARIMA model for time series analysis. Within the method, certain parameters are identified that describe the systematic pattern of the ARIMA model. These are used to properly define the trend of the data so that an accurate forecast can be made. First, the number of autoregressive terms (p) indicates how many lagged periods the dependent variable needs to be lagged as to remove any autocorrelation within forecast errors. Autocorrelation occurs when the value of a data point is dependent on the values of a previous recorded data point at a certain lag. For example, geophysical time series are often auto correlated because of the carryover process that occurs in nature, e.g. the likelihood of tomorrow being a rainy day rather than a very sunny day is greater if today is a rainy day rather than a sunny day (Meko, 2011). The autoregressive term therefore indicates how many previous (lagged) periods are considered to determine the next data point.

Secondly, because ARIMA requires time series to have a constant mean and variance, the number of differences (d) that is needed to make the data stationary is determined. Stationarity is a requirement for all time series when performing analysis, as most statistical tests are based on normally distributed significance tests (see Box 2 on page 65). In the literature a stationary process is described as a *"process whose statistical properties are the same over time; in particular, such a time series fluctuates around a fixed mean value. Examples of non-stationary time series include series, which include changes in level, trends, changes in trends, or seasonal behaviour"* (Caldwell, 2006). An ARIMA model with d=1 represents a constant trend, d=2 a linear trend and d=3 a quadratic trend and the number indicates the amount of differencing needed to make the series stationary. Taking a data point and simply calculating the difference between the previous data point does this.

The third characteristic of an ARIMA model is the order of the moving average model (q) in the equation of the predicted variable, depicted by the amount of forecasting errors. In order to make an accurate estimation of the underlying model and use this for a prediction, previous estimation errors of values are important to be known. The forecasting errors indicate how much a proposed linear model deviates from the real data. The amount of errors (or previous periods - each time series value has one error term) included is based on the trend and pattern of the suggested equation. For example, an ARIMA (0,2,2) model is a second order-differenced model that equals a linear function using the previous two forecasting errors (Duke Education, 2011).

Overall, the ARIMA model is adaptive, can be used in many situations, and can also work with unevenly spread time series – when one time series is shorter in length than another (Meyler, Kenny, & Quinn, 1998). A disadvantage of the ARIMA methods, besides its many advantages that make it a commonly used method, is that the model is often criticised as 'looking backward' too much. This makes the method generally poor at predicting critical turning points in time series data. This is mainly due to the fact that ARIMA often estimates parameters based on a constant or linear trend, when the data is differenced once or twice (d=1 and d=2) (see: (Valenzuala, et al., 2008); (Meyler, Kenny, & Quinn, 1998); (Aburto & Weber, 2007)).

Certain combinations of p, d and q for ARIMA modelling depict special types of models, the smoothing method being the most widely used. If the data that is collected fits the requirements, the ARIMA model becomes a very useful tool for this research. Another form of ARIMA modelling, where the data used is already stationary, is the ARMA method. In this case, the 'I' part, indicating the order of differencing, is not needed.

Smoothing

Smoothing is a special form of ARIMA modelling and is often used when multiple products need to be forecasted, for example in a manufacturing environment, so it's strength lie in this area. To provide an accurate forecast, managers 'smooth' historical data of the series and use the average line to extrapolate and make a forecast (Makridakis & Wheelwright, 1989). Single, double and triple exponential smoothing refers to respectively ARIMA (0,1,1), ARIMA (0,2,2) and ARIMA (0,3,3). Single exponential smoothing is often referred to as exponentially weighted moving average, where previous values are given a lower weight as we move further back from current data. Double exponential is more accurate when a trend is present in the data, thereby eliminating single exponential smoothing as an accurate method, because port data most often includes trends. Because a seasonal influence is also often present in maritime data, the third exponential smoothing method seems to be the most promising smoothing method. This method calculates a trend line for the data, the trend and a seasonal index weight for each time point in the data, represented in the data smoothing factor, trend smoothing factor and seasonal change smoothing factor. The method has an exponential factor incorporated in its name because it involves a growing number of observations for forecasting the next value. The average weight is based on a growing number of observations, thereby growing in an exponential manner.

The fact that 'smoothing' means averaging out the time series by adding weight to different intervals in the data makes it an easy method for managers to apply in multiple short-term forecasts. Therefore, these forecasts, which have to be conducted on a regular basis, can be made with relative ease and speed. This makes the smoothing method a promising method for applying in a business environment where short-term forecasts are regularly updated and need to be made for many products or variables.

Auto Regressive Moving Average (ARMA)

The ARMA model, as opposed to ARIMA, is different in that it does not include a parameter for differencing the data. This is needed when autocorrelation exists and the data needs to be made stationary, as is the case when applying an ARIMA model. If the data is non-stationary, an ARMA model is sufficient for making a forecast. A multivariate model has a dependent and independent variable and includes an AR and MA value, whereas a univariate model only contains a MA value, i.e. the amount of periods that are used in the moving average forecast.

For applications in the short-term such as wind speed forecasting, the ARMA method is often successfully applied. When determining medium term forecasts, Chu (2009) uses the ARMA model to forecast tourist demand for the coming months and quarter for 9 tourist destinations. He concludes that the ARMA model performs very well and small MAPE measures can significantly improve managerial decisions concerning the hospitality and tourism industry. A successful application of the model in weather and tourist forecasting indicates that other applications, such as the maritime industry, are interesting to investigate. A study concerning forecasting with an ARMA model in the maritime industry has not been found in the literature review.

2.5.2 Mathematical models

The above models almost all try to fit a model to the data and use this to predict the future values of the dependent variable. The next mathematical models develop a function that expresses the way the various variables are related. This way, factors or variables that influence the time-series are taken into account and facilitates a better understanding of the environment. It also makes it possible for forecasters to create certain scenarios by changing the values of inputs and studies the effect they have on the future (Makridakis & Wheelwright, 1989, p. 159).

Simple Regression

This method assumes that the data to be analysed contains a linear relationship with the dependent variable. The relationship of Y, the item to be forecasted, therefore is a linear function of X, the independent variable (Makridakis & Wheelwright, 1989, p. 159). This is an easy method that can be applied in many cases, but the main disadvantage is that simple regression cannot identify a change in the trend or periodic changes, due to the fact that a linear trend is assumed within the variable. This makes it just a basic method, applicable for simple situations, but allows researchers to get a preliminary indication of the movement of data in time.

Multiple Regression

In extent to simple regression, multiple regression can be also used to make forecasts but can thereby take into account seasonality and changes in trends. This is because multiple regression can incorporate a linear and non-linear component by determining more than one independent variable to predict the dependent variable. In order to deal with the seasonality of the time-series, a dummy variable can be added so that these can adjust for differences in data, by taking on the value 0 or 1. If the condition exists, the variable has the value 1 and if it does not exist the variable takes on value 0. Furthermore, multiple regression can be used to determine how multiple variables have a linear relationship with a dependent variable. A regression equation is the result of this analysis, depicting coefficients that each represent the influence that every independent variable has on the dependent variable.

Multiple regression is the basis of a lot of techniques, as many models are based on the concept of regression and extend it or change it slightly. Structural Equation Modelling (SEM) and Vector Autoregressive (VAR) models both rely on the concept of multiple regression but combine it with other techniques or add an extra element to the model. These techniques seem to be useful for this research as the techniques are simple to implement and can deliver accurate and valid results.

An important assumption of multiple regression is that the factors that contribute to the changes in the dependent variable are not correlated, this would create so-called multicollinearity and would distort the results of the model. Furthermore, the model needs regular updating of parameter estimates that represent the independent variables so that an up to date representation of the environment is modelled. Overall, the multiple regression model is superior over simple regression because of its linear and non-linear possibilities. Furthermore, it is a relatively simple model that can effectively make a forecast for use in various cases and research topics.

Econometric models

The econometric model uses more than one equation for making forecasts, and is considered as a special type of multiple regression model by Makridakis and Wheelwright (1989). Among other definitions that are used in the literature, the econometric model denotes a system of multiple linear regression equations, each including several interdependent variables (Makridakis & Wheelwright, 1989, p. 210). This ensures that the model can deal with an unlimited number of relationships between variables. Furthermore, the model is useful when testing and evaluating policies that are based on historic data, current data and forecasts that have been made.

From the literature it has become apparent that econometric models are not by definition more accurate than other time series models, at least in the case studied by Brodie en de Kluyver (1987). They find that simple extrapolative (time-series) methods are consistently more accurate than econometric models when used for short-term forecasting. Also, the source of the data is important to consider carefully because the outcomes of the model are highly dependable of the specific situation. Furthermore, updating the model requires experienced econometricians to constantly run and update the model. This can be a determining factor when it comes to the implementation of this model, as many requirements for newly to be designed processes include an aspect related 'ease-of-use' and maintainability. Furthermore, the literature suggests already that this method might not be very suitable for applying further on in this research.

Neural Network analysis

Neural network analysis has its origins in biology and was used in research concerning neural activity in the brain and body. Bain (1873), James (1890) and more recently McCulloch and Pitts (1943) have done pioneering research using neural networks in the biology and neuropsychological sector. As from the 1950's, neural networks began to be used for other fields of study, including informatics, engineering and business forecasting.

The concept of neural network analysis is based on the transformation of input, via multiple layers, into an output that provides a forecast for the specified period. This method is often called the 'sliding window approach' because it uses data from a specific time frame, analyses this, and creates a forecast for a future time period (Crone, 2005).

The neural network approach extracts data points from the time series in a specific time period and sends this through a number of pre-determined hidden layers. Within these layers, the weight for each data point is changed to minimise the objective function, called back propagation. This way, the output is compared with the function and the weight adjusted to give an accurate estimation. By repeating this process for a large amount of times, the error has been reduced and gives an accurate estimation of the weight for that data point. A more accurate set of weights over a time period can create a forecast with greater precision (Frank, Davey, & Hunt, 2010).

The main advantage of Neural Network analysis is its ability to deal with non-linear output when providing a forecast, as apposed to ARIMA's linear approach between time series. Aburto and Weber (2007) also point out that Neural Network analysis requires less interaction with the user, therefore making it easier to make a forecast. The model is also a data-driven self-adaptive method that learns form examples and identifies relationships to use for forecasting future time periods (Zhang, Patuwo, & Hu, 1998). Furthermore, many statistical packages have automatic function to make the forecast and this makes both ARIMA and neural network analysis an easy to use approach in businesses.

A disadvantage of the method in this context is the fact that the forecast making process of the leading indicators needs to be transparent in order to allow experts at the PoR to keep updating the model and the maintain the forecasts for future periods. When Neural Networks are used in the process and are automatically integrated in the software, they are fed with input and produce output. This way, the experts do not have insight into the way of working of the neural network and consider it a 'black box'. This would severely reduce the transparency and adaptability of the Forecasting Support System.

2.6 Conclusion

In the literature, much attention has been given to forecasting methods and the various categories and forms that exist. The qualitative, quantitative and judgemental category seems to be the most conventional distinctions that are used in forecasting. Also, the combination of forecasting tools has been touched upon and it seems that there are many advantages and disadvantages when combining certain methods. It is clear, however, that combining a qualitative forecast with a quantitative forecast delivers a more accurate forecasting model, as shown by Clemen (1990), Huang and Lee (2007), Engle, Granger and Kraft (1984), among others. This clear distinction between the nature of a method, being qualitative or quantitative, indicates the strengths and weaknesses of the methods in general, thereby providing an answer to the first part of research question 1. Qualitative and quantitative forecasting tool both have their strengths and weaknesses and it is argued that combining these methods creates a more substantiated forecast, thereby improving accuracy and reliability. Many researchers prefer a combination of methods but underline the fact that human judgement remains crucial when making a forecast. For this research a combination between expert judgement and the use of statistics such as 'leading indicators' has been investigated. This exact combination has not yet been discussed in the literature concerning forecasting in general. However, the literature research has shown that the use of multiple regression or one of it variants seem to be the most promising method for identifying a trend, creating a mathematical trend to model this and using it to forecast future periods. The models, in first instance, seem to be superior to other techniques to it ease of use, transparency and ability to deliver accurate forecasts. These are important considerations for choosing a technique that best suits the situation and desire of the PoR forecasting process.

The concept of 'leading indicators' is well known and many institutions, like the OECD and U.S. NBER, use them for analysis and monitoring of (financial) markets. In the literature, Mitchell and Burns have done some pioneering work on leading indicators and Marcellino (2006) and Heij et. al. (2011) provide some good research that shows that leading indicators can have a supporting role when making forecasts. However, Stock and Watson (1992) show that leading indicators did not pick up the latest U.S. recession and are therefore not useful. Because the current economic climate is as unstable as earlier recessions in the world economy, a general flair of attention must be kept in mind when forecasting an economic variable. In economic uncertain times, using statistics to forecast exact economic outcomes is difficult; a general trend is most often the result of a forecast using data that is influenced by some sort of economic instability.

Leading indicators in combination with other forecasting methods could well provide a solid and substantiated method for maximising the advantages of both methods and minimising the disadvantages.

Within the forecasting process, many methods exist that can interpret data and provide an underlying trend or formula to use for making the forecast. These methods have been evaluated above and show promising characteristics for identifying the leading indicators and afterwards making a forecast to be used in the information dashboard.

From the literature research in general, a knowledge gap can be identified and serves as the theoretical basis of this research. The general statement is as follows: ***Although both approaches of determining leading indicators and making a forecast are extensively discussed, the literature seems to be lacking research on the exact combination of qualitative information provided by experts and quantitative input by means of forecasts of the leading indicators.*** This combination is interesting to investigate because the individual components are proven, but the combination can be much more useful for forecasting short-term dry bulk goods in the Port of Rotterdam.

3. THE FORECASTING PROCESS AT THE PORT OF ROTTERDAM AUTHORITY

To round of the analysis phase of this research, attention is turned to the process of making a forecast at the PoR. The goal of this Chapter is to analyse the forecasting process and identify areas where a quantitative element can improve the accuracy of the forecast, as stated by sub-question 2 in Chapter 1.2. This Chapter aims to answer this sub question:

What components of the current forecasting process indicate that a quantitative element can be added to improve the process?

The forecasting process has been analysed and matched to the theoretical background provided in the previous Chapter. This way the suggested improvements to the process can be scientifically substantiated. Once these key elements in the process have been identified, the modelling and design phase can focus on these areas so that the forecasting process can be improved. Before the analysis can start, a short introduction to the Port of Rotterdam and the Port of Rotterdam Authority is provided in paragraph 3.1 and 3.2. This Chapter is divided into three main analysis methods that enlighten different views and aspect of the forecasting system at the PoR. It was decided to analyse the system from these three perspectives because they provide insight into the technical build up of the model, the environment that the model sit in and, as research is focused on designing an artefact that is used by forecasters, insight into users and their attitude towards the current forecasting process. For this reason, several techniques for gathering information have been used. Although there are many techniques for business analysis and depicting design requirements, a choice has been made for the IDEF0 technique (Ross, 1985), a network model and a survey. The forecasting process is analysed as:

1. A system of input, control, support and output;
2. A network of information exchange and collaboration between people;
3. A human steered business process.

Before dealing with the forecasting process itself, a general introduction to the Port of Rotterdam and the Port Authority is provided.

3.1 The Port of Rotterdam

The Port of Rotterdam is the largest port in Europe and has been facilitating trade of goods and commodities since the early 13th century when people first started using the river for transportation and trading purposes. Since then, the port has grown to become the 5th largest port in total throughput and the amount (+/- 430 million metric tons in 2011, see Figure 3-1) is expected to rise due to the expansion of docks and terminals in 'Maasvlakte 2'. This expands the port's area by 20%, to a total of 12.440 hectares in 2014, when the first docks come operational (Havenbedrijf Rotterdam N.V., 2012). The new docks are able to handle the largest ships currently available (up to 15.000 TEU and over 15m draft) and have been designed to facilitate the growing size of container vessels in the future. Having the facilities to handle the largest vessels available allows major international shipping companies to make Rotterdam (one of) their European port(s) of call. The construction of 'Maasvlakte 2' and the provision of modern and high-quality facilities for the shipping companies to perform their activities ensure steady revenue for the PoR by means of long-term contracts that are signed. The PoR owns wharfs and docks in the port areas and hires or leases these to the shipping companies. In 2011, revenue from rent, leasehold and wharfage was €270 million (roughly 40% of total revenue), so it is important for the PoR to keep providing proper facilities to keep attracting (new) customers (Havenbedrijf Rotterdam N.V., 2011).

Within the Hamburg – Le Havre range[3], the Port of Rotterdam has the largest amount of throughput of dry bulk cargo with a total of 87,3 million metric tons in 2011. This is roughly 20% of total throughput in the Port of Rotterdam and is transported to and from the terminals with over 1000 ships that call upon the port each year. Ships range from 30.000 to 200.000 in DWT-class and come from various destinations worldwide. Countries that export dry bulk goods that account for the majority of throughput in the Port of Rotterdam are Brazil, Canada, Columbia and the U.S.A. among others. The ratio outgoing/incoming dry bulk goods is roughly 1 to 8, implicating that Rotterdam is a port that acts as a hub for hinterland transport, either by direct transhipment, direct board-board or temporary storage. For many large industrial centres in Europe, the Port of Rotterdam is a vital link in the logistics chain through which imported products are transported by barge, train, truck or pipeline. In the 'large' Port of Rotterdam[4] there are 16 terminals that handle dry bulk goods, as shown in Figure 3-2. The terminals are large enough to facilitate the largest vessels currently in use, categorised as VLOC (Very Large Ore Carrier).

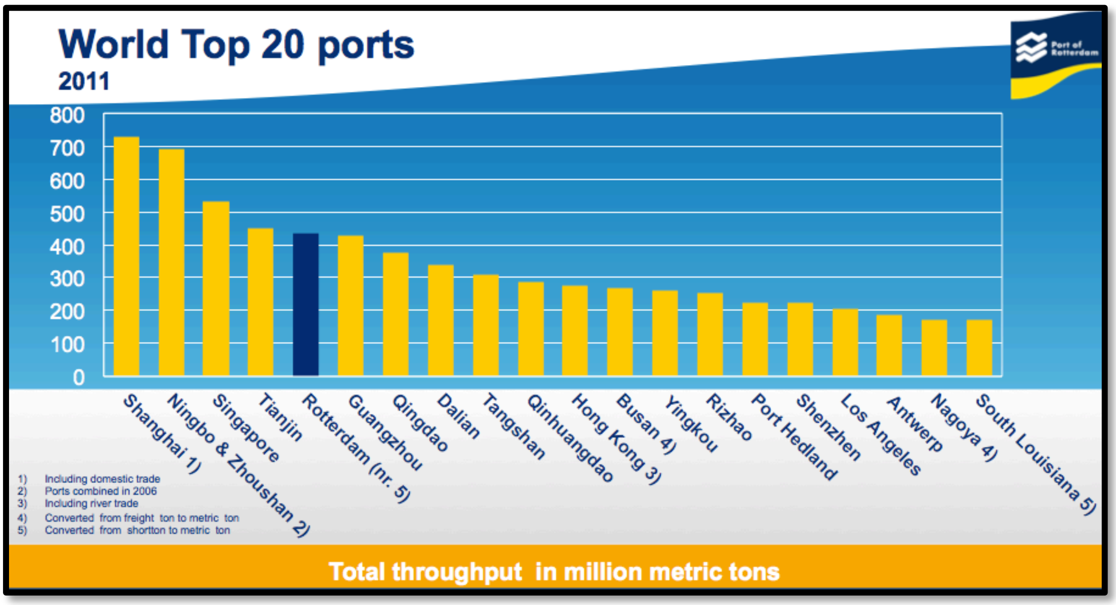


Figure 3-1: Total throughput in world top 20 ports (Havenbedrijf Rotterdam N.V., 2012)

[3] The Hamburg – Le Havre range is a commonly used area that includes major ports in the triangular area between Hamburg and Le Havre. The area contains 11 ports in North-Western Europe: Hamburg, Bremen, Wilhelmshaven, Amsterdam, Rotterdam, Sealand Seaports, Antwerp, Ghent, Zeebrugge, Duinkerk and Le Havre. The range is often used when analysing the market position of a port compared to surrounding competitors.

[4] Since the 1st of July 2011, the portmaster division of the Port of Rotterdam Authority coordinates nautical traffic management for the port of Dordrecht, throughput figures can be calculated to include or exclude Dordrecht. The term 'large' Port of Rotterdam refers to the Rotterdam and Dordrecht together, which is most often used when calculating throughput statistics at the Port of Rotterdam Authority.

Dry bulk cargo contains many products that are used mainly in the industrial sector. The commodities are grouped in four main categories:

- Agribulk
- Iron ore and scrap
- Coal
- Other dry bulk goods

Agribulk goods that are handled in the port are grains, soya (products), sorghum, rapeseed, etc. Large quantities of goods are transported from Argentina and Brazil and the biggest destination for Agribulk goods is the United Kingdom. In 2011, a total of 9,9million metric tons of Agribulk products were transported through the Port of Rotterdam (Havenbedrijf Rotterdam N.V., 2012).

Steel producers in the German hinterland are an important destination for iron ore being transported through the port. Other destinations include Austria, Belgium and France. Scrap is collected in Germany and the Netherlands and the port acts mainly as an export port for scrap. The river Rhine and Maas provide excellent infrastructure for barge vessels to transport both products to and from the Port of Rotterdam. Nearly 40million metric tons of iron ore and scrap were handled in the port in the year 2011 (Havenbedrijf Rotterdam N.V., 2012).

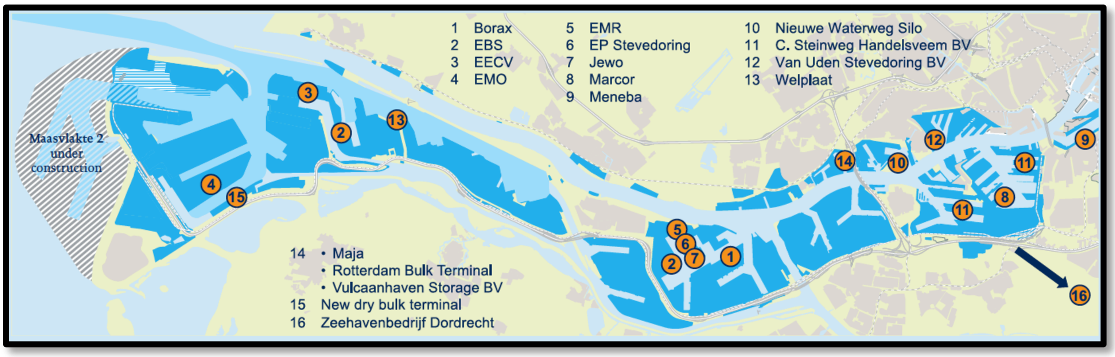


Figure 3-2: Rotterdam dry bulk terminals (Havenbedrijf Rotterdam N.V., 2010)

Although there are only 3 major coal terminals in the port, throughput of steam coal and coking coal in Rotterdam reached approximately 27million metric tons in 2011. The steam coal is mostly transported to power plants and coking coals is destined for the steel industry. Both products are mainly transported to and from Germany, France, Belgium and the Netherlands. The Europees Massagoed-Overslagbedrijf (EMO), located on the first 'Maasvlakte' (number four in Figure 3-2), roughly handles over 70% of all coal transport in Rotterdam (Havenbedrijf Rotterdam N.V., 2012).

The last category, other dry bulk goods, includes products such as mineral sands (e.g. ilmenite and rutile for titanium production), alumina and bauxite for producing aluminium, and other dry goods such as ores, ferro-alloys, pig iron and petcoke for the production of steel and other metals. Over 20% of total mineral throughput of the Hamburg – Le Havre is transported through Rotterdam (Havenbedrijf Rotterdam N.V., 2012).

3.2 The Port of Rotterdam Authority (Havenbedrijf Rotterdam N.V.)

The Port of Rotterdam Authority is the main governing body of port and acts as developer, administrator and operator of the docks and industrial complex. To ensure that Rotterdam remains a preferred port of call for many shipping companies, the PoR aims to provide the following mission statement:

> *"The Port of Rotterdam Authority develops, in partnership, the world-class European port. We continuously improve the port of Rotterdam, to make it the most efficient, safe and sustainable port in the world. We create value for customers by developing logistical chains, networks and clusters. We do this in Europe as well as in growth markets worldwide. The Port Authority is an entrepreneurial port developer, and as such the partner for world-class customers in the following market segments: the petrochemical industry, energy (oil and gas), transport & logistics. In this way, we strengthen the competitive position of the Netherlands as a whole".*

Source: (Havenbedrijf Rotterdam N.V., 2012)

Since 2004 the PoR operates as a public limited liability company, the municipality of Rotterdam owns 30% of shares and 70% belong to the Dutch Government. Although publically owned, the PoR operates as a commercial company and employs around 1200 people. The two major commercial divisions are the Containers, Breakbulk and Logistics (CBL) department as well as the Industry and Bulk Cargo department (PIM). Within the CBL&PIM department, the Business Analysis & Intelligence (BAI) team is responsible for the information supply and analysis concerning financial, economic and statistical issues. Furthermore, the BAI team coordinates the forecasting process that is made for all commodities being transported through the port. The output of the forecasts serve as valuable input for the strategic plans of the CBL&PIM departments and the PoR as a whole.

The forecasts that are made by the BAI team comprise two time frames, namely:

- Short-term (for 3,6,9 & 15 months)
- Medium-term (1 to 5 years)

At the PoR, long- term forecasts are made by the Corporate Strategy department and cover time periods of 30 years or more. The short- and medium-term forecasting process all have the same way of working but the focus of this research is on the 3-month short-term process. The process is analysed and interpreted in the following paragraphs.

3.3 The dry bulk goods market

The Port of Rotterdam has grown to become Europe's largest port at this time. Increasing trade in the world and Europe has ensured growth of transported goods through Rotterdam because of the port's location, the independence of tidal influences and the facilities for handling goods, among other factors. Furthermore, the port has excellent connections with the hinterland as the river Rhine and several railways and highways provide easy access to and from Rotterdam. This allows companies to import and export their raw materials and finished products, via Rotterdam, to and from all continents in the world. Products as these can be of any shape, size, weight and can be solid, liquid or in a gas state, the port has facilities to store and transport all sorts of products. Because this research is focused on dry bulk goods, these products will be handled and investigated. To get a better understanding of the link between the market for these goods and throughput in the port, a brief description of the dry bulk market is provided, especially concerning the interaction with the port of Rotterdam.

Most dry bulk goods are goods that are transported on a Business-to-Business (B2B) level, meaning that the products in this state do not reach the consumer in the store. They undergo a process of transformation or get used for the production of other products. Companies extracting raw materials such as coal and iron ore, for example in South America, sells their products to companies in Europe for the production of electricity and steel. These are just an example of many products, but coal and iron ore products are prominent products that are transported through the port. Often, semi-finished products such as steel billets and slabs are also handled in the port. These products are produced from the raw materials but are categorised as break-bulk goods.

The market for dry bulk goods such as coal and iron ore is often considered a stable market in the short run as supply levels of raw materials are often well known and extraction levels remain constant. This way, a constant supply of these raw materials is provided. What is more volatile is the demand market for these goods. Manufacturing companies in the car building industry or electricity production require raw materials to be extracted form mines and natural resources and processed into semi-finished products before they can be used for production. Because these companies rely on sales to customers, the demand for raw materials can often be (indirectly) related to a consumers' willingness to buy. Besides, the general economic climate, the company financial situation and other factors influence the demand for raw materials. This market is considered to be much more fluctuating and is therefore important to consider for the PoR. Gaining insight into the amount of dry bulk products will be ordered from South America by companies in Europe, and knowing if these products are likely to be transported through Rotterdam, is valuable business information that can be used for all sorts of purposes, in this case forecasting throughput.

For example, Germany is a large Iron producing country. In 2011, Iron Production reached over 27million tonnes, and the iron is used for all kinds of purposes. A large proportion is used for making steel, but also casted and galvanised iron is used for consumer goods, roofing and vehicle bodies (WSA, 2012). As most of the iron ore used for making iron is extracted in South America and Australia, it is expected that large volumes of these products be transported via the port of Rotterdam. From here on, smaller barge vessels transport the goods via the Rhine River to iron producing companies in Germany. On the opposite, finished products are transported back to Rotterdam to be shipped to customers all over the world. When researching leading indicators for Iron Ore throughput, it can be expected that production level in Germany, the car manufacturing level and other iron and steel production and use in various European countries have a significant impact on the amount of goods being transported through the port.

Besides Coal and Iron ore products, several products that make up the Agribulk category can also be expected to have an impact on throughput. These products show the opposite demand and supply pattern to coal and iron ore as the demand for these products from companies and consumers is relatively steady. Supply of products such as grain, corn and rapeseeds are dependent on crop growth. A bad crop-growing season can decrease supply levels drastically, having an effect on the amount of Agribulk products that will be shipped via Rotterdam. Again, production levels of these products might well have an impact on the throughput in Rotterdam and these statistics are therefore vital to investigate in this research.

3.4 The current short-term forecasting process

As stated, the forecasting process was analysed from three perspectives within the 'systems approach' towards the process. Each perspective uses a different method to map or gather information concerning an aspect of the process. Evaluating the system of input, control, support and output was done using an *Integrated Definition for Process Modelling (IDEF0) model*, the exchange of information and collaboration was analysed by a *business process model* (Smith & Fingar, 2003) and the human interaction with the process was evaluated according to a *survey* spread amongst forecasters.

3.4.1 Forecasting dry bulk goods throughput as a *system* of in- and output

A forecasting session was attended to get an idea of interaction between experts, knowledge sharing and collaboration to create a forecast. Specifically, the process was assessed on several main forecasting elements, in order to see if these had a qualitative or quantitative character. The system of input, output, control and support is best described by making an IDEF0 diagram. This is a common technique used for analysing business processes and gives a clear top-down approach that can include as much detail as desired. IDEF0 is used to graphically represent the coherence between the most important activities of a process that are needed to achieve a set goal. A top level IDEF0 model is identified as the A_0 model and represents the process in its highest level of abstraction, one process block to represent the activity. The power of IDEF0 lies in its ability to decompose a process and thereby identify sub processes of the activity being performed. Similar diagrams to the A_0 model in Figure 3-3 are drawn and labelled A_1, A_2 etc. according to their hierarchy level (figure 3-4). Creating a more in depth analysis can help engineers to discover the core of the process and identify bottlenecks of the process (Honig, Kolfschoten, & Warnier, 2012). By modelling the forecasting process, better insight can be gained into the elements that allow a quantitative tool to support the process.

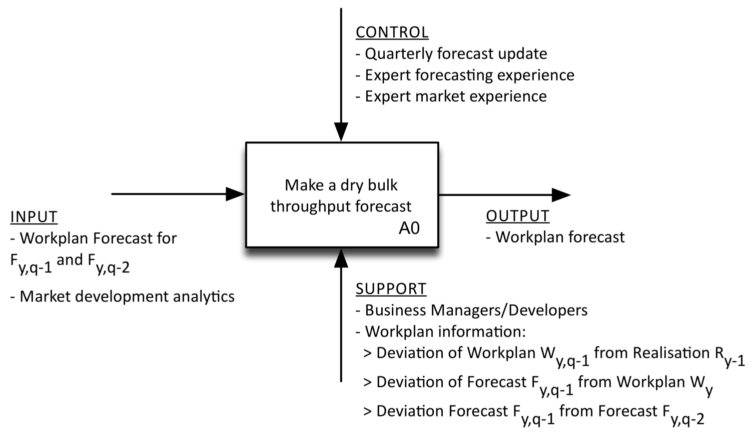


Figure 3-3: IDFE0 A0 model

Analysing the workplan (A1)

The forecasting process starts with information provided by the BAI department. This concerns data on the four dry bulk goods in the 'workplan', the forecast for the previous quarters and deviations of these forecast with throughput realisations. The forecasts are used as input into the process, are analysed and adapted if needed. The deviations are used as support for analysing the workplan forecasts' accuracy. As the forecasts concern a 3-month prediction and thus are made every quarter, the letter q indicates the quarter to be forecasted and y indicates the year involved. Graphs and data tables for each dry bulk good are produced by BAI and used as input for the forecasting process. The experience that experts have gained on forecasting helps to create an impression of the forecast that is indicated in the workplan and controls this process. Furthermore, decisions on how, when and why to make a certain argumentation or forecasting decision is controlled by the experts' experience throughout the entire forecasting process. Distinction is made between forecasters expertise on forecasting itself and their knowledge about changes, developments and trends in the markets that are closely connected to activity in the port. The control of the process is an important aspect of this process as it determines how well the process is performing and determines if additional measures need to be taken to improve the accuracy in the future. The output of process A1 is the analysed workplan forecast.

Exploring market development (A2)

Market information that the experts gather is used for evaluating current local and international market changes. Information comes from customers in the port, but also news sources and market reports concerning developments in the dry bulk sector. The market experience refers to the human side of making a forecast, the ability to predict certain changes and sudden shocks in market trend. This is what many quantitative forecasting methods find hard to indicate or cannot incorporate at all. Big developments that have a large impact on the dry bulk market, such as the closure of a coalmine or the construction of a new power plant, are evaluated and their impact is assessed. When this process is completed, the knowledge about the market is used as support for process A3: referencing the forecast.

Referencing the forecast (A3)

This is the main activity of the forecasting process where the information about the forecast are referenced and tested against current market developments. Experts have evaluated the information separately and need to ensure that the current forecast (from the workplan) is in line with the market. This is done using their experience and results in either a forecast that matches current conditions or a forecast that needs to be adapted.

Adapting the forecast (A4)

If a forecast is not accurate enough and therefore does not align with market conditions, experts need to adapt the forecast. Based on their knowledge, they change the forecast in the way they think it aligns. Once adapted, the forecast is evaluated in process A3 and a final check is performed to ensure that the forecast matches market developments. Once approved, the workplan forecast leaves the system and is ready to be used in the BAI departments' reports that are used for decision-making by other involved groups at the PoR (see Chapter 3.4.2). The forecast consists of a forecast for expected tonnage and price per tonnage. This allows the financial department, an important user of the short-term forecast, to make decisions about expected income.

Analysing the IDEF0 diagram

Drawing an IDEF0 diagram has shown that the transformation process is well executed, but that a lack of quantitative information in support of the process refrains the forecasters from making accurate forecasts. At the moment, accuracy is adequate and usable but, as was stated as one of the aims for this research in Chapter 1.1, the accuracy can be further improved. According to several literature sources, using both qualitative and quantitative information for forecasting can provide a more accurate forecast. The process has clear characteristics of a qualitative nature as decision are often made on the gut feelings and experience that the experts have, thereby often providing a subjective contribution. Because of this, certain characteristics of qualitative forecasting methods, such as the 'Grass Root' method and the 'Delphi' method are clearly visible (for more information on these methods please refer to (Chase, Jacobs, & Aquilano, 2005).

Furthermore, the 'workplan' serves as an indication of expected throughput but is based on a pre determined yearly distribution and must not be relied upon too much. This might lead to path dependence, a common concept where persons are attracted to a familiar path when making a decision, and follows this because it is a safe and known option. This discourages people to think beyond decisions and sudden shocks and changes are unaccounted for. As was noticed, forecasters often accepted the proposed values from the 'workplan' when the uncertainty about future months is high. Although a long term trend is present in the time series, making a forecast based on a distribution from previous years does not create a volatile forecast that incorporates expected peaks and troughs.

Another aspect of the system that can be improved is the information that experts have about the market. At the moment, information from customers and news sources is gathered and evaluated, but this information is often delayed or not published at all due to the fact that companies want to keep the information confidential (or releases it after a certain time period).

Conclusion

The analysis of the system has shown that developing quantitative support, such as leading indicators, can give forecasters a 'second opinion' to base their decisions upon. The Process Renewal Consulting Group Inc. shows that, based on their experience with many successful companies such as Merrill Lynch, IBM, Johnson & Johnson and AT&T, roughly 85% of improvements are made in the supporting or controlling aspects of the process (Long, 2003). Therefore, the greatest opportunity for adding the tool is in the support of the process, because the tool is not explicitly part of the transformation process, whereas the information from BAI is converted into a forecast and is therefore real input into the process.

To gain most effective support, the decision support tool can be consulted when performing activities A2 and A3. As was mentioned, (qualitative) information is provided for the process but this only concerns the throughput goods Agribulk, Iron Ore, Coal and Other dry bulk goods, but no quantitative information is used concerning market developments. At the moment, no quantitative information that is up to date is supporting the processes where the market is explored and where the forecast is referenced to the market developments. The support of process A2 is currently of a qualitative character and this area poses the most suitable position for adding a quantitative element. This way, both qualitative and quantitative information can be used to explore market developments and the output of this process (explored market information) is used as support for referencing the forecast. Here, forecasters reference the forecast from the workplan against market developments and assess whether the forecast aligns or not.

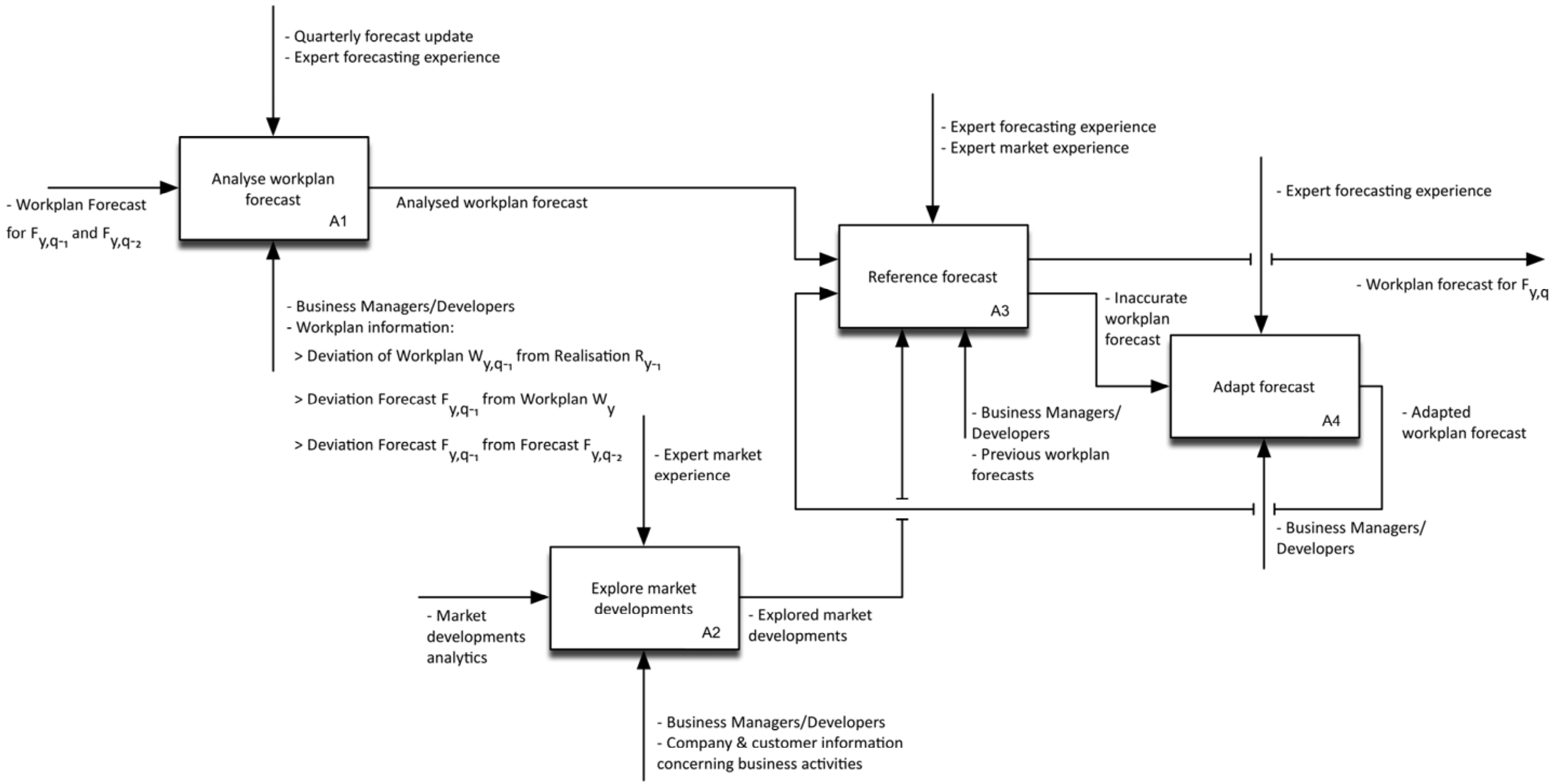


Figure 3-4: Decomposed IDEF0 diagram

3.4.2 A *network* of collaboration and information exchange

The dry-bulk short-term forecast is intended to provide an estimate for throughput and price per tonne for the four main dry bulk goods (Agribulk, Iron ore and scrap, Coal and other bulk goods). Experts from the PIM department provide information and their opinion on the future development of the goods. A manager from the BAI team coordinates the discussion and the forecasting process overall. Figure 3-5 shows a graphical representation of the information flows and the cooperation between various persons within the PoR. The forecasting process is therefore considered a multi actor setting, whereby various actors are involved from making the forecast to using the forecast. The output of the forecasting process by the experts (on the left of Figure 3-5) is presented to the 'management team' (MT) for evaluation. The management team evaluates the usefulness of the output and determines whether further work can be performed on the subject. Furthermore, when additional budget is requested for further work, the MT decide upon this. They revise and approve the forecasting figures for evaluation by the 'Directie Team' (DT). For the design of the FSS, it is important to consider the practical use of the system. Users and their managers must be able to get a clear overview of the forecasts that have been made. Design requirements need to be set up together with people at the PoR who have experience with working with decision support tools in general. These people can provide relevant information for designing a FSS that is both accurate and useful for making forecasts.

If revisions are needed, the forecast is sent back and changes can be made. Once accepted by the MT, managers from the DT assess the forecast results and give a final approval before they are sent to various departments for strategic decisions and financial analyses.

The 'Centraal Plan Bureau' (CPB) uses the forecast to get an understanding of developments in the Port of Rotterdam, as activity in the port is an important contributor to the overall Dutch economy. The CPB mainly uses forecast for the throughput of the dry bulk goods as compared to leading indicators themselves. The developments and forecasts for throughput goods are considered more relevant for use in assessing economic performance of the Netherlands.

Within the PoR, the forecast is used for financial analysis – to assess the cash flow and determine whether revenue targets that have been set for the current year are realistic and achievable. Otherwise, intervention is needed to keep the financial situation on track. The forecast output is therefore presented in two statistics, the price per tonne and the expected throughput of a particular good. Multiplying these statistics provides the finance department with a forecast concerning the expected port dues for Rotterdam. As explained, port dues make up 50% of the PoR's income and are vital for development of the port and staying competitive. Providing accurate forecasts for the financial department are therefore crucial as the quarterly forecasts also deliver an indication of the whole year forecast provided in the workplan. The supervisory board also uses the forecast to monitor the port's situation regarding throughput figures and can intervene if needed.

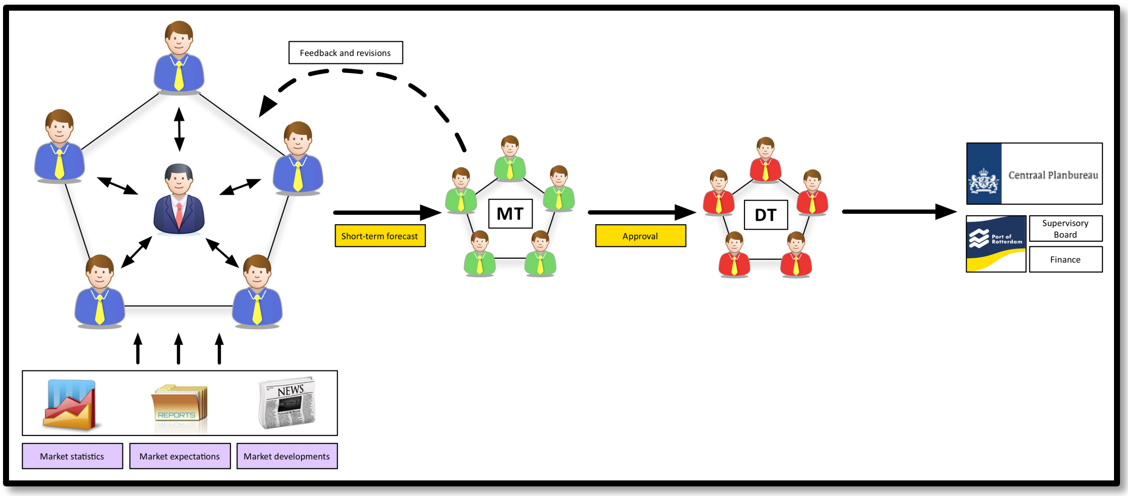


Figure 3-5: Network interaction around forecasting process

Conclusion

When the forecasting process is viewed as a complete system within the organisation it becomes clear that multiple feedback and go/no-go decisions are made to ensure that the results of the forecasts are accurate and realistic, although accuracy of forecasts can only be determined afterwards. However, the main strength of this process is that several people check the results and use their knowledge to assess the forecast. These can only be based on the mainly qualitative forecast that has been made by the experts so it is important to add a quantitative element to the forecast that is sent to the MT and DT so that their involvement is increased and a more substantiated go/no-go decision can be made.

3.4.3 A *human* steered business process

A survey amongst experts has been performed in order to create insight into the opinions and experiences that experts have with the forecasting process. It is important to consider this information as this research adds an element to the current process of expert judgement and therefore must not interfere with the work that experts are doing now. As stated in the literature, a combination of two methods can be very powerful but the quantitative element must be implemented to the side of expert judgement, as to not let experts feel that a model is taking over their tasks, when they do not desire this.

The survey consisted of several questions, as stated in appendix 1 and has been used to assess the current process as well as serve as a basis for the requirements of the decision support tool. A survey is an appropriate tool for gathering this kind of information as supposed to personal interviews. This way, all respondents provide an answer within the same scale, in this case of ordinal scale, thus making it easier to develop quantitative analysis from the results. The choice for conducting a survey was also based on the fact that respondents can answer at their own convenience, thereby making the method not as intrusive as other methods, such as a personal interview (Creative Research Systems, 2012). The survey was distributed among the experts that make the forecast, hereby providing a first hand view on aspects of the process that are working well and ones that can be improved. Although the amount of respondents is low, because of a limited amount of people working on the forecasts, the results are still be able to provide useful information for the rest of this research. Wilson (2010) describes that having a large sample size is not always necessary for doing quantitative analysis. When the aim of the analysis is to ‘summarise and describe’ data, Wilson talks about ‘descriptive statistics’, thereby not requiring a large sample size. When using the data for analysis in relation to the wider population, researchers need a sample size of at least 30 cases in order for the test to be valid (Wilson, 2010). For this research, where the aim is to identify qualitative information from the experts and represent them in a quantitative way, having few respondents is satisfactory. The survey that was distributed among seven experts from the PIM/CBL department who are involved in the forecasting process and the full set of results are shown in appendix 1.

Because the forecasting process is mainly qualitative, the survey asked respondents to provide an answer based on their impression or satisfaction of the process. This was done on a scale from one to ten, where ten indicates full satisfaction with the way things are done and performed as they are now. The results of the survey were recorded in graphs using the numerical scale to keep in mind the difficulty of adding a quantitative element to a mainly qualitative process, because the design and implementation of the tool must be done with regard for the work that the forecasters perform. The tool must not replace the forecasting process; it must be a supporting tool for the forecasters when making a forecast. By gaining information about the feeling that the forecasters have about the process before, the design can be adapted and at aimed at a particular aspect of the process where the forecasters feel improvements need to be made or additional information needs to be provided as to improve the forecasting process.

Overall evaluation of the forecasting process

Questions one till four of the survey focused on the process as a whole, whereby context, format, efficiency and the method are analysed. The results show respondents agree that the current forecasting process, whereby collaboration reaches a joint agreement, is a pleasant way of working. The context of the process, which asks respondents about the contribution of the forecasting process to the CBL/PIM department, is rated around 7.6 on average. The efficiency and the type of method used to make a forecast are rated at 7.8 each. Although all questions have received high marks, improvement is possible in the context of the process. The process needs to be altered so that it can deliver an improved supporting role for business activities in the CBL/PIM department. An exact approach to achieve this becomes apparent when analysing the next questions posed in the survey.

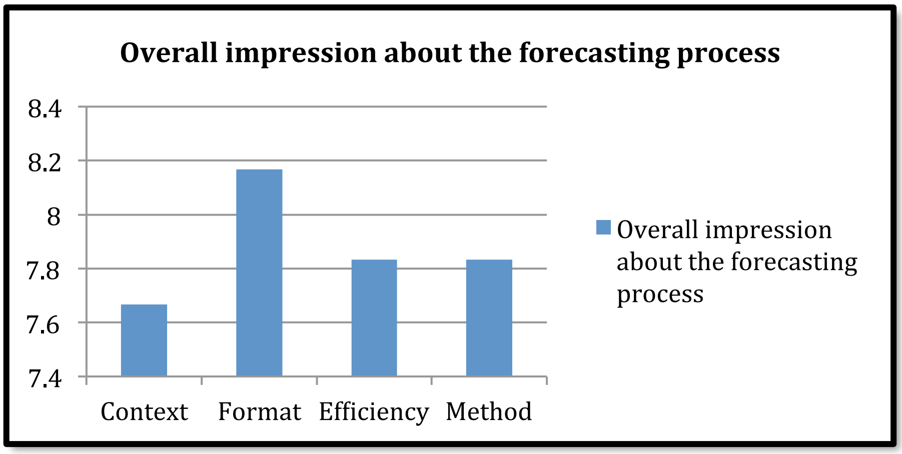


Figure 3-6: Survey results expressing overall impression of the process (n=7)

Quality of information and its effect on the result and accuracy of the forecast

The quality of the information, such as the workplan, previous realised throughput figures and differences between previous forecast results, have a big impact on the result of the forecast according to the survey. The result of the forecast concerns the actual forecasted value and the accuracy indicates whether this value corresponds to real market data. It can be concluded that input is an important aspect of the whole process and serves as a fundament for adequate results. The quality of information is also related to the accuracy of the forecast, to a lesser extent but a relationship is logical and was expected beforehand.

Quantity of information and its effect on the result and accuracy of the forecast

When questioning the quantity of information and its effect on the result and the accuracy, the relationship is reversed as to the quality of information. Even though the marks are lower in this case, respondents indicate that the quantity has more effect on accuracy than on the result of the forecast. This shows a clear relationship between quality and the result of the forecast and quantity and the accuracy of the forecast. Therefore, the design focus must be laid upon providing an extra form of information into the process, so that the accuracy of the forecast can be improved. This is reinforced by the aim of the PoR concerning this research – to deliver a decision support tool that can help improve the forecasting process.

Support of the process

The information that forecasters base their decision on are grouped into three categories, namely business climate, customers and market trends. When posing the question whether information from these three groups would help improve the process as a whole, the results show high scores. This indicates that this type of information is of high value to the forecasters and when known, can help to improve the process. Customer[5] information is most desired as this is reliable information concerning terminal expansion, new trade routes or deals and agreements with other companies that affect the volume of dry bulk goods being transported through Rotterdam. As was indicated in the survey under the general comments question, much of this information is very hard to get due to confidentiality issues imposed by companies. Business climate and market trends question the activity in the port and the dynamic market surrounding and influencing the volume of trade.

Conclusion

The survey has shown that a reverse relationship exists between the quality and quantity of input and the results and accuracy of the forecasts. The research objective, set out in Chapter 1.1, points towards adding a quantitative element that can help improve the accuracy of the forecast, among others. As the results confirm, adding a quantitative element to the input helps to achieve a higher accuracy of the forecast. To provide maximum support for the process, the quantitative tool should be focused on providing information about the business climate and market trends.

[5] Customers here refer to the customers of the PoR – the companies in the port of Rotterdam that facilitate trade to and from the port. Large dry bulk companies are the 'Ertsoverslagbedrijf Europoort CV' (EECV) and the 'Europees Massagoed- Overslagbedrijf' (EMO).

3.5 Conclusion

The forecasting process at the PoR has been analysed from three perspectives, as a system of in- and output, as a network of collaboration and information exchange and as a human steered business process. These methods have identified strong and weak points of the process and areas for improvement have been discussed. The analysis has shown that the input from BAI is of high importance to the result of the process. Feedback moments in the network of collaboration provide reflections so to keep the forecast as accurate as possible but the lack of in-depth knowledge about forecasting prevents the accuracy from reaching top level. The survey has shown that adding a quantitative element to the process helps improve the process, providing the tool is focused on business climate and market trends. The analysis has shown that most contribution of the quantitative element can be provided in the support of the process, thereby providing an answer to research question 2. Often when forecasters are unsure about the expected developments, or have no qualitative information to base their decision upon, they choose a conservative forecast. The analysis has shown that the presence of a quantitative forecasting tool can help to give direction to the forecast that experts have to make. Therefore, the focus of this research is on providing as accurate forecasts of the leading indicators as possible, while also considering important aspects that influence commitment and usage by the experts. This means that the design of the system has to be twofold, focus must be on the leading indicators and their forecasts as well as developing an information dashboard that need to be adopted by the experts at the PoR. Much of these proposed improvements are translated into design guidelines and requirements for the Forecasting Support System and the information dashboard. These are discussed in the next Chapters.

4. MODEL CONCEPTUALISATION AND METHODOLOGY

After establishing the key aspects that can be improved from the forecasting process at the PoR, focus can be turned to the design phase of this research. It is important to establish clear guidelines for the design of the system so that it can be designed in the most efficient way and that the output can contribute maximal to the forecasting process. It is important to have an overview of the design process as well as the expected result, so that these factors can be kept in mind when designing the Forecasting Support System. This Chapter focuses on the second part of research question 1 and depicts several design guidelines for designing a FSS. Research question 1 was formulated as follows:

What are strengths and weaknesses of short-term forecasting methods and what guidelines for the design of a FSS can be identified?

This Chapter sets out the research to determine the leading indicators and sets objectives that are aimed for when designing a Forecasting Support System. It has been concluded in the previous Chapter that supporting the forecasting process with a quantitative tool increases the accuracy and substantiate the forecasting process. The Forecasting Support System must focus on market development and economic activity that has a relationship with throughput of dry bulk goods in the port. This Chapter sets out what is to be expected from the leading indicator system.

4.1 Guidelines for designing a Forecasting Support System

Besides being focused on market developments and trends, the forecasting tool must possess other important aspects for it to blend into the current forecasting process. Fildes et al. (2006) state the following three key features of a Forecasting Support System (FSS) so it can successfully integrate the statistical forecast within the qualitative process.

1. A database that includes multiple time series of various nature
2. A quantitative forecasting technique
3. Facilities that allow the application of managerial judgement

Although defined in a general context, the features form the basis for this research. The following Chapters describe the process of preparing the time series for statistical analysis, determining the leading indicators and presenting them in an information dashboard. For the design of the Forecasting Support System, key attributes of a 'trustworthy system', defined by Sage and Armstrong (2000), are stated and allocated. Specific design requirements for the information dashboard are discussed in Chapter 8.1.

To illustrate one attribute that is essential for this research; the information dashboard must be adaptable, evolvable and maintainable because trends and patterns in leading indicators might change over the year, requiring a re-evaluation of indicators. Furthermore, the system must be reliable and verifiable. The forecasts that are produced need to be accurate and the method of determining the forecast needs to be transparent so that forecasters have insight into the method of determining leading indicators. Figure 4-1 shows other key aspects of a 'trustworthy system' that have been used for the development of the Forecasting Support System.

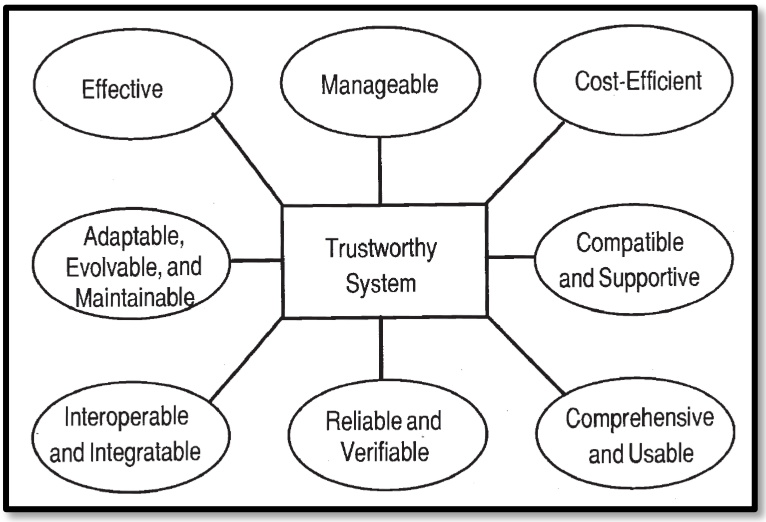


Figure 4-1: Attributes of a 'trustworthy system' (Sage & Armstrong, 2000)

Sage and Armstrong's theory describes eight key aspects of a system in general that must be incorporated to make a system 'trustworthy'. Although this is just one characteristic that system can incorporate, it is an important characteristic in this project, as the implementation of the system is dependent on the level of trust that experts have in the system. Furthermore, the attributes that Sage and Armstrong propose also include key attributes that contribute to creating a solid and reliable system. The success of the system rests on the interrelationship between people, technology and the environmental setting (Sage & Armstrong, 2000). Below, the attributes are stated and explained, thereby providing important aspects that need to be considered when designing the FSS. In Chapter 10.1, the attributes are evaluated and a conclusion is provided to assess whether or not the FSS incorporates these attributes.

- *Effective*
  The FSS must provide quantitative information that is relevant for making a forecast, split out per throughput good.

- *Manageable*
  Users of the system must be aware of the functions and capabilities of the FSS. This allows them to effectively work with the model and use it for their support if needed.

- *Cost-Efficient*
  The leading indicator FSS is a pilot project at the PoR and there is little budget reserved at this moment. Costs must be kept to a minimum.

- *Compatible and Supportive*
  A quantitative tool provides the most effective support to the current forecasting process and the focus on the quantitative nature ensures the tool is compatible with the current process.

- *Comprehensive and Usable*
  The FSS must be designed to provide a thorough representation of the leading indicators for each throughput good but a balance must be kept with regard to the amount of information presented.

- *Reliable and Verifiable*
  The FSS must provide statistics on the accuracy of the forecasts to provide forecasters with insight into how well the leading indicator can be forecasted.

- *Interoperable and Integratable*
  One of the most important elements, the information dashboard needs to be implemented in the forecasting process without interfering with the current activities performed.

- *Adaptable, Evolvable and Maintainable*
  The dashboard supports the quarterly forecasting sessions and therefore needs to be regularly updated and maintained. This asks for consideration of software to be used for determining trends and making the forecasts.

4.2 Individual vs. aggregate forecasts

The forecasting technique used in this research delivers individual forecasts for each of the leading indicators. Aggregate forecasting often involves the combination of multiple indicators and their impact on the dependent variable, as shown in Figure 4-2, where three indicators are combined to deliver an aggregate forecast. Because the aim of this research is to gain insight into market developments and changes that affect the throughput of dry bulk goods the scope is around the individual forecasts. In the forecasting process at the PoR, the aggregate forecast are to be made by combining quantitative information from the individual indicators as well as judgement and decisions made by the forecasters. Considering only an aggregate forecast makes the process too much of a quantitative process, which is not desired as the literature and practices from experts have shown that a combined forecast is much more effective than a single one. The scope of the research, indicated by the red dotted line, delivers multiple forecasts for the leading indicators and thereby provides adequate support to the forecasting process at the PoR. The combined forecasting process, where the individual leading indicators are combined with qualitative information from the experts eventually delivers an aggregate forecast, but this is beyond the scope of this research.

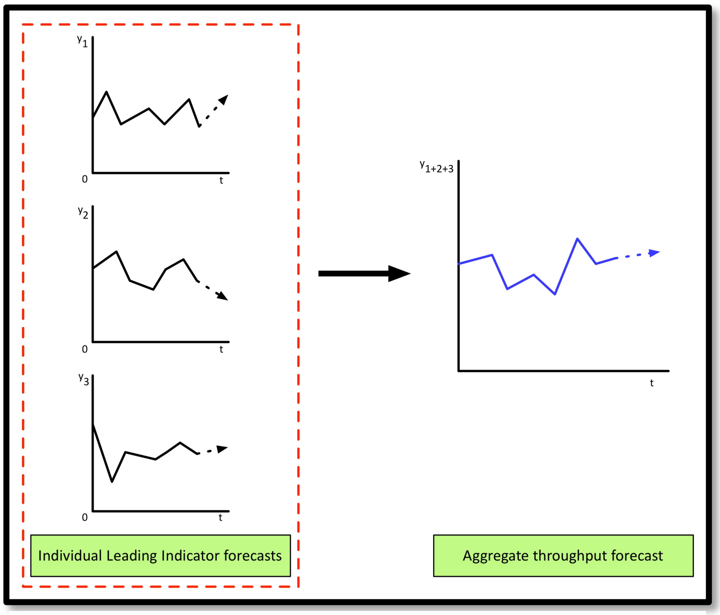


Figure 4-2: Individual vs. aggregate forecasts

4.3 Methods for time series analysis

In the previous section, a general approach to improving the forecasting process has been set out. This section will delineate the statistical analysis that has been performed to determine leading indicators for dry bulk throughput in the Port of Rotterdam. From Chapter 2, the most promising method for determining time series trends and using these for forecasting is the multiple regression method. This is an easy to implement method that produces accurate forecasts while remaining transparent for changes to be made. Before delineating the steps that need to be taken in order to perform one of these methods, it is important to consider the various correlation and causality techniques that are closely associated with the statistical models.

4.3.1 Correlation between time series

For determining the correlation between two time series, a distinction can be made between three types of correlation. First, **Auto Correlation** is often used when analysing a single time series. The correlation coefficient describes the relation that the time series has with itself. It is said to be deterministic, indicating that a correlation exists between lagged values (Yanovitzky & Van Lear, 2007). A time series that has a seasonal trend has a correlation at lag periods that characterise the seasonal trend, for example a peak in demand for electricity for heating homes in the months November, December and January. The peaks over a couple of years will align and this is noticeable by the auto correlation.

Secondly, the **Cross Correlation Function (CCF)** is used to determine the correlation between two time series at various lag lengths. As Root defines; *"The Cross Correlation Function (CCF) is helpful for identifying lags of the x-variable that might be useful predictors of y."* (Root, 2011). The correlation is calculated for each of these lags and the most significant lag period gives an indication of the coherence between them. Even thought the Cross Correlation Function has a few drawbacks, it is a commonly used method for doing a preliminary analysis concerning the relationship between time series. This preliminary analysis is often done when computing causality tests between variables. Freeman (1983) and Chung (2005) use CCF before determining Granger causality and conclude that they can give a decent indication of causality but is no guarantee for actually existing. This is because the Cross Correlation Functions are sensitive to the chosen lag length, thereby affecting the accuracy of the results and furthermore, the CCF can't identify a direction of the causality, only whether it might exist or not (Feige & Pearce, 1979). The direction is important to consider as is shown when the leading indicators for this research are determined.

A third type of correlation that is often used for determining the frequency and intensity of long-range time series is called **Spectrum Analysis**. The data is broken down into smaller parts and Fourier transformation can be applied to determine a mathematical function of time. This method is not applicable here because it is based on the frequency domain rather than the time domain. This means that data is recorded on how much data points are recorded within a specific range, rather than a data point for a set time interval as is the case in the time domain analysis.
From these methods of preliminary analysis, the Cross Correlation Function seems the most promising method for determining a correlation between the time series. Other researchers have used CCF to determine correlation and conclude that, although its drawbacks, can still serve as a preliminary test for causal influences (for more information please refer to (Zhu, 2010); (Aytac & Wu, 2010); (Freeman, 1983).

Distinguishing between Correlation and Causality

In statistics, the relationship between two variables is often described by means of their correlation or causality. These commonly used terms have become standard practice for researchers but it is important to distinguish between them, and furthermore, to realise that when two variables correlate, they do not necessarily have causality between them. To explain further, correlation between two variables describes the strength of the relationship between two variables. A positive correlation indicates that an increase in the values of one variable reflects an increase in the values of the correlating other variable. A negative correlation indicates that an increase in variable one is reflected by a decrease in variable two. For example, when the demand for a product increases and this increases the price for the product, a positive correlation is present.

Causality refers to a relationship between variables whereby one causes the other, so a change in one variable causes another variable to react to this. Also, this can be a positive or negative reaction to the change. An example of a causal effect is the amount of calories that you burn when exercising. In this example, both correlation and causality are present. There is a positive correlation between exercise and burned calories and doing more exercise causes more calories to be burned, but this is not always the case.

Another example to explain the difference is the following; when fire fighters are attempting to extinguish a fire, there is a positive correlation between the number of fire fighters and the size of the fire. However, this does not mean that bringing more fire fighters increases the fire's size. This shows that there is a correlation, but no causal effect. Therefore it cannot always be assumed that when correlation is present, a causal relationship also exists. In this research, clear distinction also needs to be made between the two terms, as correlation and causality if often also found between economic variables or time series.

Box 1: Correlation and Causality. Examples from (Scocco, 2012)

4.3.2 Causality

As has been discussed, the identification of leading indicators was done based on the causality between time series because the research is aimed at finding significant changes that cause the dry bulk goods in the port to change. In Chapter 2.2, the work performed by Sir Clive Granger has been discussed with regard to the integration of qualitative and quantitative forecasting methods. Granger also spent a lot of time on the concept of causality and developed an extension to simple causality between time series. His theory describes how 'Granger causality' takes into account the effect that a variable has on another and especially how this variable can help to better cause or explain the other variable, as can be seen in Figure 4-3. Granger causality involves two tests, one to determine an impact of variable X onto variable Y and one in the opposite direction. If both tests show a causal relationship, it can be said a feedback relationship exists between the variables. For this research, the focus is on the initial relationship, so feedback relationships are outside the scope. They can, however, be of interest for further research as is touched upon later in this report. Figure 4-3 explains how one part of the equation (that from X->Y) is determined. The other part of the equation, to determine the feedback relationship, is set out of the scope of this research.

$$If\ \sigma^2\ (Y|U) < \ \sigma^2(Y|\overline{U-X}), we\ say\ that\ X\ is\ causing\ Y, denoted\ by\ X_t\ \rightarrow Y_t.$$
$$We\ say\ that\ X_t\ is\ causing\ Y_t\ if\ we\ are\ better\ able\ to\ predict\ Y_t\ using$$
$$all\ available\ information\ than\ if\ the\ information\ apart\ from\ X_t\ had\ been\ used.$$

Figure 4-3: Definition of Granger causality, adapted from (Granger, 2001)

In general, there are two ways in which one can apply Ganger's causality test. First, a direct method can be used to determine how much one variable can help to predict another. This is called the pairwise Granger causality test. Secondly, a multivariable method can be applicable when several variables are believed to have influence on a single, dependent variable. This Vector Autoregressive (VAR) model will give a more complete picture of the relationships that a variable has with other variables. Furthermore, the Autoregressive part indicates that lagged values of the regressand (dependent) variable are also included in the model, as well as the lagged values of the regressing variables. This increases the explanatory power of the model and delivers casual effects at specific lag lengths. The number of lag lengths to include in the model is however seen as a weakness of using the Granger causality method. This is because changing the number of lags slightly can cause significant changes in the results, thereby leading to wrong conclusions (Gujarati, 2003). In this research, Akaike's Information Criterion (AIC) was used to determine at which lag length the model could be best predicted. This test shows modellers at which lag length the predicted model best fits reality, in other words at what point most information is lost as to describe reality best. The calculations are done for a set of lag lengths and the most optimal lag length (the length at which the model can have most explanatory power of the regressand variable) is given as output (Akaike, 1974).

Alternatives to Granger causality testing in a VAR model

Although the use of Granger causality in a VAR model seems to be the most promising method in for this research, certain other methods are similar but have been analysed as inferior to VAR models.

- Structural Equation Modelling (SEM) is identical to VAR modelling in that it includes several regressing variables and a regressand variable. The main advantage of a VAR over SEM is that a VAR model also includes all regressing (independent) variables as a regressand (dependent) variable, thereby allowing a modeller to also asses feedback relationships – not only the causal effect from multiple independent variables to a dependent variable but also vice versa (Gates, Molenaar, Hillary, Ram, & Rovine, 2010).
- General multiple regression methods are less accurate because they only consider time series that align to each other, they do not take into account the autoregressive part. This is the real strength of a VAR model that allows it to produce more accurate results concerning the relationship between the variables (Gujarati, 2003).

4.4 Conclusion

This Chapter has delineated the application of a theoretical framework for designing a 'trustworthy' system and has set up some important guidelines for designing a Forecasting Support System. By doing so, research question 1 has been answered and the preliminary analysis has been completed. Furthermore, an important scope of this research was introduced, setting the border for the level of determination of leading indicators. The methodologies for time series analysis that have been applied in this research have been explained and accounted for. Determining a causal effect between variables is preferred over correlation, as insight into the explanatory power of variables can be determined. The identification of correlation can merely suggest a causal effect is present but this needs to be tested using statistical analysis. The next Chapter describes the methods that have been performed and discusses the model output and results.

PART II: DETERMINING THE LEADING INDICATORS

INTRODUCTION
CHAPTER 1

PART I: PRELIMINARY ANALYSIS
CHAPTER 2, 3 & 4

Research question 1:
What are strengths and weaknesses of short-term forecasting methods and what guidelines for the design of a FSS can be identified?

Research question 2:
What components of the current forecasting process indicate that a quantitative element can be added to improve the process?

PART II: DETERMINING THE LEADING INDICATORS
CHAPTER 5 & 6

Research question 3:
Which economic drivers can be identified as 'leading indicators'?

Research question 4:
Is the quantitative forecasting tool a reliable and accurate source of information to support the forecasting process?

PART III: THE FORECASTING SUPPORT SYSTEM
CHAPTER 7, 8 & 9

Research question 5:
How does the forecasting support system need to represent information, be implemented and be maintained to effectively support the forecasting process?

EVALUATION, CONCLUSIONS & RECOMMENDATIONS
CHAPTER 10 &11

5. IDENTIFICATION OF LEADING INDICATORS

This Chapter sets out the research that has been done to determine the leading indicators for dry bulk goods in Rotterdam. In the introduction Chapter, the following sub question has been set out and is answered in this Chapter:

Which economic drivers can be identified as 'leading indicators'?

First, the steps in statistical analysis that have been taken are summarised. Secondly, the steps are described and the most important results are discussed. Further elaboration on the methods and results is provided in the appendices. The choice of software package is explained in appendix 2. Finally, to round up this Chapter, conclusions and further steps are discussed.

Steps towards determining leading indicators

Determining leading indicators by means of a VAR model brings the following steps that need to be taken. The sub Chapters further elaborate on the steps taken and explain more about the characteristics that time series need to incorporate.

1. **Gathering of market and throughput data to be used for statistical analysis.**
   Careful selection of variables ensures completeness of the model so that significant relationship can be examined without making the model too large. A large model easily becomes unclear.
2. **Data preparation:**
   Statistical analysis requires correct data coding and identical characteristics of the time series. Three important characteristics of time series that need to be ensured:

   - *Sample size*
     The sample size of the time series needs to be large enough to ensure a complete analysis of the time series. For example, yearly data series are not suitable for identifying monthly changes.

   - *Seasonal influences*
     All time series need to be free of seasonal influences because publically available data is often already deseasonalised. A seasonal trend in one time series shows an altered relationship with another time series as supposed to time series being bot seasonally adjusted.

   - *Stationarity*
     This is important in time series analysis because time series need to be comparable and, in order to perform statistical tests (test hypotheses), they need to have similar trends i.e. a stationary (non changing) development throughout the time interval. This is required to perform hypothesis testing in statistical analysis, as is the case when testing for Granger causality.

3. **Calculating Cross-Correlations functions (CCF) between time series.**
   As is explained in Chapter 4.3.1, the CCF provide a good early indication of causality between time series. Box 1 explains how correlation and causality are important statistics that often appear together in time series analysis.
4. **Differencing the time series that are not stationary**

Making a time series stationary means to take the difference of the values so that the time series is transformed into a line that shows changes rather than real values. This way, the mean of the time series always hovers around the zero line, thus creating a stationary time series.

5. **Determining the leading indicators by estimating a VAR model to determine Granger causality.**
   As discussed, the VAR model is an appropriate method for analysing time series. Because we are interested in the causal effect of one variable onto another, finding causality is much more explanatory than correlation by itself. The VAR model helps to to determine the causal effects.

5.1 Gathering of data and selection of time series

Now that the objectives of the research, the trend determination and forecasting method have been selected, the data for statistical analysis can be gathered. In cooperation with the PoR, the four main categories of dry bulk goods have been selected and are used in this research as the dependent variables. The distinction is according to PoR classifications of products and each of these four goods are forecasted every quarter. The four variables are stated below and their data was retrieved from the PoR database:

- Agribulk
- Iron ore and scrap
- Coal
- Other dry bulk goods

In order to determine leading indicators for these product groups, a list of economic variables was composed, in cooperation with a dry bulk expert at the PoR. A validation session was organised to assess the impact and importance of variables, which led to the following list of variables to be included in the research. The list includes general economic variables but also specific market statistics that might be relevant only for a specific dependent variable. Their unit of measurement, value, time frame and source are indicated in the table. Appendix 3 provides clarification about the composition of variables and the reasons for including them in this research.

Variable	Unit	Value	Time frame	Source
Real GDP the Netherlands	Current prices	x1,000,000,000 U.S. $	Per year	IMF
Real GDP Germany	Current prices	x1,000,000,000 U.S. $	Per year	IMF
Real GDP EU	Current prices	x1,000,000,000 U.S. $	Per year	IMF
Real GDP China	Current prices	x1,000,000,000 U.S. $	Per year	IMF
Real GDP World	Current prices	x1,000,000,000 U.S. $	Per year	IMF
IP the Netherlands	index	2005=100	Per month	OECD
IP Germany	index	2005=100	Per month	OECD
IP EU	index	2005=100	Per month	OECD
IP China	index	2005=100	Per month	MBS
IP World	index	2000=100	Per month	CPB
World Trade	index	2000=100	Per month	CPB

Relevant World Trade	index	2000=100	Per year	CPB
IC the Netherlands	index	no base year	Per month	Eurostat
- Expected Business Activity	Survey	% deviation from zero line	Per month	CBS
- Expected Ordering Position	Survey	% deviation from zero line	Per month	CBS
- Expected Stock	Survey	% deviation from zero line	Per month	CBS
IC Germany	index	no base year	Per month	Eurostat
- Business Climate	index	2005=100	Per month	IFO
- Business Situation	index	2005=100	Per month	IFO
- Business Expectations	index	2005=100	Per month	IFO
IC EU	index	no base year	Per month	Eurostat
IC China	NO DATA			
IC World	NO DATA			
CC the Netherlands	index	no base year	Per month	Eurostat
CC Germany	index	no base year	Per month	Eurostat
CC EU	index	no base year	Per month	Eurostat
CC China	NO DATA			
CC World	NO DATA			
PPP the Netherlands	Current prices	x1,000,000,000 U.S. $	Per year	UNData
PPP Germany	Current prices	x1,000,000,000 U.S. $	Per year	UNData
PPP EU	Current prices	x1,000,000,000 U.S. $	Per year	UNData
PPP China	Current prices	x1,000,000,000 U.S. $	Per year	UNData
PPP World	Current prices	x1,000,000,000 U.S. $	Per year	UNData
Baltic Dry Index	NO DATA			
Spark/dark spread	NO DATA			
Iron Production in Germany	amount	x1000 tonnes	Per month	WSA
Steel production in Germany	amount	x1000 tonnes	Per month	WSA
Automotive industry in Germany	amount	number of cars	Per year	OICA
Cokesimport Germany	amount	x1000 tonnes	Per year	EuroStat
Electricity production in the Netherlands	amount	Terajoule	Per year	EuroStat
Electricity production in Germany	amount	Terajoule	Per year	EuroStat
Harvest yield	NO DATA			
Commodity prices	NO DATA			
Mining yield Germany	amount	x1000 tonnes	Per year	EuroStat

Table 5-1: Initial list of variables

For some time series, data was not retrievable due to the fact that a subscription was required to obtain the data. As was indicated in the scope delineation in Chapter 1.4, little budget is currently available for this project, so these time series cannot be used for further research.

Identifying economic indicators that seem usable for this research have been selected according several main criteria, as defined by Boehm and Summers (1999). Not all time series that initially appear to be good indicators can be used for statistical analysis. By ensuring that the time series incorporate the characteristics by Boehm and Summers, it can be stated that economic variables that are used represent true economic and market developments and are usable for statistical analysis. The variables have been evaluated and needed to:

- Be a significant economic variable;
- Be appropriate from the point of view of statistics;
- Be subject to no doubts;
- Be purified from seasonal fluctuations;
- Be regularly available (at least quarterly, best is monthly);
- Show in all the researched time the cohesion of dependency with times of a decrease and an increase of the referred value.

The dependency means that the indicator in all researched cycles should be convergent with economic fluctuations, exceed them or be lagging behind. This has been satisfied because all variables show fluctuations with the general economy, and can be clearly seen by the trend of the data in 2008, where the financial crisis has had a clear impact on the time series.

The first three criteria of the list have been accounted for by the validation session at the PoR. The seasonal influences, the availability of data and the cohesion of dependency is tested for in the coming sections. Chapter 5.2 sets out the required size of the data and the time interval, as well as test for seasonality. Chapter 5.3 explains the CCF to determine if cohesion is present between the time series. Further requirements for the time series to be used are also stated here. A final list of variables that was used to make the VAR model is shown in Chapter 5.3.2.

5.2 Data preparation for statistical analysis

As discussed in the previous section, three important characteristics of the time series need to be ensured. They are explained below. The criteria posed here have an effect on the list of variables and might remove them before VAR analysis can be performed.

1. Number of observations

In statistics, the number of observations that are required to perform accurate analysis is much debated. Although there are no specific lower limits to the amount, and the rule 'the more, the better' is often applied, some researchers have posed some preconditions. Box & Jenkins (1994) and Tabachnick & Fidell (2007) propound that at least 50 observations are necessary for analysis. It is important to have many observations and to have them in regular intervals, so to get a complete picture of the data and be able to account for unexpected changes that might influence the trend of a series.

For VAR modelling, Toda and Phillips (1994) state that at least 100 observations are needed. They argue that 50 observations create adequate results, 100 produce good results and 200 is excellent. Time series that have been gathered for this research generally contain a complete set of monthly data from January 1997 to December 2011. This yields over 180 observations, which is enough to perform accurate analysis.

Some time series from the initial list in Chapter 5.1 are only available as yearly data. This would not yield enough observations and furthermore cannot be a very explanatory indictor. This is because yearly data is not being able to provide accurate trends that concern a short-term period of 3 months, which is applicable for this research. For this reason, the yearly data have been removed from the list and has not been further used in this research.

2.Seasonality is removed from time series

To be able to statistically compare time series and develop results from this research, the variables need to be free of seasonal influences. Kyd states, *"Seasonal sales typically are difficult to analyse. In good periods, it's hard to know whether good sales are better than usual; in bad periods, it's hard to know if bad sales are worse than usual"* (Kyd, 2012). In the dry bulk shipping market, seasonal patterns are often visible in the winter months, when the demand for coal is higher due to higher electricity production for heating. Also, harvest yields in the summer might have an effect on the amount of Agribulk being transported through the port. Market data retrieved from publically accessible databases is often already deseasonalised, and this needs to be verified. However, it is important to ensure that all time series have been deseasonalised, including the dependent dry bulk variables.

All market data has been previously been deseasonalised but it is unclear whether the dependent time series Agribulk, Iron Ore & Scrap, Coal and Other dry bulk goods need to be seasonally adjusted. As no information is available about the seasonal effect in Iron and Steel production in Germany, these time series are also analysed. Graphing the time series and drawing ACF and PACF graphs can do this.

ACF-PACF Graphs

In order to test for seasonal influences in time series, the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) are useful tools. ACF-PACF graphs are often used for determining parameters for ARIMA modelling, but are used in this case for determining whether time series contain a seasonal trend or not (Root, 2011). Autocorrelation indicates whether passed values of a time series can help to explain present or future values, in other words whether there exists a correlation between values. ACF are correlations of data points of the time series with itself, thereby testing for various lagged time intervals in the data (Tabachnick & Fidell, 2007). This way it becomes possible to see if lagged time series are correlated with the current time series. A bar that crosses the 95% confidence level lines identifies a significant lag period. This indicates that the data point is highly correlated with the previous one. For example, a significant correlation at lag one and lag 12 indicates that a yearly seasonal trend is present, a data point that repeats itself each year. The same is applicable for a shorter trend, as indicated in Figure 5-1, where the correlations clearly indicate that a seasonal trend is present. PACF graphs are drawn automatically and have been used to determine whether or not a time series is stationary or not.

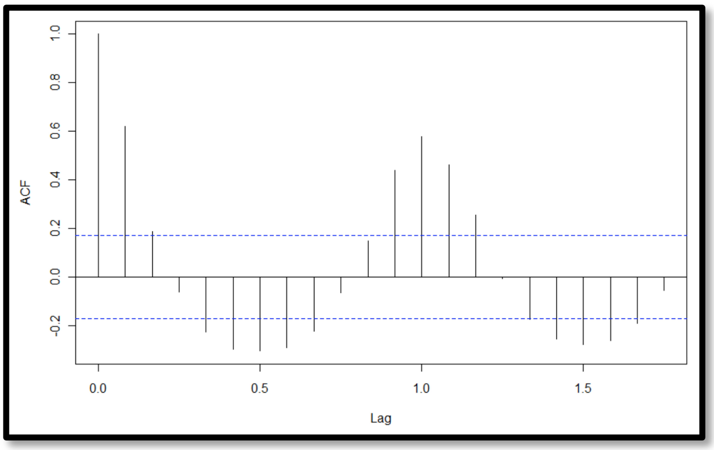
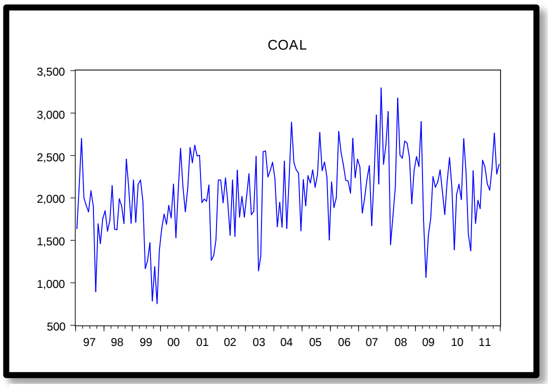
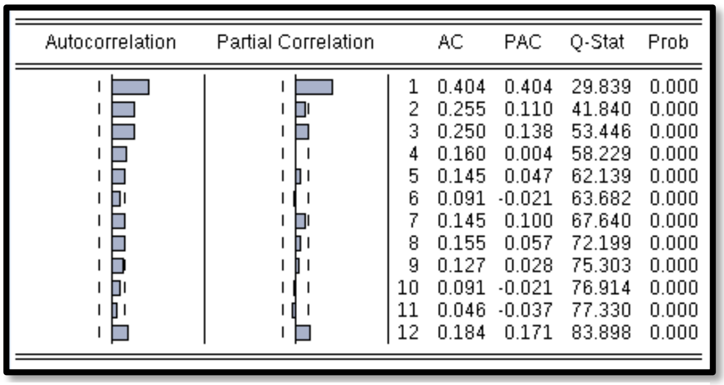


Figure 5-1: ACF-PACF graph of a time series with seasonal trend (Root, 2011)

Besides drawing ACF-PACF graphs, it is useful to visually inspect the data by plotting a line graph. The line graph and ACF-PACF graph of coal are shown below, they indicate that a seasonal pattern is present. The ACF values (Autocorrelation bars on the left) show significance at lag 1,2,3,4,8 and 12, thus indicating that correlation exists between lag 1 and the rest of the lagged periods (The ACF-PACF are rotated 90 degrees due to different output styles used by statistical programme as apposed to picture of Root). Lag 12 indicates a yearly trend is present so the time series needs to be seasonally decomposed before advancing to the rest of the analysis. All other line graphs and ACF-PACF graphs can be found in appendix 4.





Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.404	0.404	29.839	0.000
		2	0.255	0.110	41.840	0.000
		3	0.250	0.138	53.446	0.000
		4	0.160	0.004	58.229	0.000
		5	0.145	0.047	62.139	0.000
		6	0.091	-0.021	63.682	0.000
		7	0.145	0.100	67.640	0.000
		8	0.155	0.057	72.199	0.000
		9	0.127	0.028	75.303	0.000
		10	0.091	-0.021	76.914	0.000
		11	0.046	-0.037	77.330	0.000
		12	0.184	0.171	83.898	0.000

Figure 5-2: Left; line graph of Coal throughput. Right; ACF-PACF graph of Coal

From the line graph and ACF-PACF graph analysis, the following time series need to be seasonally decomposed:

- Iron Production in Germany;
- Steel production in Germany;
- Agribulk;
- Iron Ore and Scrap;
- Coal;
- Other dry bulk goods.

Seasonal decomposition

In statistical software packages, seasonal adjustment is often included as an option and can be performed quickly and without errors. In this case the Census method 1 or ratio-to-moving-average method is used to transform the series. This is common method that makes an index that corresponds to the seasonal variation of the time series. Each month has a seasonal index and to calculate a non-seasonal influenced value, the monthly index is multiplied with the average of that month over the last year.

From graphs of the time series it can be seen that the line can be either additive or multiplicative. An additive model is represented by adding to the previous value, where as a multiplicative model multiplies with the previous value. In a multiplicative graph, the line graph would show a step upward or downward slope as time progresses. This is because multiplying increases the values significantly more than adding. Because the graphs of the time series that need to be seasonally adjusted show seasonal variation that is independent of the level of the data, the additive model seem most appropriate. Furthermore, the magnitude of the seasonal peaks tends to be of the same magnitude every year, therefore eliminating the possibility of it being a multiplicative model (Linde, 2005). The additive model is described by:

$$Xt = T_t + C_t + S_t + I_t$$

$$where:$$

$$T_t = trend$$
$$C_t = \ the\ cycle$$
$$S_t = seasonal\ component$$
$$I_t = irregular\ component$$

By applying the additive model, the seasonal factor of the data is extracted and corrected for each series. A correction factor, in percentages, is given for every lag period, thereby accounting for a negative or positive variation. Appendix 5 shows the line graphs, ACF-PACF graphs of the time series that have been seasonally decomposed.

After seasonal adjustments, all ACF-PACF graphs have changed pattern. Iron Production and Steel production in Germany have a sharp declining ACF graph and a PACF that peaks at lag 1 and then remains not significant. This indicates that these time series are seasonally decomposed (no significant lags other than at 1 in the PACF graph) but are still non-stationary and therefore need to be made stationary in the next step. The dependent variables I, Iron Ore & Scrap, Coal and Other dry bulk goods show slight changes in the line graphs but the ACF-PACF graphs show signs of non-stationarity, which is blocking the seasonally decomposed pattern of only one significant lag at lag period one. This suggests that the variables need to be made stationary before being used for statistical analysis.

3.Time series are stationary

Besides time series being seasonally adjusted, a prerequisite for some statistical analyses is that the series are stationary, *"A stationary time series is one whose statistical properties such as mean, variance, autocorrelation, etc. are all constant over time. Most statistical forecasting methods are based on the assumption that the time series can be rendered approximately stationary (i.e., "stationarized") through the use of mathematical transformations."* (Duke Education, 2012). When time series are constant, this allows them to be compared on the basis of statistical tests because they are normally distributed – most data points lie around the mean (in this case somewhere around zero) and higher and lower values are within the bell shaped curve, as is also shown in Box 2 on page 65. The bell shape indicates that the chance of observing a value that lies 'too' far from the mean is close to zero. Hypothesis testing, as is the case with Granger causality and many other statistical methods, requires data to be normally distributed. If a time series is not stationary, the mean value is not constant over time and this would require new hypotheses to be established and tested for each time interval where the mean is different.

Stationarity can also be identified by visual analysis of ACF-PACF graphs. The partial correlations are self-correlations but without the intervening lags, so a direct correlation between two time series is shown (Tabachnick & Fidell, 2007). Both the ACF-PACF graphs can be used for determining whether a time series is stationary or not. A non-stationary time series is characterised by having significant lags for half a dozen or more lag numbers, rather than declining rapidly to zero, as can be seen in Figure 5-3. Another pattern that indicates non-stationarity is when the ACF pattern is damped first, becomes negative and then becomes positive again. This also suggests that a seasonal pattern is present in the data, which can be confirmed by inspecting the line graphs. In both cases, the PACF graph shows a single peak at lag 1, another indication of non-stationarity (Tabachnick & Fidell, 2007).

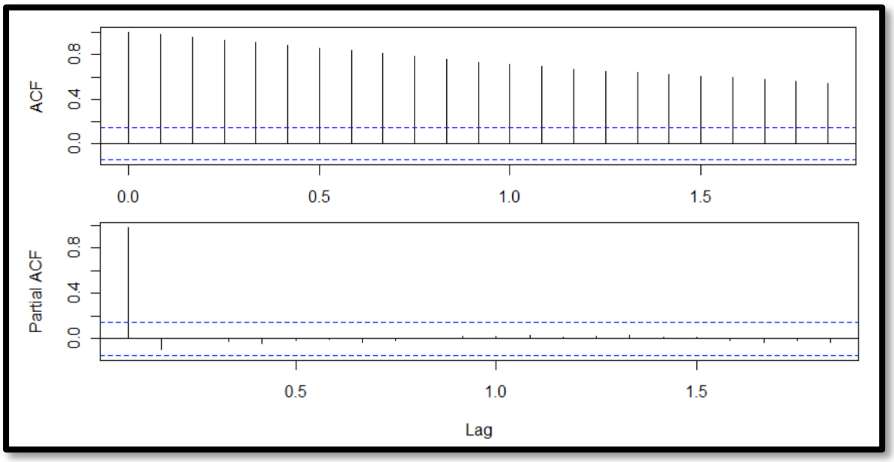


Figure 5-3: Example of a non-stationary time series (Root, 2011)

Although we establish that some time series are not stationary at this stage, they are not differenced until after the calculation of the cross correlations. This is because cross correlations do not test hypothesis and do not require the data to be stationary. When calculating correlations between two stationary time series that have been 'flattened' due to differencing, the results are bound to be very low as peaks and troughs are not as visible as before. It can be said that using stationary time series for calculating correlations decreases the correlation coefficient considerably. Analysis of the line graphs, ACF and PACF graphs and differencing of the non-stationary time series is done in Chapter 5.4.

5.3 Cross Correlation Functions

The Cross correlation functions (CCF) can be describes as a set of correlations between two variables at different lag periods. A dependent variable Y_t can be correlating with leading or lagging variables of X_{t-h}, where h indicates the lag period that can be set. The lag period can be negative (indicating X is lagging Y, or the correlation is strongest when comparing a Y value now with an X value a few months later) or positive. A positive value of h indicates leading behaviour, and this research focuses on the leading variables. For example there could be a high correlation between X_{t-3} and Y_0. This indicates that shifting the X variable 3 months to the past has a high correlation with the Y value now. In other words, there is a correlation between what happens in variable X at a certain time and what happens in variable y three months later.

The CCF can identify correlations between time series, and this hints towards there being a causal relationship as well but this needs to be tested first. Therefore, the CCF can give an early warning about causality, as correlation and causality are often related, but cannot be proof of leading indicator relationships between variables. Causal relationship testing would have to verify the presumption made by the CCF.

5.3.1 Decision rules for variables

Cross Correlation Functions are often included as an option in many statistical packages, making it an easy to retrieve statistic that can greatly explain the relationship between time series. Before calculating the CCF between variables, certain decision rules for determining which cross correlations are relevant for identifying as a leading indicator, need to be established. Chung (2005) set up the decision rules and decision rules specific for this research have been added to the list.

The following rules determine what variables have been selected for further analysis:

1. The economic variables (IVs) that have significant cross correlations with dry bulk throughput goods (DVs);
2. The economic variable must be leading, so the lag period must be positive. Lagging and coincidental indicators are ignored here[6];
3. The economic variable (IV) that has the highest correlation coefficient with the dry bulk throughput good (DV) among selected variables;
4. The economic variables (IVs) that have no correlation higher than 0.8 with any other economic variables (IVs) in the same category;
5. The economic variable must be available on monthly basis and must be updated every month so that correlations can be determined on a regular basis and because forecasting the variables requires the latest data to be used.

Rule 4 was added to the list to ensure that the problem of multicollinearity does not occur. This is an important assumption for VAR testing that ensures that a variable does not take away any explanatory power, due to its high correlation, of an independent variable that influences the dependent variables. This phenomenon is further explained in the next Chapter.

The last rule in the list, rule 5, has been added to confirm that the latest data are available so that a forecast can be made on the basis of current data. This is especially important when making a one-month forecast. When data is not available immediately, making a forecast for the coming month, based on the current value, is not possible. Because the VAR model uses current data to forecast future data, the time series need to be up to date.

The results of the cross correlations, before removal due to the decision rules are shown below:

[6] Although for this research only leading indicators are considered, the lagging correlations can also provide important information concerning the relationships between variables. They can, for instance, be used at the PoR, for verifying market effects and changes to policy concerning the transport of goods from the port to the hinterland.

	Agribulk	Iron Ore & Scrap	Coal	Other dry bulk goods
	Significant lag Cross Correlation	Significant lag Cross Correlation	Significant lag Cross Correlation	Significant lag Cross Correlation
World Trade	-8 -0.455	-20 -0.291	4 0.424	0 0.338
IC the Netherlands	8 0.362	2 0.548	-13 -0.204	-1 0.337
- Expected Business Activity	12 0.336	3 0.550	34 -0.209	3 0.375
- Expected Ordering Position	8 0.365	1 0.527	-14 -0.221	21 -0.316
- Expected Stock	12 0.232	3 0.461	7 0.236	3 0.455
IC Germany	9 0.285	1 0.427	6 0.301	1 0.487
- Business Climate	-13 -0.288	3 0.328	6 0.309	0 0.507
- Business Situation	-16 0.298	-19 -0.308	6 0.301	0 0.520
- Business Expectations	11 0.281	4 0.495	7 0.250	5 0.461
IC EU	10 0.375	2 0.548	6 0.256	1 0.394
CC the Netherlands	11 0.390	3 0.398	-5 -0.329	-23 -0.344
CC Germany	6 0.257	-19 -0.236	-11 0.237	0 0.387
CC EU	10 0.415	3 0.443	-8 -0.339	22 -0.411
Iron Production in Germany	8 0.383	1 0.684	-6 -0.229	21 -0.260
Steel production in Germany	8 0.309	1 0.637	4 0.250	16 -0.252

Table 5-2: Cross Correlations between time series

As can be seen from the results, some variables have been removed as a result of the preparation of the data conditions in Chapter 5.2. Yearly dated variables and variables that were not available due to financial restrictions are no longer included in this research.

For each variable, the lag period at which the correlation is strongest is shown in the first row, followed by the correlation coefficient in the second row. In general, a correlation coefficient of 1 indicates perfect correlation and 0 indicates no correlation. A negative correlation indicates a contrary relationship, for example where a peak and trough in the data match each other. A positive correlation coefficient indicates that when one variable increases, the correlating other variables also increases. Lag periods and their correlation figures marked in green are leading the dry bulk goods. For example, Industrial Confidence in Europe correlates with the throughput of Iron Ore and shows significance at lag 2, with a correlation value of 0.548 (Table 5-2). This indicates that the time series shows equal or contrary peaks and troughs, depending on the cross correlation being positive or negative. The positive lag number indicates that IC_EU leads Iron Ore throughput in the port. Negative cross correlations indicate that the peaks and troughs are contrary, so IC_EU peaks, the throughput of Iron Ore peaks 2 months later. This works vice versa if the cross correlation were negative.

By plotting a line graph, the relationship between the time series can be further analysed by identifying specific time periods where the lines show equal or contrary behaviour (see Figure 5-4). In this figure, which shows part of the total time series data that has been enlarged for better viewing purposes, peak and troughs can be identified and compared with each other. The time series IC_EU has been transformed to shift 2 time periods in the leading direction of throughput of Iron Ore. This means that peaks and troughs should be aligned if significance is present. The 'IC_EU_Lead_2' line shows equal peaks and troughs with Iron Ore throughput, which can be explained by the positive cross correlation with the dependent time series. Plotting the values for IC_EU hints towards it being a leading indicator for Coal throughput but it needs to be confirmed by performing a causality test. Furthermore, the Granger test has to determine which lead period (when multiple lag periods are significant) have the strongest causal effect and can therefore count as the leading period of the indicator. Figure 5-4 is just to shows the relationship between time series when the cross correlation is negative or positive. Table 5-2 shows the significant leading periods (in green) between other variables and the dry bulk goods.

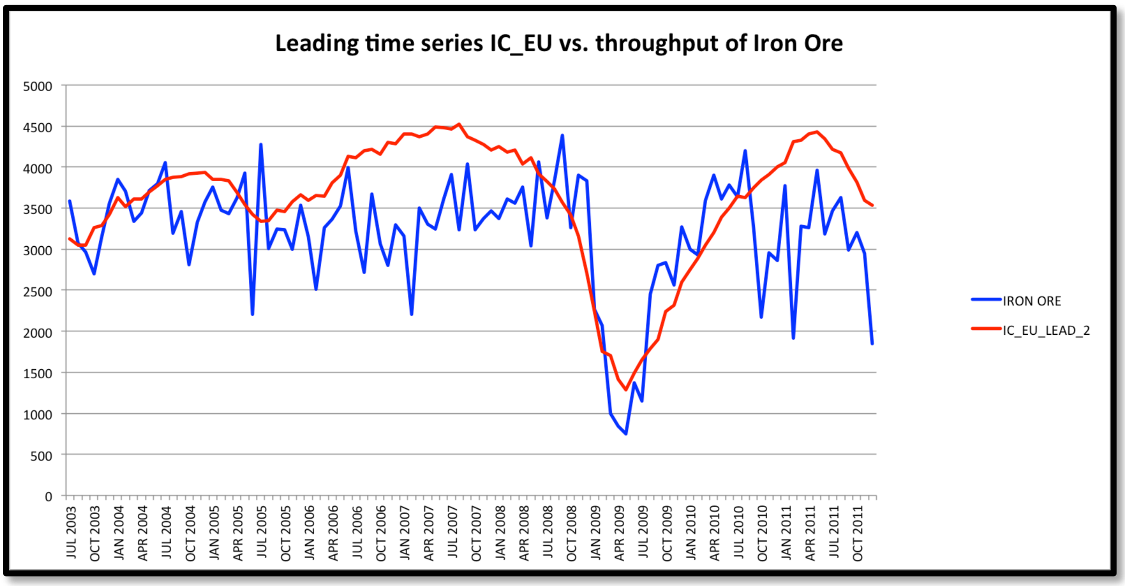


Figure 5-4: Industrial Confidence vs. Iron Ore throughput

From the results, one of the high correlating variables is Iron Production in Germany that correlates with Iron Ore & Scrap throughput at a lead period of one month. The correlation coefficient of 0.684 suggests that there might well be a causal relationship between these variables. The relationship is logical due to the fact that much of the iron ore needed for Iron Production in Germany comes to Europe via Rotterdam. As steel production is closely linked to this, the correlation coefficient is also very high.

Another relationship that is noticeable is the correlation between business expectations and the throughput of other dry bulk goods. Business expectations lead the throughput by five months and correlates at 0.461. The longer lead-time is the result of the business expectations being a view on the future by businesses (see appendix 3), meaning that business are ordering or producing products according to their expectations of the future and this activity is noticeable in the throughput in the Port of Rotterdam.

5.3.2 Final list for VAR analysis

As shown, certain decision rules were set up to determine which variables were used for the VAR model. In the process of calculating cross correlation and making Table 5-2, the first three decision rules have already been accounted for. For example, it was the case that Steel production had more leading lag periods but that the correlation was lower. This takes into account the three rules and thus only the result is shown here.

Rule 4 and 5 require another approach. In order to determine if the time series are correlating, a matrix with groups of variables with corresponding correlations was drawn up. For example, the Consumer Confidence variables were grouped and their correlations were calculated. This was done to account for multicollinearity. As touched upon, multicollinearity occurs when one independent variable takes away explanatory power of another, because the variables are highly correlated. If Consumer Confidence in the Netherlands has a casual effect on Coal throughput and Consumer Confidence in Germany correlated highly with that of the Netherlands, then if both variables are included the strength of the causal relationship is divided over the two variables, taking away explanatory power (a lower causal effect) of Consumer Confidence in the Netherlands. For this research, it has been decided to exclude highly correlating variables and refer to them when assessing the results of the VAR model. For instance, if Consumer Confidence in the Netherlands turns out to be a leading indicator for coal, and it correlates highly with Consumer Confidence in Germany, then it can be concluded that Consumer Confidence in Germany also has some sort of influence on Coal throughput. Therefore, correlations coefficient above 0.8 force one of the variables to be removed.

The following amendments have been made to the list of variables:

- Consumer Confidence in Europe was removed due to high a correlation with Consumer Confidence in the Netherlands. Keeping Consumer Confidence in the Netherlands in the model is also more relevant;
- The Expected Ordering Position and Expected Business Activity have a high correlation with Industrial Confidence in the Netherlands and were therefore removed;
- Expected business climate and Expected business situation have a high correlation with industrial Confidence in Germany and were therefore removed;
- Industrial Confidence in the Netherlands and in Germany correlate highly with Industrial Confidence in Europe so they were removed. This decision was made to keep a general package of variables, at various aggregation levels and industrial indicators from the Netherlands and Germany were already represented by Expected Stock and Business expectation;
- Industrial Production in the Netherlands and Germany were removed due to high correlations with Industrial Production in Europe and the world;

- Steel production was removed due to a high correlation with Iron Production. It was decided to keep iron production as this an elementary material for many more products, including steel;
- Industrial Production in the world was removed due to a high correlation with world trade;
- On the basis of rule 5, Industrial production in Europe was also removed from the list of variables. This time series is not updated every month and can therefore not be used for forecasting purposes.

This leaves the following seven variables for statistical analysis in the VAR model. All time series have been prepares adequately and comply with the different decision rules that were set up.

- Consumer Confidence in Germany (CC_DE)
- Consumer Confidence in the Netherlands (CC_NL)
- Business Expectations in Germany (EXP_BE)
- Expected Stock in the Netherlands (EXP_ST)
- Industrial Confidence in Europe (IC_EU)
- Iron Production in Germany (IRON_DE)
- World Trade (WORLDTRADE)

And the four dry bulk goods as dependent variables:

- Agribulk
- Iron Ore & Scrap
- Coal
- Other dry bulk goods

Limitations of the Cross Correlation Functions

An important note to consider is the fact that CCF can provide a lot of information concerning the relationship between two variables, but that the correlation does not necessarily indicate a causal relationship between the variables. Now that correlations have been calculated, the VAR model can endorse the causal relationships set by the CCF. Furthermore, a VAR model is superior to CCF as it provides more knowledge about the influencing factors of the dry bulk goods, it can take into account the impact of multiple time series rather than calculating the correlation between two variables. As concluded, the CCF have provided a good indication of relationship between variables, but this relationship needs to be proven by a VAR model.

5.4 Creating stationary time series

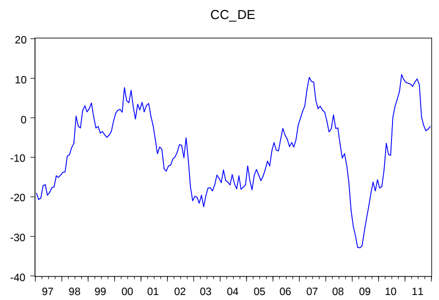
The time series that have been used for statistical analysis need to be made stationary, i.e. they need to exhibit a constant mean, variance and autocorrelation over time. As was discussed in Chapter 5.2, making a series stationary can be done by differencing – converting the time series to show the change to the previous point rather than a data value on its own. This way the time series show changes in trend and become a stable and horizontal line of data points hovering around the zero line. Identifying stationarity can be done by ACF-PACF and line graphs as well as executing an Augmented Dickey-Fuller test.

5.4.1 Line graphs and ACF-PACF graphs

The ACF-PACF graphs can help to establish whether a time series is stationary, as well as the line graphs of time series. In appendix 5, the line graphs and ACF-PACF graphs are shown, indicating that most time series are non-stationary. This is due to the fact that most ACF graphs have multiple significant lag periods that do not decline to zero. This indicates that a data point is auto correlating with a previous data point, thereby extending the trend or direction of this previous point. This makes the line of the time series go up or down even further. When multiple periods are auto correlating, the trend is strengthened even more and the line graphs do not show a horizontal trend, indicating non-stationarity.

The line graphs and ACF-PACF graph in appendix 5 display that all variables show signs of non-stationarity. All ACF graphs have multiple significant lag periods that do not decline to zero quickly and the line graphs display an upward or downward moving slope, rather than a horizontal trend. The figure below shows the line graph and ACF-PACF graph of Consumer Confidence in Germany. This is a clear example of a non-stationary time series – the ACF graph show multiple significant lags and the PACF graph spikes at one and remain insignificant for the rest of the periods. From the line graph, a general downward trend is also visible.

Consumer Confidence DE



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.959	0.959	168.25	0.000
		2	0.906	-0.163	319.38	0.000
		3	0.853	-0.012	454.14	0.000
		4	0.785	-0.222	568.96	0.000
		5	0.703	-0.184	661.38	0.000
		6	0.616	-0.075	732.84	0.000
		7	0.532	0.009	786.50	0.000
		8	0.444	-0.071	824.12	0.000
		9	0.364	0.083	849.45	0.000
		10	0.293	0.048	865.98	0.000
		11	0.225	-0.040	875.75	0.000
		12	0.152	-0.141	880.26	0.000

Table 5-3: Line graph and ACF-PACF graph of Consumer Confidence in Germany

Because stationarity is very important for statistical analysis and the accuracy of results, a second test for stationarity was performed. As opposed to visual inspection of the line graphs and ACF-PACF graphs, a statistical test called the Augmented Dickey-Fuller test was performed. Hereby, hypotheses are tested that indicate the presence of stationarity or not. This requires some more insight into significance intervals used for testing the hypotheses.

Statistical analysis and significance intervals

In statistics, many methods include the testing of hypotheses and provide a test statistic that can reject or accept a null hypothesis or alternative hypothesis. Whether or not to reject a hypothesis depends on the test statistics, a critical value that is determined by the confidence interval that the researcher sets. This assumes that the data being investigated is normally distributed and that the values hover around the mean. Moving towards the left or right decreases the probability of a data point being present so at the end of the curve, only a small chance is present that this data point is present in the data. A hypothesis tests whether or not a value is probable to lie beyond the critical value and thereby wrongly reject or accept the hypothesis.

The critical values of a test are shown by the area under the graph up to the red lines, depending on the significance level (if a 10% significance level is taken, there is more room for error but the test results are larger). For example, when taking a 5% significance level and the test statistic is smaller than the corresponding critical value (left of the 5% mark, so in the green and yellow shaded area), you can say with 95% confidence (in a one sided test) that you will not unrightfully reject the null hypothesis. So if it lies in the white zone then the statistic is larger than the critical value, you cannot reject the null hypothesis. This concerns a one sided test and often two sides tests are done where 5% is indicated at both sides of the distribution and a value can belong to the top 5% or the bottom 5%. Whether you take a one or two-sided test depends on the hypothesis you want to investigate. If this is aimed at investigating whether a value is bigger than a certain criteria or not, then a one sided test is appropriate. When investigating whether a value lies in between a certain range, a two-sided test is used.

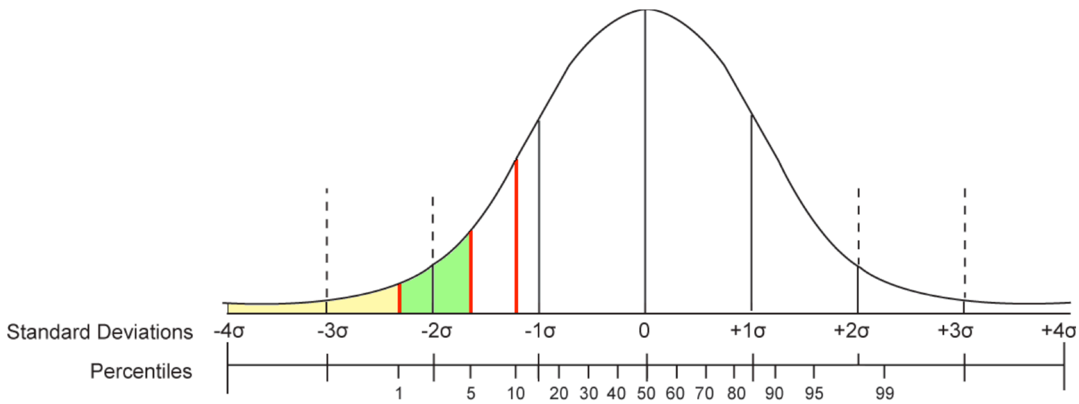


Figure 5-5: Picture adapted from (MacLennan, 2011)

Box 2: Significance interval in statistical analysis

5.4.2 Augmented Dickey-Fuller test

The Augmented Dickey-Fuller is a test for the existence of a unit root – a statistical term for the feature of a process that evolves over time and can cause skewed results if not properly dealt with. This is called statistical inference and describes that conclusions are drawn based on random variables or variation. If this is not addressed for, outliers and extreme values are included in the analysis and the data therefore does not take the shape of the bell curve, as shown in Figure 5-5. Therefore, it is important to test if a unit root is present or not.

Testing for stationarity/unit root requires setting a hypothesis. The hypothesis was tested according to a result value and the critical value of the significance interval (in this case 5%). When the zero hypothesis is not rejected, the series is non stationary and it needs to be differenced. After differencing, the ADF test can be performed again to see if a unit root is still present or not. Differencing a second time might be necessary. If the zero hypothesis is rejected, we can say (with a confidence level of 95%) that we have correctly rejected the zero hypothesis and assume that the alternative hypothesis is applicable. In other words, the confidence interval means that we have a 5% chance of wrongly rejecting the null hypothesis.

The hypotheses are as follows:

H_0: There is a unit root in the corresponding time series
H_1: There is no unit root present in the corresponding time series

Note that this concerns a one-tailed test, so the ADF test determines whether the result is lower or higher than the critical value, thereby indicating whether or not to reject the zero hypothesis. The white area under the graph in Figure 5-5 shows the significance interval. If the test result is lower than the critical value, it is in the green and yellow part of the curve, indicating that is has no unit root.

For the ADF test, the critical value (T) that indicates the 95% confidence interval is -3.4351. Thus, the results in Table 5-4 can be interpreted as follows:

- If T < ADF critical value, we reject the null hypothesis and accept the alternative hypothesis, i.e. a unit root is not present and the time series is stationary.
- If T > ADF critical value, we do not reject the null hypothesis, i.e. a unit root is present and the time series is non-stationary.

The results of the Augmented Dickey Fuller test are shown in the table below.

Time Series	ADF statistic (T)		ADF statistic after differencing (T_1)
Agribulk	-9.9679		-
Iron Ore & Scrap	-4.6569		-
Coal	-8.8724		-
Other dry bulk goods	-4.4041		-
CC Germany	-3.2455		-11.4857
CC the Netherlands	-1.8844		-12.7924
Business Expectations	-4.1474	✗	-8.2470
Expected Stock	-3.7470	✗	-16.6040
IC EU	-3.9818	✗	-4.2051
Iron Production in Germany	-3.2129		-12.7889
World Trade	-3.6420	✗	-4.8972

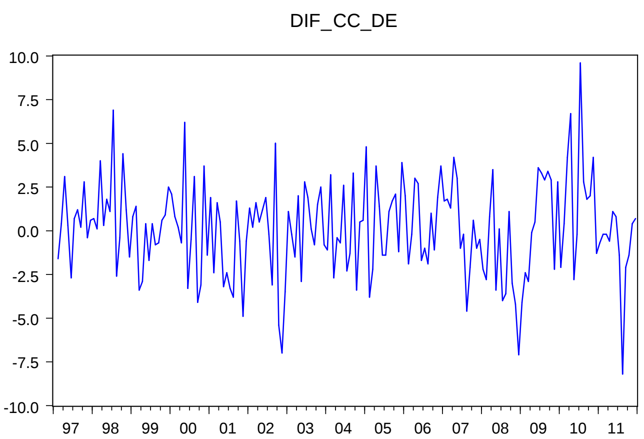
Table 5-4: Outcome of the ADF test at 1st level and after first differencing the time series

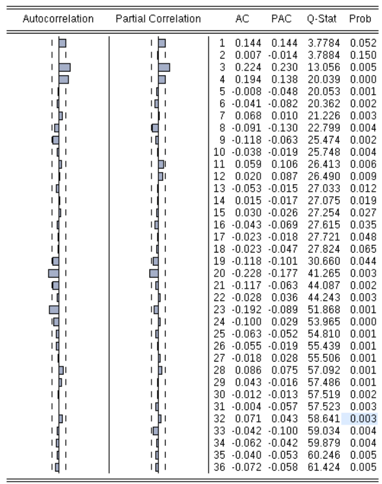
Although the ADF test is widely used in statistics and can deliver accurate results, not all researchers are positive about the use of the ADF test. Some argue that the results are weak and that only rarely the correct critical values are shown (for example, see Mashtaq (2011) and (Hassler & Wolters, 1994)). To account for the doubt that has been raised over the ADF test, line graphs and the ACF-PACF graphs have also been consulted to test the ADF conclusions. After performing the ADF, some variables still showed signs of non stationarity in the trend, as the ACF graph showed many significant lag periods that do not quickly decline to zero.

Because stationarity of the data is very important for achieving accurate results in the VAR model, it was decided to difference as yet the time series that passed the ADF test (i.e. the ADF concluded they were stationary) but showed signs of non stationarity in the ACF-PACF graph. These variables are marked with a (✗). After differencing, it was concluded that all T_1 values are greater than the critical value of the ADF test and therefore all time series are stationary and can be used in the VAR model. The line graphs and ACF-PACF graph, shown in appendix 6, also indicate that all time series are stationary.

Below, the time series of Consumer Confidence in Germany is plotted again to show the effects of differencing. The ACF-PACF graphs have been made with 36 lags instead of 12, as was done before in Chapter 5.2. This is to ensure that no pattern in present or a recurring effect takes place beyond 12 lags. Comparing the line graph to the previous one shows a much more stable graph. It can be clearly seen that the mean of the graph is horizontal and that peaks and troughs are clearly shorter or less extreme than before. This indicates that the variance of the data points has been reduced. The ACF-PACF graphs show no significant lag periods in patterns, indicating that there is no autocorrelation present. The time series are declared stationary.

Consumer Confidence DE





Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.144	0.144	3.7784	0.052
		2	0.007	-0.014	3.7884	0.150
		3	0.224	0.230	13.056	0.005
		4	0.194	0.138	20.039	0.000
		5	-0.008	-0.048	20.053	0.001
		6	-0.041	-0.082	20.362	0.002
		7	0.068	0.010	21.226	0.003
		8	-0.091	-0.130	22.799	0.004
		9	-0.118	-0.063	25.474	0.002
		10	-0.038	-0.019	25.748	0.004
		11	0.059	0.106	26.413	0.006
		12	0.020	0.087	26.490	0.009
		13	-0.053	-0.015	27.033	0.012
		14	0.015	-0.017	27.075	0.019
		15	0.030	-0.026	27.254	0.027
		16	-0.043	-0.069	27.615	0.035
		17	-0.023	-0.018	27.721	0.048
		18	-0.023	-0.047	27.824	0.065
		19	-0.118	-0.101	30.660	0.044
		20	-0.228	-0.177	41.265	0.003
		21	-0.117	-0.063	44.087	0.002
		22	-0.028	0.036	44.243	0.003
		23	-0.192	-0.089	51.868	0.001
		24	-0.100	0.029	53.965	0.000
		25	-0.063	-0.052	54.810	0.001
		26	-0.055	-0.019	55.439	0.001
		27	-0.018	0.028	55.506	0.001
		28	0.086	0.075	57.092	0.001
		29	0.043	-0.016	57.486	0.001
		30	-0.012	-0.013	57.519	0.002
		31	-0.004	-0.057	57.523	0.003
		32	0.071	0.043	58.641	0.003
		33	-0.042	-0.100	59.034	0.004
		34	-0.062	-0.042	59.879	0.004
		35	-0.040	-0.053	60.246	0.005
		36	-0.072	-0.058	61.424	0.005

Table 5-5: Line graph and ACF-PACF graph of Consumer Confidence in Germany after differencing

5.5 Granger Causality using a Vector Autoregressive (VAR) model

The time series have been prepared for statistical analysis after CCF functions have shown that correlations exist between the variables. To test whether or not a causal relationship is also present between the variables is also present, a VAR model has been set up and executed. The advantage of a VAR model over other methods is its ability to test multiple independent variables for one dependent one as well as create a forecast based on the output of the model. This is in line with the need of this research – to identify leading indicators and forecast them so that they can be used in the information dashboard.

Before causality tests can be performed, the Akaike Information Criterion (AIC) is calculated to determine the lag length of the dependent variable. Chapter 4.3.2 has indicated that the lag length of the model is vital for achieving correct model output and the AIC test indicates a leg length for the model that results in the independent variables being most explanatory for the dependent variable. Chapter 5.5.1 elaborates on the AIC, Chapter 5.5.2 explains the VAR model and discusses the results.

5.5.1 Akaike's Information Criterion (AIC)

The Granger causality tests' results are very dependent on the amount of lag periods included in the test. These lag periods indicate at which lag of the dependent variables, the independent variables have the strongest causal influence on the variable. It is important to perform this test, as an incorrect lag length does not produce a realist view of the leading indicators and cause variation in the results. Lütkepohl (2007) states that selecting a higher lag length than is true for the model causes an increase in the forecast error of the VAR, noticeably in the Mean-Square-Forecast-Error. This is the result of the VAR model using more coefficients of the independent variables to forecast the dependent variable. When these lagged coefficients are not significant and therefore should not be included in the VAR, the forecast error is bound to be higher. Selecting a lag length that is lower than the true lag length of the model results in 'underfitting' and leads to auto correlated errors in the model. The VAR model takes uncorrelated errors as prerequisite for a correct model so determining the correct lag length is important for estimating a correct VAR model as well as making a correct forecast using the VAR model. The AIC is a test to determine at which lag the time series can be best explained, and is represented by a relative goodness of fit of the model. In other words, a statistic of the amount of information lost when trying to model reality. This is performed for every lag length and the most exact lag length is given as result. For each test, comprising of all the independent variables and a dependent variable, the AIC criterion has been calculated. The results of the test are shown below:

Dependent variable	Lag length of model
Agribulk	1
Iron Ore & Scrap	3
Coal	1
Other dry bulk goods	3

Figure 5-6: Optimal lag length as a result of AIC test

For example, for Agribulk, it means that throughput is best forecasted when taking the t_{-1} value of the independent variables. For Iron Ore and Scrap, taking t_{-1}, t_{-2} and t_{-3} gives the best representation of the relationships. For Coal and Other dry bulk goods, a lag length of respectively 1 month and 3 months are calculated. Finding a lag length for each throughput good that is applicable to all the independent variables does have some caveats. The lag length is based on the common explanatory power of the independent variables at that length. It could be the case that when variables are investigated in a pairwise Granger test, the optimal lag length might be different. However, it is important to consider the combined influence of variables and therefore a VAR model must be designed that takes into account all the independent variables, not just one. This is the advantage of VAR over univariate models, as a third variable in a relationship might influence the relationship significantly.

5.5.2 VAR model

The VAR model can be estimated using the Eviews software (see appendix 2). Four models are made; one for each dry bulk good and their corresponding lag period, established by the AIC, is used. The VAR model takes each variable as the dependent variable and the rest as independent variables, thereby calculating a coefficient that must be multiplied with the corresponding values of the time series. So in the case of the Iron Ore & Scrap model, a coefficient for t-1, t-2 and t-3 of all independent and the dependent variables are calculated. These coefficients indicate the relationship that each independent variable has with the dependent variable and can later on be used to forecast the variables.

Because Granger causality is based on testing hypothesis, a confidence interval is used to determine whether or not to reject the zero hypothesis or not. The hypotheses for the VAR model are:

H_0: The independent variable does not Granger causes the dependent variable.
H_1: The independent variable Granger causes the dependent variable.

For the VAR model, the significance level (p) for accepting or rejecting the hypotheses is 0.10, thus:

- If $p < 0.10$, we reject the null hypothesis, i.e. the independent variable Granger causes the dependent variable.
- If $p > 0.10$, we do not reject the null hypothesis and assume the alternative hypothesis, i.e. the independent variable Granger does not cause the dependent variable.

A significance level of 10% has been set for the VAR model; this is because the CCF's have shown that there is already a relationship between the independent and dependent variables. Therefore, the margin for error can be extended a bit more to ensure a complete view of the indicators is given. When setting a smaller confidence level, the model might get too restricted and might not show all leading indicators that do have an influence.

Dependent variable: IRONORE

Excluded	Chi-sq	df	Prob.
CC_DE	1.054005	3	0.7882
CC_NL	10.75251	3	0.0131
EXP_BE	5.453522	3	0.1414
EXP_ST	6.313370	3	0.0973
IC_EU	8.254747	3	0.0410
IRON_DE	10.02860	3	0.0183
WORLDTRADE	4.007714	3	0.2606
All	86.11839	21	0.0000

Table 5-6: VAR model results Iron Ore & Scrap

IRONORE = 1274.868 + (-0.075*CC_DE_{t-1}) + (9.124*CC_DE_{t-2}) + (-10.975*CC_DE_{t-3}) + **(16.061*CC_NL_{t-1}) + (-23.939*CC_NL_{t-2}) + (17.358*CC_NL_{t-3})** + (-26.159*EXP_BE_{t-1}) + (-16.469*EXP_BE_{t-2}) + (-55.679*EXP_BE_{t-3}) + **(-57.817*EXP_ST_{t-1}) + (-17.292*EXP_ST_{t-2}) + (9.815*EXP_ST_{t-3})** + **(-4.600*IC_EU_{t-1}) + (27.882*IC_EU_{t-2}) + (81.307*IC_EU_{t-3})** + **(0.098*$IRON\_DE_{t-1}$) + (0.214*$IRON\_DE_{t-2}$) + (1.015*$IRON\_DE_{t-3}$)** + (-5.654*$WORLDTRADE_{t-1}$) + (33.115*$WORLDTRADE_{t-2}$) + (28.152*$WORLDTRADE_{t-3}$) + (0.099*$IRONORE_{t-1}$) + (0.287*$IRONORE_{t-2}$) + (0.215*$IRONORE_{t-3}$)

The results of the VAR model for Iron Ore & Scrap (Table 5-6) shows that four leading indicators have been identified. The probability figures in green are below 0.10, thereby indicating a significant relationship with Iron Ore & Scrap throughput. The coefficients matrix has resulted in the following equation for the trend of Iron Ore & Scrap throughput. It shows all indicators (the leading indicators in bold) and the coefficients for each lagged variable from t_{-1} to t_{-3}. In the equation, the dependent variable Iron Ore is also included. This is a characteristic of the VAR model; the value that has been forecasted is based on other variables as well as on its own. This is the Auto regressive part of the VAR model. It is therefore imperative to acknowledge that Iron Ore & Scrap throughput is determined by all variables in the model, but that the indicators in bold are significant, and can therefore be characterised as significant leading indicators.

From the results in Table 5-6, CC_NL and IRON_DE have the largest influence on the throughput of Iron Ore & Scrap (largest Chi-Sq. and smallest Prob.). Consumer Confidence in the Netherlands has a leading effect on Iron Ore & Scrap throughput due to the fact that the indicator is determined by historical situations, current situations and future expectations of the economic market. Consumers are asked questions about how they think the market has been and is performing at the moment. The indicator also questions consumers about whether they are prepared to buy consumer products or that they feel the market is not right at the moment. An increase in Consumer Confidence can have an (delayed) effect on the amount of products consumers want to buy – TV's, fridges and other consumer products. Once demand for these products go up, the demand for Iron Ore as base material to make these products eventually also increase. The delay of 3 months can be explained by the fact that reserves, stationed in the Port of Rotterdam, are sent to the companies first. This means that the delay in increase in demand from consumers to the production companies receive more Iron Ore is low. As the stock of Iron Ore in the terminal decreases more quantities are ordered from South America. The Journey from point of excavation in South America to Rotterdam could well take a month and the actual production time might add to the delay, therefore explaining the delay of 3 months in the VAR model that is applicable for Consumer Confidence in the Netherlands. The relationship between Iron Ore & Scrap throughput and Consumer Confidence in the Netherlands is visually shown by a line graphs in Figure 5-7. In the graph on the left, the leading indicator Consumer Confidence, is plotted against Iron Ore & Scrap throughput. The graph represents change in the leading indicators (in red, right scale) and actual values of dry bulk goods (in blue, left scale), as the VAR model has used differenced series for the leading indicators. By plotting these data, the change in trend of the leading indicator and its effect on the dry bulk good can be shown and analysed. The leading indicator has been smoothed to create indication of the trend rather than showing exact data points. When supporting the forecasting process it is important to show the trend of the indicator and allow experts to make a forecast based on this information. Displaying a trend instead of a exact value ensures that the Forecasting Support System does not interfere with work already done by the experts, keeping them comfortable with using the provided information and statistics. The 3-month lead period has been incorporated into the line graph so what happens to Consumer Confidence in the

Netherlands is affecting Iron Ore & Scrap throughput immediately in the graph. This allows for better analysis of alignment of peaks and troughs.

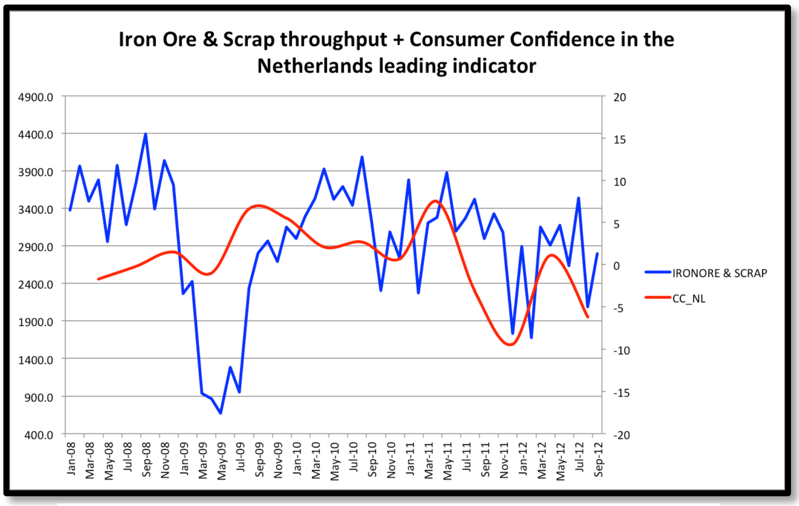


Figure 5-7: Line graph of Consumer Confidence in the Netherlands

The fact that the Iron Production in Germany is a leading indicator for throughput in the port is not surprising, as iron for building machinery, cars and appliances requires iron ore to be produced into iron. Once Iron Production in Germany increases, this has an effect on the amount of iron ore needed and more iron ore is requested for production. Almost 50% of requested iron ore in Northwest Europe comes through Rotterdam and mainly arrives from Brazil, Canada, Australia, South Africa and Sweden (Havenbedrijf Rotterdam N.V., 2012). This makes Iron Ore & Scrap products a highly important product for Rotterdam and explains the large amount of leading indicators. The load that arrives in Rotterdam is then overhauled onto smaller ships and transported to Germany via the Rhine River.

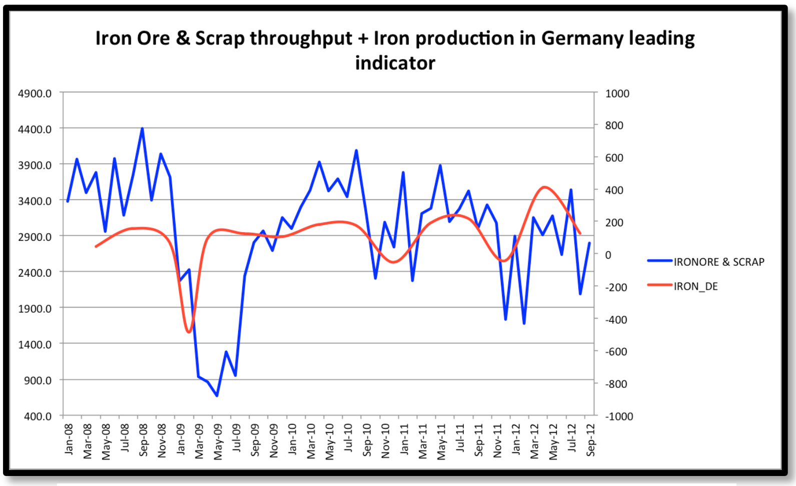


Figure 5-8: Line graph of Iron Production in Germany

Iron Ore & Scrap

Closely linked to the Consumer Confidence in the Netherlands, is the expected stock of companies in the Netherlands. As explained, the demand for Iron Ore increases as Consumer Confidence increases and this is noticeable in the expected stock levels of companies. The need for stock increases to be able to produce the products that consumers demand. However, the indicator here describes whether producers think they have loo little stock, enough stock or excess stock. When producers assess their stock as too small, the statistic is positive and vice versa for stock that is enough or more than enough. Considering the line graph of Expected Stock in the Netherlands, an inverse relationship is noticeable – an increase in Expected Stock leads to a decrease in Iron Ore & Scrap throughput. This is due to the fact that the indicator shows positive numbers for a lack of stock, so more stock are ordered, thus increasing the amount of Iron Ore & Scrap being transported through the port. The raw materials are used to manufacture products and resupply stocks of companies.

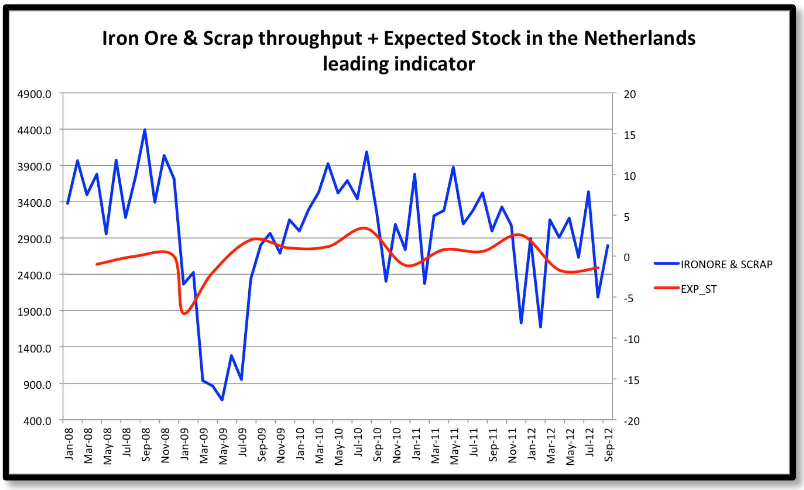


Figure 5-9: Line graph of expected stock in the Netherlands

The fourth indicator for Iron Ore & Scrap throughput is the Industrial Confidence in Europe. Although this is an indicator on an aggregate level, it can accurately deliver leading information about throughput. The indicator concerns the prospects of companies, their expectations considering sales and their financial situation. An increase in this statistic increases the demand for making products of all kinds and thus, with a lead-time of 3 months, increase Iron Ore & Scrap throughput in the port. The VAR model has resulted in a corresponding trend of the leading indicator, although the crisis year of 2008 and 2009 have not been picked up very well by the indicator, as supposed to other leading indicators.

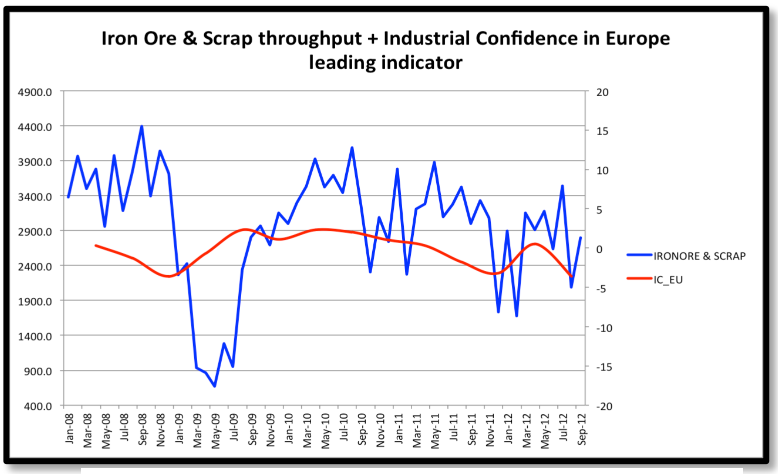


Figure 5-10: Line graph of Industrial Confidence in Europe

Feedback relationships in the VAR model

Another advantage of the VAR model is that every variable is taken as a dependent variable and the results are shown by EViews. This allows the investigation of feedback relationships. When a variable is significant towards the dependent variable, a reverse relationship may also exist. This way, the dependent variable of the first model may become a leading indicator for the independent variable in the first model. When both are established as leading indicators, a feedback relationship is present. In the case of Iron Ore & Scrap throughput, the variables EXP_ST, IC_EU and IRON_DE have a feedback relationship with Iron Ore & Scrap throughput. It can be concluded that Iron Ore and & Scrap throughput also Granger causes EXP_ST, IC_EU and IRON_DE.

Feedback relationships can be investigated further in future research but are not included in this project. Here, the focus is on leading indicators for the dependent variables so the feedback relationships are ignored.

Box 3: Feedback relationships in the VAR model

Agribulk

From the VAR model, the following results for Agribulk indicate that Consumer Confidence in Germany is a leading indicator for Agribulk. It corresponding significance value is below 0.10 indicating that the zero hypothesis can be rejected and that Consumer Confidence Granger causes Agribulk throughput in the Port of Rotterdam.

Dependent variable: AGRIBULK

Excluded	Chi-sq	df	Prob.
CC_DE	5.915785	1	0.0150
CC_NL	1.745235	1	0.1865
EXP_BE	0.026882	1	0.8698
EXP_ST	2.621851	1	0.1054
IC_EU	0.419238	1	0.5173
IRON_DE	0.256277	1	0.6127
WORLDTRADE	0.740025	1	0.3897
All	11.47301	7	0.1193

AGRIBULK = 468.225 + **(-11.045*CC_DE$_{t-1}$)** + (-4.508*CC_NL$_{t-1}$) + (1.392*EXP_BE$_{t-1}$) + (-11.552*EXP_ST$_{t-1}$) + (5.304*IC_EU$_{t-1}$) + (-0.050*IRON_DE$_{t-1}$) + (5.023*WORLDTRADE$_{t-1}$) + (0.451*AGRIBULK$_{t-1}$)

Table 5-7: VAR model results Agribulk

The line graph does not immediately show an accurate representation when comparing Consumer Confidence with Agribulk. After consulting a dry bulk expert at the PoR no logical explanation could be found for the relationship between Consumer Confidence and Agribulk throughput. Because Agribulk is a collection of product, a possible relationship can be present between Consumer Confidence and one of the products in the collection. In order to fully understand the leading indicators for Agribulk, a product specific VAR model can be made, using solely indicators that are expected to influence the individual products in the Agribulk collection.

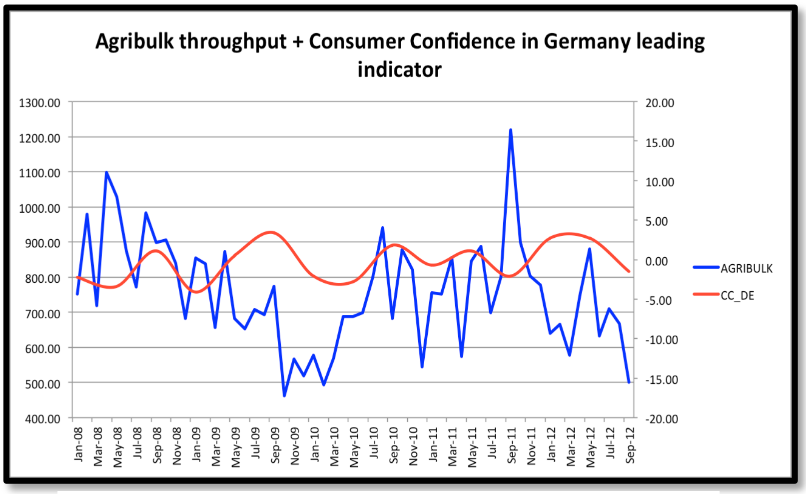


Figure 5-11: Line graph of Consumer Confidence in Germany

Coal

The final two leading indicators, Consumer Confidence in the Netherlands and Iron Production are, besides being leading indicators for Iron Ore & Scrap, also leading indicators for Coal throughput.

Dependent variable: COAL

Excluded	Chi-sq	df	Prob.
CC_DE	0.048054	1	0.8265
CC_NL	8.315359	1	0.0039
EXP_BE	1.466219	1	0.2259
EXP_ST	0.147674	1	0.7008
IC_EU	0.523737	1	0.4693
IRON_DE	3.416462	1	0.0645
WORLDTRADE	0.705969	1	0.4008
All	13.28342	7	0.0655

$$\mathbf{COAL} = 1133.952 + (-2.477 \cdot CC\_DE_{t-1}) + \mathbf{(-24.467 \cdot CC\_NL_{t-1})} + (-25.599 \cdot EXP\_BE_{t-1}) + (-6.824 \cdot EXP\_ST_{t-1}) + (14.782 \cdot IC\_EU_{t-1}) + \mathbf{(0.453 \cdot IRON\_DE_{t-1})} + (-12.195 \cdot WORLDTRADE_{t-1}) + (0.452 \cdot COAL_{t-1})$$

Table 5-8: VAR model results Coal

The collection Coal can be split up in steam coal and cokes coal. Steam coal is used for energy production in industry and power plants, whereas cokes coals are used for the production of Iron. The segregation can help to explain the relationship between the two variables. As steam coal is mainly used for producing electricity, a relationship between these variables might be present. The general experience that PoR experts have is that economic prosperity is linked with the type of electricity demand. Once consumers are more confident in the market and have a higher prosperity, attention can be spend on alternative electricity generation and consumers might be tempted to switch to cleaner energy when they feel they can afford it. Because electricity produced from steam coal is much cheaper than, for example wind energy, demand for this type of electricity increases as consumers have less money to spend. This relationship is visible in the line graph in the beginning of 2009, when Consumer Confidence declines and the throughput of coal increases.

A cautionary note must be made that this relationship can be one of many (indirect) relationships between the two variables. Of course, other factors might also influence the relationship, which are unclear at the moment. A more thorough VAR model, focused on coal only, can lead to gaining more insight into the exact drivers of Coal throughput.

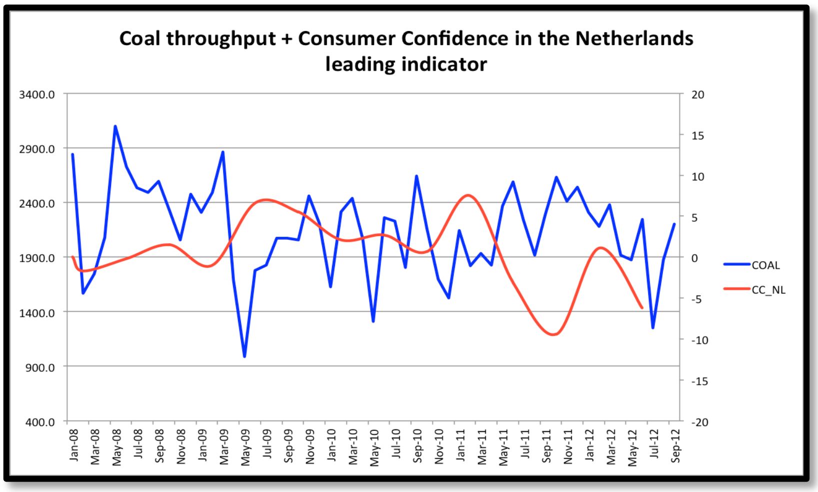


Figure 5-12: Line graph of Consumer Confidence in the Netherlands

As already touched upon, the throughput of coal is closely linked to Iron Production in Germany. The throughput of Cokes Coal, which is used for the production of iron, increases as Iron Production in Germany increases. The general trend of Iron Production is represented in the line graph but the model does not adequately notice important turning points. As has been revealed before, changes in the trend are indicated by the model but sudden drops or increases in the data are not anticipated. This suggests that using a separate forecasting method might create more accurate values. However, for the purpose of this research the general trend needs to be forecasted in order to support the forecasting process at the PoR. Furthermore, using the VAR model for trend identification as well as forecasting creates more transparency in the model, an important aspect when attempting to implement the Forecasting Support System into the current process.

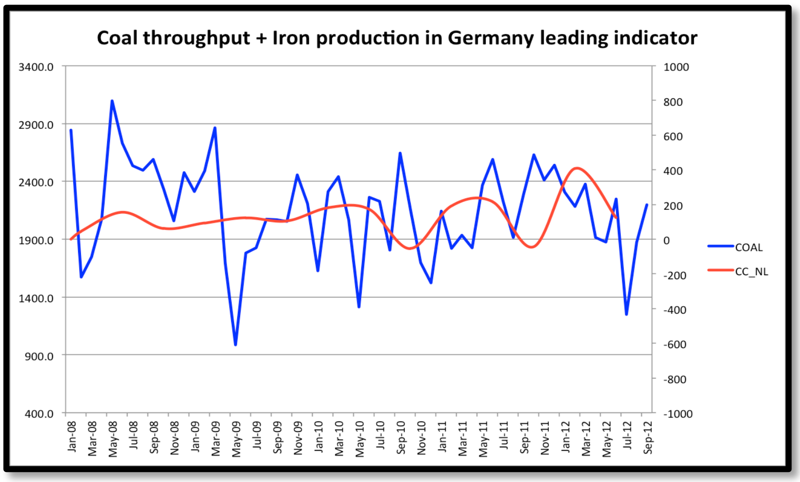


Figure 5-13: Line graph of Iron Production in Germany

Other dry bulk goods

No leading indicators have been identified for the Other dry bulk goods. The coefficients show that all significance values are above 0.10. The reason for this is the diversity of products being counted as 'other dry bulk good'. The diversity of products in this group makes it too general to determine exact leading indicators, as is the case with Iron Ore & Scrap for example.

Dependent variable: OTHERDB

Excluded	Chi-sq	df	Prob.
CC_DE	5.691039	3	0.1276
CC_NL	2.278000	3	0.5167
EXP_BE	3.480792	3	0.3233
EXP_ST	6.235419	3	0.1007
IC_EU	1.258908	3	0.7389
IRON_DE	4.827351	3	0.1849
WORLDTRADE	2.622753	3	0.4535
All	30.35015	21	0.0852

OTHERDB = 420.158+ (8.529*CC_DE_{t-1}) + (4.844*CC_DE_{t-2}) + (1.132*CC_DE_{t-3}) + (0.332 CC_NL_{t-1}) + (3.990*CC_NL_{t-2}) + (2.924*CC_NL_{t-3}) + (-2.862*EXP_BE_{t-1}) + (-7.345*EXP_BE_{t-2}) + (-11.106*EXP_BE_{t-3}) + (0.462*EXP_ST_{t-1}) + (1.311*EXP_ST_{t-2}) + (16.547*EXP_ST_{t-3}) + (-3.218*IC_EU_{t-1}) + (8.247*IC_EU_{t-2}) + (-4.749*IC_EU_{t-3}) + (-0.161*$IRON\_DE_{t-1}$) + (-0.060*$IRON\_DE_{t-2}$) + (0.096*$IRON\_DE_{t-3}$) + (-1.261*$WORLDTRADE_{t-1}$) (7.911*$WORLDTRADE_{t-2}$) (6.206*$WORLDTRADE_{t-3}$) + (00.053 *$OTHERDB_{t-1}$) + (0.299*$OTHERDB_{t-2}$) + (0.202*$OTHERDB_{t-3}$)

Table 5-9: VAR model results Other dry bulk goods

The individual forecasts have been discussed above. The following figure gives a visual representation of the leading indicators for each throughput good. The result of the VAR model shows that all indicators have an impact on the throughput good, the yellow boxes indicate that these indicators are significant leading indicators that Granger cause the dry bulk throughput goods. The lag lengths of each of the models are indicated in the circle in the top right corner of the dry bulk goods. The variables, EXP_ST, IC_EU and IRON_DE have a star on their box; this indicates that a feedback relationship is present. As indicates in Box 3, these feedback relationships are interesting to keep in mind when making a forecast but are not considered any further in this research.

5.6 Conclusion

To be able to determine the leading indicators for the dry bulk goods, and thereby provide an answer to research question 3, economic variables and market data needed to be analysed using various statistical techniques. Preparation of the data and the setting of decision rules for data have resulted in the exclusion of some of the variables initially selected for use. This has reduced the scope of the model but was necessary to be able to achieve accurate results.

By calculating the Cross Correlation Functions between each of the variables, an early indication of causality was discovered. A correlation between variables did not guarantee a causal relationship as many variables have shown. For example, a correlation between expected stock in the Netherlands and the throughput of other dry bulk goods has not resulted in a causal effect being present. On the other hand, the two leading indicators for Coal, Consumer Confidence in the Netherlands and Iron Production in Germany exhibit a causal influence but have no sign of a leading correlation. Overall, the CCF has provided little concrete information concerning the relationships and cannot be used on its own to determine leading indicators. A VAR model needed to proof the presence of a causal influence on the dry bulk goods.

Preparation for the VAR model included ensuring the time series were stationary. Using the ACF-PACF graphs, line graphs and the Augmented Dickey Fuller test, the time series were examined for changing means, variances and autocorrelations in the data. After differencing the time series that were not stationary, the VAR model was estimated.

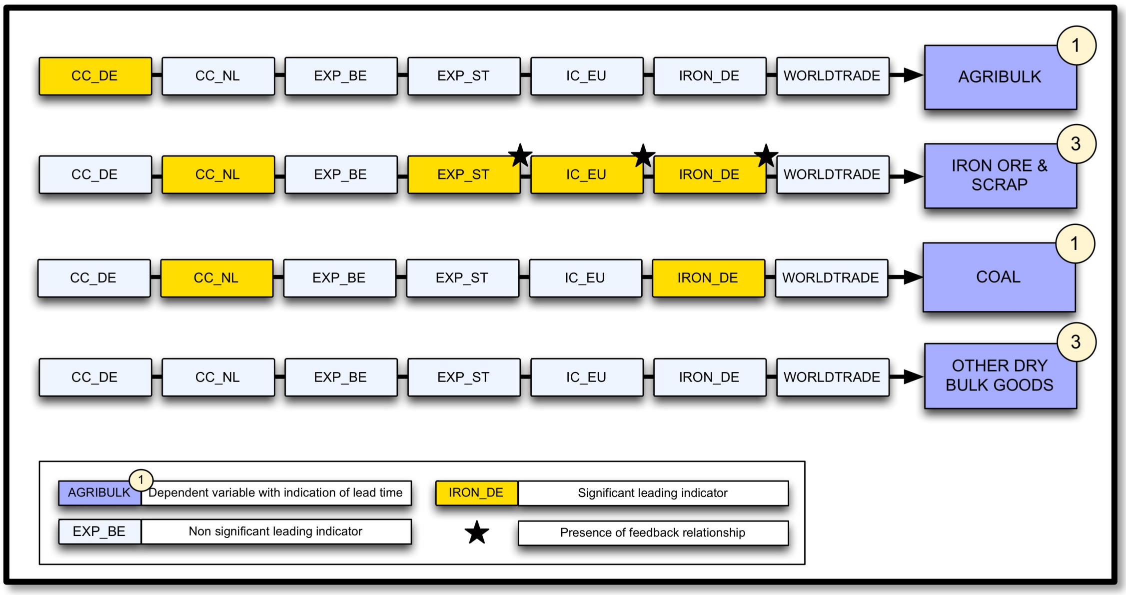


Figure 5-14: Leading indicators identified by the VAR model

A final statistical test, Akaike's Information Criterion has resulted in an optimal lag length for each of the models. This way, the most explanatory model for the dry bulk goods could be modelled, considering a lag period that explained the relationship between the time series. The VAR model has resulted in a set of indicators for each of the dry bulk good models and has shown that leading indicator have been identified for three of the four product groups. It is due to the diversity in products of the 'other dry bulk goods' group that no leading indicators have been identified. If a case specific VAR model is set up, which uses more specific economic and market indicators for other dry bulk goods, more insight is created into potential leading indicators for this product group. Although the Agribulk model has resulted in one leading indicator being identified, the same counts here. Splitting up the group into its various sub products, more insight can be gained.

Iron Ore & Scrap products and Coal have shown that respectively four and two leading indicators can be identified. Assessing their impact on the dry bulk goods, the relationships between the variables seem logical and can be explained by economic principles of supply and demand or by experts, who have knowledge about the shipping market and the relationships.

6. VERIFICATION AND VALIDATION

The identification of leading indicators and the forecasts that have been made of these variables represent the Forecasting Support System. Before providing this information in an information dashboard, verification and validation of the model and output must be performed. This Chapter covers the work done, present results and provide conclusions about key performance indicators of the Forecasting Support System that are vital for supporting the forecasting system at the PoR. This Chapter answers research question 4:

Is the quantitative forecasting tool a reliable and accurate source of information to support the forecasting process?

In Chapter 6.1, the verification methods for this research are discussed. Verification is aimed at the build up of the model and whether or not this has been done in a correct way. For statistical analysis using statistical packages, many methods and variations of methods are possible for doing research. Choosing the correct methods and performing them correctly is important for achieving accurate results. Chapter 6.2 focuses on the validation of the model and assesses if the model shows the intended results and if these results are accurate and usable in business processes at the PoR. Chapter 6.3 provides a conclusion of this Chapter and rounds up the verification and validation phase.

6.1 Verification of the VAR model

This research has used several statistical analysis methods for the determining and forecasting leading indicators for dry bulk goods in the port. Because of the switch from SPSS software to Eviews software, modelling support and a verification session could not be carried out at the TU Delft, simply because SPSS is the standard package for statistical analysis at the TU Delft. Therefore, a verification session was held at the Rijksuniversiteit Groningen. Together with a professor of the economics, econometrics and finance department of the Economics and Business faculty, the input for the model and the build up of the model were discussed. The verification session provided good insights into data preparation and VAR model building for determining causality between time series. Many tips and suggestions provided caused the building of the VAR model to be far less time consuming than anticipated before.

The verification session has confirmed that using the current size of the data set is advantageous for creating an accurate representation of the trend of the leading indicators. Because the literature does not provide exact guidelines for the minimum required observations for VAR modelling, having the amount verified by an expert is important and reassuring. The use of Cross Correlation Functions was also endorsed for creating an early indication of leading indicators. However, agreement was quickly established concerning the conclusions of using CCF: It can effectively be used to indicate some relationship between variables but much more informative is the effect of causal relationships, which were determined by a VAR model.

For the VAR model, the importance of multicollinearity was emphasised during the verification session. After the session, the effect of multicollinearity was introduced in the preparation phase of the model, rather than accounting for it during the actual model execution. This lead to an extra decision rule for determining which variables could be used in the VAR model. This important consideration has reduced the size of the model by decreasing the amount of possible indicators being tested, but has a beneficial effect on the accuracy and size of the explanatory power of the leading indicators.

6.2 Validation of the model output

For the Forecasting Support System to provide relevant information for the forecasting process, validation of the model output was performed. By performing an ex post forecast and validating the output with users of the information dashboard – the visual output of the model – the accuracy and the appropriateness of the system can be validated. Chapter 6.2.1 describes the method and results of the ex post forecast and Chapter 6.2.2 reviews the validation session with the user of the system.

6.2.1 Ex post forecasting the leading indicators

As shown in Figure 6-1, an ex post forecast comprises of forecasting several time periods within the current data set. This makes it possible to evaluate the accuracy of the forecast based on the observations that have already been recorded. After this, ex ante forecasting can be performed to forecast into the future and supply information that are used for the information dashboard.

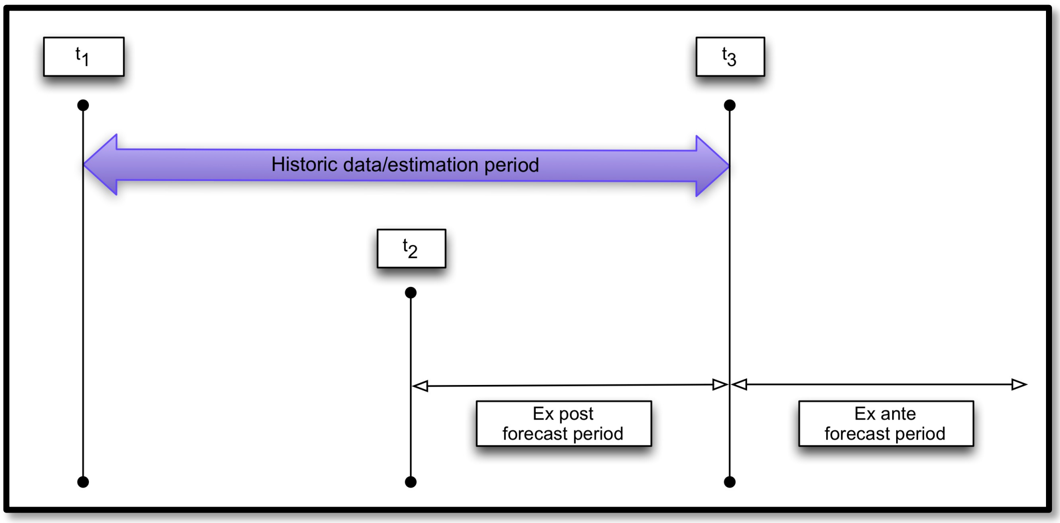
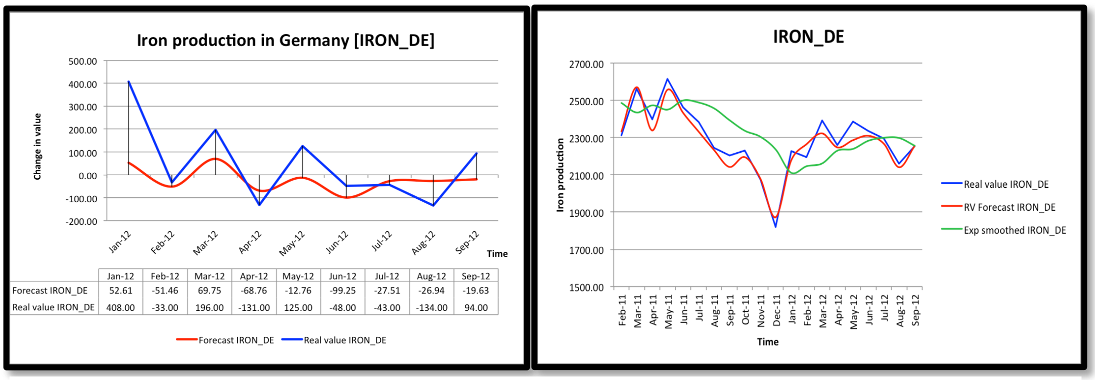


Figure 6-1: Ex post forecasting (adapted from (Pindyck & Rubinfield, 1998))

The estimation period that was used for ex post forecasting ranges from January 2012 to September 2012, so this includes the latest data available. The forecast for each variable was put alongside observed data points and the information was plotted in a line graph. Figure 6-2 shows the result for the forecasts of Iron Production in Germany, from the Coal model.

The forecast of Iron Production in Germany (in red) is a good estimation of real observations made. The line graph shows figures expressed as changes, as the VAR model uses differenced time series for analysing relationships between variables. Because the aim of this research is to provide a forecast of the trend of the leading indicators, the deviation of the forecast is not as important as the trend that the forecast shows. Therefore, it is important to analyse whether or not the trend is of the forecast aligns with the observations made. Peaks in observations in March 2012 and May 2012 are well forecasted by the model, indicating that the model is useful for forecasting leading indicators.



	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12
Forecast IRON_DE	52.61	-51.46	69.75	-68.76	-12.76	-99.25	-27.51	-26.94	-19.63
Real value IRON_DE	408.00	-33.00	196.00	-131.00	125.00	-48.00	-43.00	-134.00	94.00

Figure 6-2: VAR forecast and exponential smoothing vs. real values of IRON_DE

This Chapter shows line graphs for each of the leading indicators plotted along changes in the value. This is because the VAR model has used differenced time series and the values are therefore expressed as changes. For the verification and validation this can be beneficial because it allows change values to be compared with forecasted change values. After verification and validation, line graphs are plotted on axis displaying real values (corresponding to the original scale of the time series), so that the forecasts are better interpretable.

Overall, the trends of the leading indicators are well forecasted by the VAR models, often showing good alignments between the forecasts and the observed values. Major events in May 2012 and July 2012 have distorted the forecasts, causing them to be off target occasionally. The collapse of the Dutch Cabinet under Mark Rutte in April 2012 and the announcement of JPMorgans' $5.8billion loss in May 2012 and the decision made by the European Central Bank (ECB) in July 2912 to lower lending rates for banks have had large impact on the leading indicators, especially on the Consumer Confidence in the Netherlands. The dependency of the collapse can partly be accounted for by the amount of US stock and bonds that Europeans own (roughly one third of US stocks and bonds for non-residents). The lowering of the lending rate by the ECB has resulted in a regain of Consumer Confidence after July 2012 and as a result, companies have sold redundant stock from previous months. Iron Production in Germany has been relatively unaffected by these changes in the financial markets and the forecasts show stable development along the time frame.

Concluding, the leading indicators have shown to be accurate forecasts for the trend of the time series. As was expected, certain sudden peaks and troughs have been hard to be picked up by the forecasts. The line graphs show evidence of this as the leading indicators have had little predictive power at major events in the historic timeline. Generally speaking, such 'Black Swan' events have not been picked up well by the forecasts, but predicting these events is very difficult. Black Swan events have a great impact on the system; it concerns any type of trigger and the results of these events lie outside the realm of regular expectations (Taleb, 2010). Many examples are related to economic impact, environmental changes or changes in demography and society. Walker set out some examples such as the global recession of 2009 (started by the mortgage crisis of 2007) and the earthquake in Japan in 2011, causing a tsunami and nuclear catastrophe, thereby hindering supply chain operations of companies all over the world (Walker, 2011).

6.2.2 Measures of forecasting accuracy

Besides visually inspecting the line graphs of the forecasts, certain measures can help to statistically represent the accuracy of the ex post forecasts. Several accuracy measures can be used for this purpose, depending on the scale of the data and their values. Measures such as the Mean Square Error (MSE) and Mean Absolute Error (MAE) are scale dependent measures and therefore cannot be used to compare forecast accuracy across data sets that have different scales (Hyndman & Koehler, 2005). Therefore, these methods are not applicable at the moment for the output of the VAR model. For example, Consumer Confidence and Iron Production are measured in different values. Furthermore, the forecasts would have to be expressed in real values, rather than differences.

Scale independent measures, such as the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Percentage Error (RMSPE), do allow forecasts to be compared between different series. However, as is stated by Hyndman & Koehler (2005), time series that hover around the zero line are not suitable for analysis. This is because the percentages are based on calculations that divide by the real values. If these values are zero, or close to zero, dividing by a small number would yield a large forecast error, while the actual error between the forecast and the real value might be relatively small. When the time series are converted to show real values as the scale, some variables still hover around zero. This is due to the fact that the variables are constructed this way by the institutions that develop the statistics.

Therefore, it has been decided to not use these measure to compare forecasts but to compare forecasts over a set time period with another time series analysis method; exponential smoothing. This method is often used in time series analysis and provides a smoothed trend over the corresponding time period. An exponential component assigns a weight to values that are most recent, thereby putting more emphasis on the latest data available. The fact that the trend is forecasted by the methods makes it applicable here for comparing the results of the VAR model, and for this reason it was decided to use the exponential smoothing method.

For evaluating forecasting accuracy by comparison to exponential smoothing, the time series of the leading indicators have been expressed in real values, so that the output of the accuracy measures is directly related to the real values of the variables. Comparing the VAR output with the exponential smoothing for each variable allows scale dependent accuracy measures to be used. Percentage errors are not possible as the time series still hover around zero. The Mean Absolute Error (MAE) and the Mean Relative Absolute Error (MRAE) have been calculated and the results are shown in Table 6-1. Calculating the MAE allows us to get an indication of the accuracy of the forecasts in absolute values and the MRAE provides absolute errors relative to the forecasted values. Both measures are used to evaluate if the VAR model is more accurate at forecasting values than the exponential smoothing method.

		MAE		MRAE	
		VAR model	Exp. Smoothing	VAR model	Exp. Smoothing
Agribulk	CC_DE	0.74	2.87	0.53	1.19
Iron Ore & Scrap	CC_NL	1.57	5.83	0.02	0.55
	EXP_ST	1.26	2.12	0.80	0.84
	IC_EU	0.83	3.13	0.15	1.34
	IRON_DE	155.69	130.39	0.06	0.02
Coal	CC_NL	1.81	5.83	0.16	0.55
	IRON_DE	38.57	130.39	0.01	0.02

Table 6-1: MAE and MRAE test results

The results show that, in general, the VAR model is more accurate at forecasting values than the exponential smoothing method. Both the MAE and the MRAE show lower absolute errors for the VAR model. In the case of the Agribulk model, where Consumer Confidence in Germany is the leading indicator, the MAE for the VAR model is 0.74, compared to 2.87 for the exponential smoothing method. This indicates that the forecast made by the VAR model is, on average, 0.74 off target from the real value. For the exponential smoothing method, this is 2.87. For the MRAE, where the errors are relative to the real values, the results show 0.53 versus 1.19. As is visually also shown in the figures below, the forecast of the VAR model are more accurate forecasts than the exponential smoothing method. Below, each of the VAR model results are shown categorised per throughput good.

Agribulk VAR model

The leading indicator for Agribulk throughput, Consumer Confidence in Germany, shows a relatively good trend that is forecasted compared to the real observations made. The trend is well followed as from February 2012 (see Figure 6-3). An exception occurs in May 2012 and the two months following. First, a peak in real values in May 2012, and afterward a declining trend whereas the forecast remains steady. The relationship between Consumer Confidence and Agribulk throughput was not immediately recognised as being a logical relationship by the experts at the PoR. This could be due to the fact that little knowledge about leading indicators for Agribulk throughput are know and statistical analysis has shown that Consumer Confidence is in fact a leading indicator for Agribulk throughput.

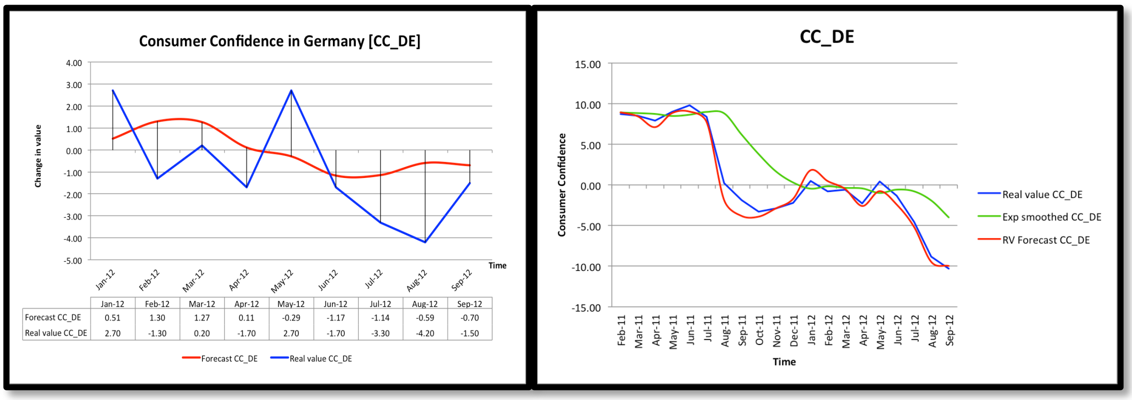


Figure 6-3: VAR forecast and exponential smoothing forecast vs. real values of CC_DE

Iron Ore & Scrap VAR model

When focusing on the leading indicators for Iron Ore & Scrap throughput, Consumer Confidence in the Netherlands shows a decent forecast when compared to observed values.

The general trend of the line is forecasted well and again, sudden changes are not picked up by the forecast. This was expected before performing the VAR model as the model is based on a complete time series, mainly to satisfy the minimum amount of observations requirement for VAR modelling. Therefore, a general trend is forecasted well but peaks and troughs are hard to forecast (Figure 6-4). However, the forecasting process at the PoR use forecasts as support for their decision, these forecasts are not a replacement for the forecasts made by the forecasting process. As this leading indicator has a lead period of three months, the relationship between it an Iron Ore & Scrap products can be explained by the manufacturing industry and peoples' need for consumer products. The experts at the PoR substantiated this relationship, thereby validating this leading indicator.

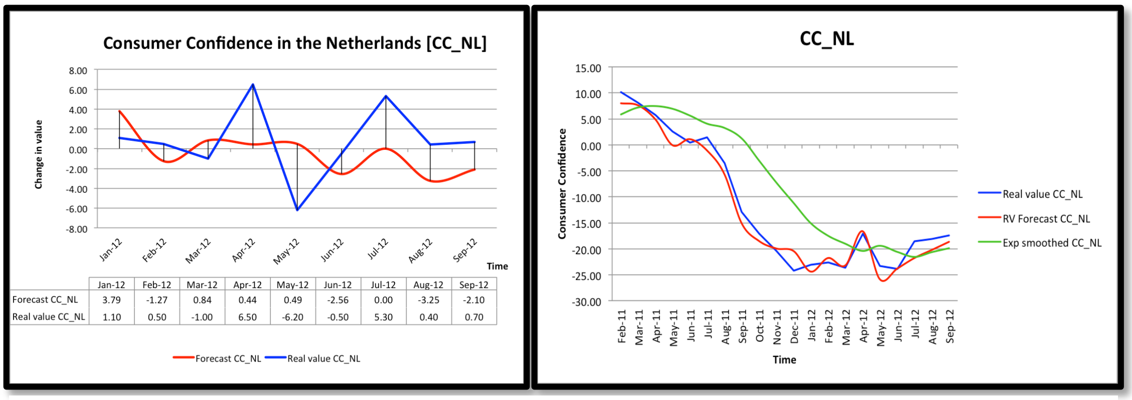


Figure 6-4: VAR forecast and exponential smoothing vs. real values of CC_NL

The expected stock levels of companies are very hard to forecast, as can be seen in Figure 6-5. This is due to the fact that the economic climate is very volatile at the moment, thereby causing projections about the future often to be off target. The forecast for Expected Stock in the Netherlands does give a reasonable indication of the trend but is not correct in forecasting the changes between May 2012 and July 2012. After consolidation with experts at the PoR and some market research, some logical explanations can be found for the sudden changes in May and July 2012. These changes in trend are recognisable in more of the leading indicators, not only this one.

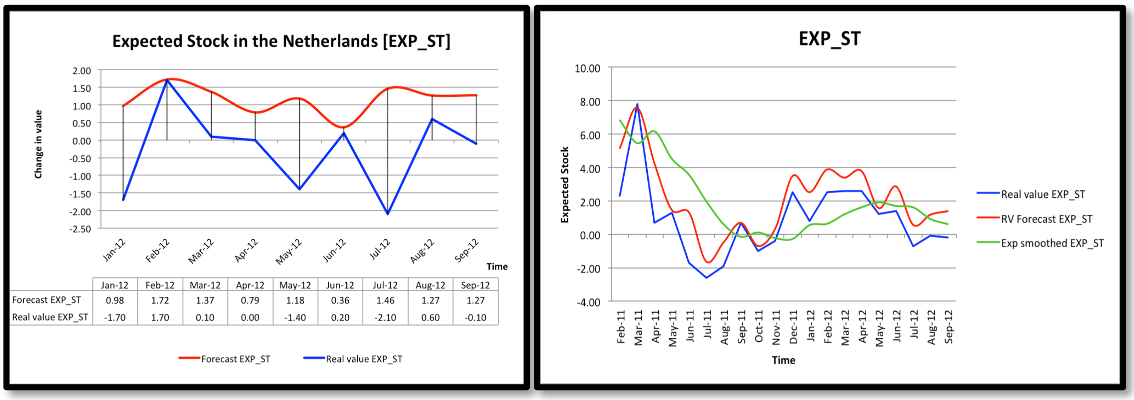


Figure 6-5: VAR forecast and exponential smoothing vs. real values of EXP_ST

One explanation for the negative change in stock – indicating that companies have too much stock in their warehouses for them to sell – is possibly the collapse of the Dutch government in April 2012, thereby plummeting Consumer Confidence in the Netherlands the next month (CBS, 2012). When Consumer Confidence is low, companies have low sales levels and as a result do not sell their stock, causing it to build up (indicated by a negative trend in the graph). Another cause of Consumer Confidence and therefore also Expected Stock to decline is the announcement by JPMorgan Chase concerning their $5.8billion loss in May 2012 (CNN Money, 2012). The interconnectedness and mutual dependency of the American and European markets account for this rapid response. Trade between Europe and the United States has developed enormously over the last decades, as 12% of Europe's imports come from the United States, whereas 18% of imports into the United States come from Europe. Furthermore, the American financial system has turned into a global financial system and Europeans own over a third of all US stocks and bonds for non-residents (Draghi, 2008). This implicates that market fluctuations in the United States, such as the JPMorgan news, have large effects on consumers in Europe, especially the ones that own bonds and stocks in America. This is further reflected by the demand for products and thus explains the further decrease in the balance of stock not being sold by companies.

The forecasts being off target in July 2012 can possibly be accounted for by the deterioration of the Euro crisis and the subsequent action by the European Central Bank (ECB) by lowering its lending rates in order to stimulate the economy and regain the flow of credit in the market (Black & Randow, 2012). This allows banks and therefore consumers to lend money at a lower rate, increasing the amount of mortgage applications, loans and credit card spending. As a result of the ECB's decision, a clear increase in Consumer Confidence in the Netherlands is shown in July 2012 and the Expected Stock level increase rapidly the next month, after consumers have regained confidence and are prepared to buy goods and products. This has reduced the amount of stock not being sold by companies.

Industrial Confidence in Europe is also severely affected by changing economic markets and therefore the forecast for this leading indicator is off target in May, as well as some other months (see Figure 6-6). The general downward trend is forecasted reasonably and especially the previous three months have seen an accurate forecast being made. Forecasters at the PoR have recognised the Industrial Confidence indicator as an important indicator for throughput in Rotterdam but pose that, as is confirmed by the results, the indicator is too general to be a very accurate estimator for Iron Ore & Scrap throughput. As the indicator includes Confidence levels for all EU countries, the amount of explanatory power for Rotterdam is too weak.

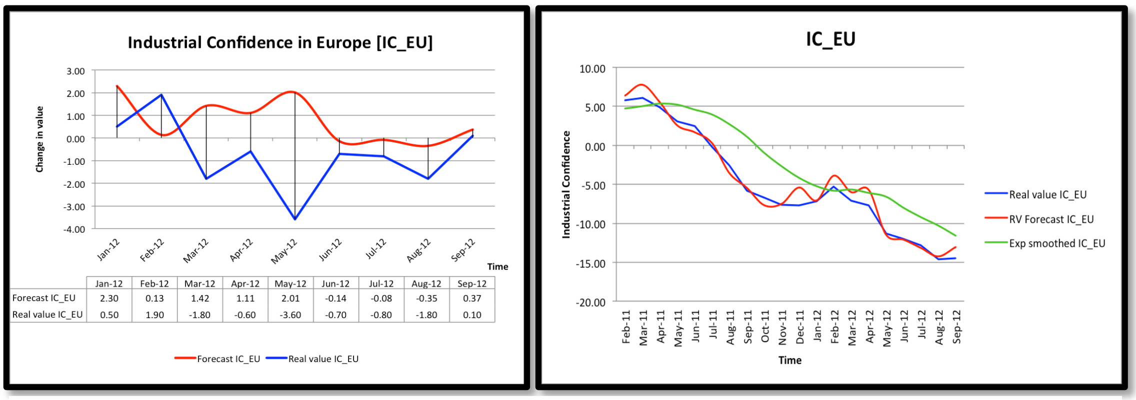
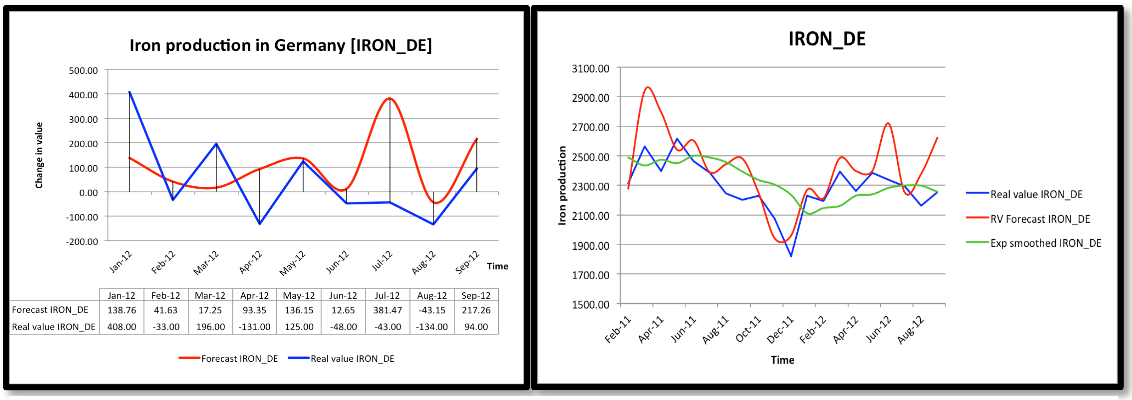


Figure 6-6: VAR forecast and exponential smoothing vs. real values of IC_EU

Iron Production in Germany from the Iron Ore & Scrap model shows a more stable forecast that is not as much affected by the changes in financial markets as the other indicators. The general trend of the forecast is well shown, with a single peak in July 2012. Again, it could be that case of sudden market changes that might have had en effect, such as last minute cancelations of transport of raw materials for the production of iron.



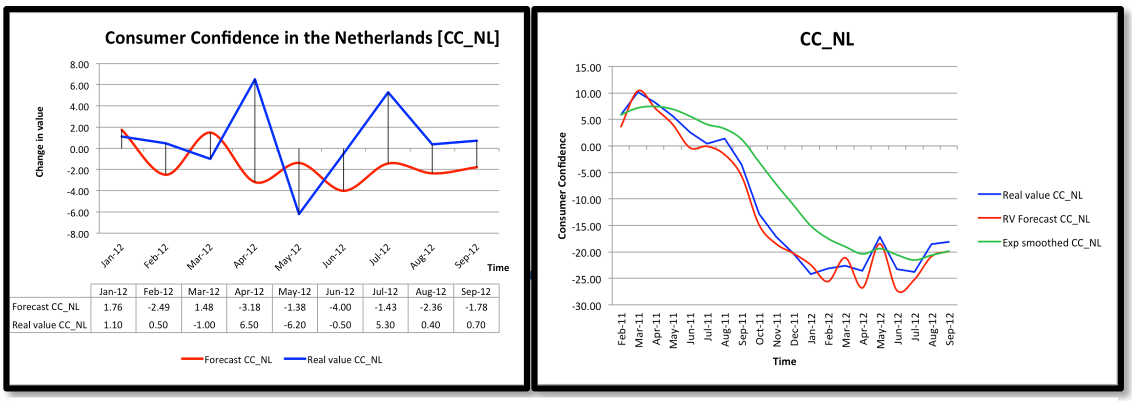
	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12
Forecast IRON_DE	138.76	41.63	17.25	93.35	136.15	12.65	381.47	-43.15	217.26
Real value IRON_DE	408.00	-33.00	196.00	-131.00	125.00	-48.00	-43.00	-134.00	94.00

Figure 6-7: VAR forecast and exponential smoothing vs. real values IRON_DE

estimates are more accurate than the VAR model (Figure 6-7). This has been due to the fact that the VAR model has not correctly forecasted the value for June 2012, resulting in a larger average error. Although, the difference between the errors is minimal, and this expresses the difference in absolute values, the VAR model does still represent a better forecast when consulting the line graph. Changes in direction, peaks and troughs are anticipated better by the VAR model, as can be seen in Figure 6-3. This immediately describes a negative side of using accuracy measures for these forecasting models. Because the absolute error is calculated between values, no attention is given to the forecasts actually forecasting a trend that aligns with the real values. It can be concluded that the VAR models, in most cases, provide a more accurate forecast of the real values. In all cases analysed, the line graphs show that the VAR model is more accurate that the exponential smoothing method in forecasting changes in the direction of the trend.

Coal VAR model

As was seen in the forecast for Consumer Confidence the Netherlands in the Iron Ore & Scrap model, the general trend is forecasted reasonably well. The real values in blue are the same for this graph and the previous one, but the forecast is different. This is due to the fact that the VAR model uses different coefficients in this model, thereby creating a different forecast. Again, a plummeting Consumer Confidence in May 2012 has caused the forecast to be off target. Good news from the ECB has shown an increase in Consumer Confidence and this is reflected by the graph of the forecast. Experts at the PoR have confirmed that this leading indicator is very volatile towards market changes but is a good indicator for the throughput of Coals in the Port of Rotterdam.



	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12
Forecast CC_NL	1.76	-2.49	1.48	-3.18	-1.38	-4.00	-1.43	-2.36	-1.78
Real value CC_NL	1.10	0.50	-1.00	6.50	-6.20	-0.50	5.30	0.40	0.70

Figure 6-8: VAR forecast and exponential smoothing vs. real values of CC_NL

Iron Production in Germany is the second leading indicator for the Coal model. The graphs have been discussed in Chapter 6.2.1 and are not discussed any further in this Chapter.

6.2.3 Validation with dry bulk experts

Two validation sessions with experts at the PoR were carried out, at different stages of the research. The first session took place after an initial selection of variables to be used in the analysis. The list of market indicators was discussed with experts in terms of the indicators' relevance to the dry bulk market. From this session, the focus on indicators from the Netherlands, Germany, Europe, China and the world was acknowledged and experts confirmed certain indicators from these places were indicators for dry bulk goods. Furthermore, removing some initial indicators and adding indicators proposed by the experts amended the list. The result of this validation session led was the input for the first statistical analysis steps in this research, the preparation of data. The list of variables is shown in Table 5-1.

A second validation session discussed the results of the VAR model forecasts with experts and potential future users of the Forecasting Support System. Presenting the results (Figure 5-14) and the corresponding ex port forecasts in Chapter 6.2.2, forecasters immediately recognised relationships between the leading indicators and the dry bulk goods. The information in the results figure aligns with the market knowledge that experts have and use for making the dry bulk forecasts. This confirms that the VAR models have accurately reproduced the relationships in the market and that the causal relation of the leading indicators can be exposed by means of statistical analysis. The fact that the model has reiterated the relationships between leading indicators and dry bulk goods in the port, makes the model serve as an excellent support tool for the qualitative forecasting process at the PoR at the moment.

The leading indicators for Coal and Iron Ore & Scrap throughput were evaluated as being significant market developments that the experts can endorse. The fact that multiple leading indicators were revealed for the throughput of Iron Ore & Scrap was due to the fact that this category of products only comprises of products made from Iron Ore, thereby representing a very segregated type of product. This is opposite of the amount of leading indicators for Agribulk and Other dry bulk goods, as these categories comprise of a collection of multiple products an goods. The leading indicator for Coal throughput, Consumer Confidence in the Netherlands, was directly associated with demand for electricity in the Netherlands. The experts at the PoR clearly distinguish a relationship between electricity demand and Coal throughput in the port and would have liked to see this relationship be recognised by statistical analysis. The relationship between Consumer Confidence in Germany and the throughput in Agribulk was not directly identified as a logical relationship. This could be the start of a leading relationship that was not known before and the experts acknowledged that in future, the leading indicator could be tested for a continuing leading relationship and consulted for making a forecast for Agribulk throughput.

The validation session with the experts has shown that the VAR model has provided a good representation of the relationships that exist between the market developments and the throughput in the port. The model has reiterated the knowledge that experts have at the moment. According to the experts, room for improvement is visible in the Agribulk and Other dry bulk goods model, where only one leading indicator has been identified. These two product groups are very diverse and comprise of several products, making it very hard to identify relationships from market knowledge and information provided by the market. They feel that using more specific economic variables results in more concrete leading indicators being identifies for these goods. Several specific variables, such as harvest yield and electricity production in the Netherlands, were initially selected for use in this research but were removed from the analysis due to a lack of data. Therefore, a recommendation made by the experts for future research is to split up Agribulk and the Other dry bulk goods into specific products and produce a VAR model for these goods. A broader database with more data sources, possibly retrieved by paid subscription or from companies in this sector, can help to provide specific variables and dedicate a research project to Agribulk and Other dry bulk goods.

6.3 Conclusion

The verification and validation methods have shown that the VAR model can accurately and effectively identify and forecast the leading indicators. It has been shown that the tool is reliable and accurate, confirming research question 4. Although some peaks and troughs (some of them categorised as 'Black Swan' effects) have not been accurately picked up in the forecast, the trend of the leading indicators can provide adequate support for the forecasting process. Forecasting the trend is adequate when implementing the tool within a qualitative process, as the forecast determines the expected regular pattern of the indicator and it is up to expert judgement to explain and forecast any foreseeable events that might lead to irregularities in the expected values (Fildes & Goodwin, 2003). The balance between the use of qualitative and quantitative information needs to be considered carefully in order to provide a successful FSS for implementation at the PoR.

A validation session with experts at the PoR has resulted in acknowledgment that the VAR model can accurately represent market conditions and can identify leading indicators for dry bulk goods in the Port of Rotterdam. The model has reiterated knowledge about the leading indicators already known and has statistically substantiated what the experts know about the dry bulk markets.

PART III: THE FORECASTING SUPPORT SYSTEM

INTRODUCTION
CHAPTER 1

PART I: PRELIMINARY ANALYSIS
CHAPTER 2, 3 & 4

Research question 1:
What are strengths and weaknesses of short-term forecasting methods and what guidelines for the design of a FSS can be identified?

Research question 2:
What components of the current forecasting process indicate that a quantitative element can be added to improve the process?

PART II: DETERMINING THE LEADING INDICATORS
CHAPTER 5 & 6

Research question 3:
Which economic drivers can be identified as 'leading indicators'?

Research question 4:
Is the quantitative forecasting tool a reliable and accurate source of information to support the forecasting process?

PART III: THE FORECASTING SUPPORT SYSTEM
CHAPTER 7, 8 & 9

Research question 5:
How does the forecasting support system need to represent information, be implemented and be maintained to effectively support the forecasting process?

EVALUATION, CONCLUSIONS & RECOMMENDATIONS
CHAPTER 10 & 11

7. FORECASTS FROM THE VAR MODEL

After establishing the leading indicators for each of the four dry bulk goods and performing verification and validation on the model, forecasts are needed for the support system. After making the forecasts, the FSS can be implemented into the current forecasting process and attention can be turned to the maintainability and extension of the model, as stated in research question 5:

How does the Forecasting Support System need to represent information, be implemented and be maintained to effectively support the forecasting process?

Making a forecast for the leading indicator sets a direction of the expected trend and the effect on the dry bulk good can then be shown. This way, the Forecasting Support System and the information dashboard can support the process at the PoR without interfering with current work performed by the experts. Together with expert knowledge and experience, the individual forecasts of the leading indicators are to be transformed into a forecast for one of the dry bulk goods (see Figure 4-2).

Using the VAR model for forecasting has some advantages over using other methods. First, the coefficients that the model estimates for the dependent throughput good are also estimated for all of the independent goods. So the VAR model actually estimates 8x4=32 models, taking each variable as the dependent variable once. This allows the leading indicators to be forecasted based on the coefficients from the model; no extra forecasting tool has to be used. Secondly, the use of the coefficients for forecasting and their dependency on previous data values ensures that the VAR model estimates a non-linear trend. This is much more explanatory than a linear trend and can help the forecasters by displaying a direction of the trend that is influenced by recent observations, thereby making it adaptive and allowing it to present changes in the direction of the trend. A third advantage of the VAR model is the ease of use, especially because the model can be used at the PoR to determine leading indicators for other goods in the port and forecast them to support the forecasting process for these goods, for example containers and liquid bulk goods. Using the same model for both purposes is effective and delivers accurate results that align each other. If a different forecasting tool is used, the forecast might not align with the underlying trend of the data, determined by another method, and thereby create inaccurate results.

From the VAR model, the following leading indicators have been identified and they are forecasted in order to help support the forecasting process at the PoR. The significant leading indicators are:

Agribulk	Iron Ore & Scrap	Coal	Other dry bulk goods
CC_DE	CC_NL EXP_ST IC_EU IRON_DE	CC_NL IRON_DE	

Table 7-1: Leading indicators for the throughput goods

Forecasting the leading indicators requires the time series to be up to date. Chapter 7.1 elaborates on the preparation of data for forecasting. Chapter 7.2 shows the method and results of the forecasts. A conclusion in Chapter 7.4 rounds up this Chapter.

7.1 Preparation of data

Because the VAR model estimates coefficients for each of the included lag periods and a forecast is made by multiplying these coefficients by the data values, the time series need to be up to date. As was shown by Akaike's Information Criterion the model would incorporate either 1-month lag or 3-month lag time. This means that in order to forecast a variable the latest and the three latest figures need to be known. For this reason, the decision rules in Chapter 5.3.1 included rule 5, demanding time series to be up to date. Because all variables are included in making a forecast for one leading indicator, every time series needs to be up to date.

The data points from January 2012 to September 2012 were included in the time series, allowing the months October, November and December to be forecasted by the model. The data for 2012 was retrieved from the same sources as the original time series came from.

7.2 Forecasting the leading indicators

A complete data set has been used for making forecasts of the leading indicators. The results of the forecasts are vital for the information dashboard that is to be used by the experts. An indication is given concerning the trend of the data as well as a forecast for the coming three months is provided. This allows forecasters to get a good understanding of the development of the leading indicator over time.

The forecast for Consumer Confidence in the Netherlands from the Iron Ore & Scrap VAR model is based on the coefficients of the model. A forecast can be made by replacing past observations of the variables with their variable code. For making a forecast for October 2012, the data values for September, August and July of CC_DE, CC_NL itself, EXP_BE etc. are needed and are multiplied with the coefficient. The VAR model also estimates a constant for the equation (0.299).

CC_NL = 0.299 + (0.087*CC_DE_{t-1}) + (0.106*CC_DE_{t-2}) + (0.118*CC_DE_{t-3}) + (-0.126*CC_NL_{t-1}) + (-0.123*CC_NL_{t-2}) + (-0.031*CC_NL_{t-3}) + (0.235*EXP_BE_{t-1}) + (0.094*EXP_BE_{t-2}) + (-0.014*EXP_BE_{t-3}) + (0.280*EXP_ST_{t-1}) + (0.254*EXP_ST_{t-2}) + (0.018*EXP_ST_{t-3}) + (0.714*IC_EU_{t-1}) + (-0.120*IC_EU_{t-2}) + (0.082*IC_EU_{t-3}) + (-0.005*$IRON\_DE_{t-1}$) + (0.000*$IRON\_DE_{t-2}$) + (0.004*$IRON\_DE_{t-3}$) + (-0.018*$WORLDTRADE_{t-1}$) + (-0.048*$WORLDTRADE_{t-2}$) + (-0.305*$WORLDTRADE_{t-3}$) + (0.034*$IRONORE_{t-1}$) + (0.001*$IRONORE_{t-2}$) + (0.000*$IRONORE_{t-3}$)

The forecast for Consumer Confidence in the Netherlands, in Figure 7-1, is continuing an upward trend from a down point in May and June 2012. The forecast is very accurate over the last nine months. A slight misfit exists in the forecast for June 2012 and, as discussed in the previous Chapter, this is due to several political and economic situations and the build up towards it. The downward trend towards May 2012 indicates consumers may have seen the political situations coming and have not been optimistic about the future months of the economy. Consumer Confidence has proven to be a very volatile indicator, relying heavily on consumers feeling. Evaluating the forecasts with current values shows another sudden drop in consumer confidence in October and November and this can be explained by the instable political climate in the Netherlands at the moment. A new government is proposing policy measures for the coming years, thereby focusing on reducing the country's debt levels. One of these measures, the idea of an income dependent health insurance price, has had a large impact on people's expectations about the future, thereby plummeting consumer confidence. These sudden shocks, as was the case because the policy came as a surprise to many people in the Netherlands, has ensured that the forecast is not accurate for the months September and October.

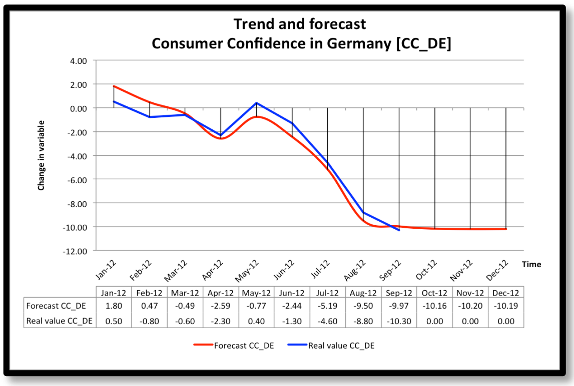


Figure 7-2: Trend and forecast of Consumer Confidence in the Germany

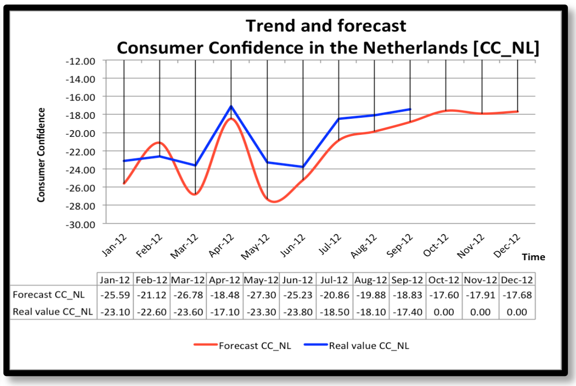


Figure 7-1: Trend and forecast of Consumer Confidence in the Netherlands

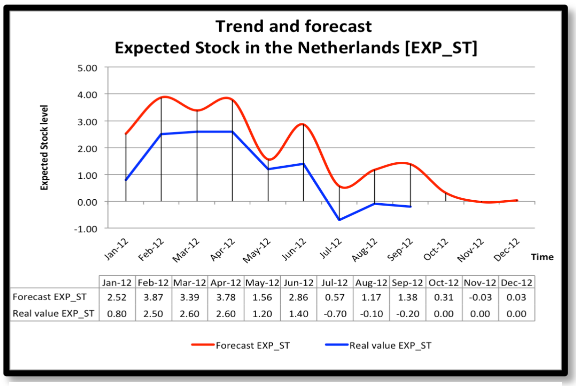


Figure 7-6: Trend and forecast of Expected Stock in the Netherlands

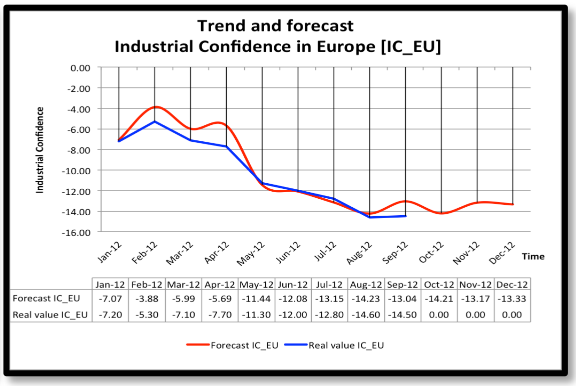


Figure 7-5: Trend and forecast of Industrial Confidence in Europe

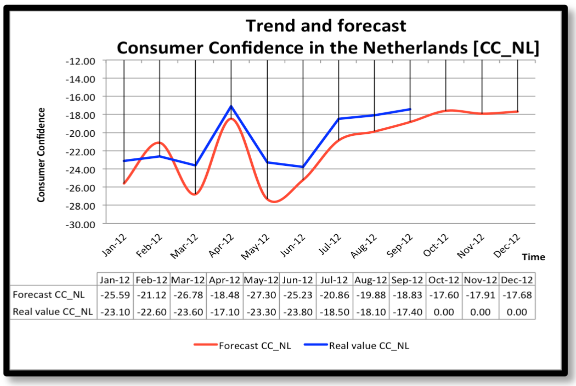


Figure 7-3: Trend and forecast of Iron Production in Germany

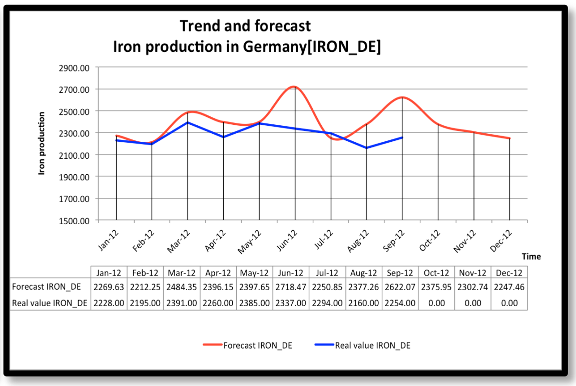
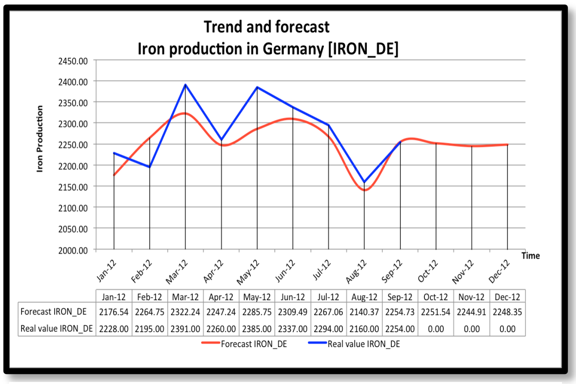


Figure 7-4: Trend and forecast of Consumer Confidence in the Netherlands



	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12
Forecast IRON_DE	2176.54	2264.75	2322.24	2247.24	2285.75	2309.49	2267.06	2140.37	2254.73	2251.54	2244.91	2248.35
Real value IRON_DE	2228.00	2195.00	2391.00	2260.00	2385.00	2337.00	2294.00	2160.00	2254.00	0.00	0.00	0.00

Figure 7-7: Trend and forecast of Iron Production in Germany

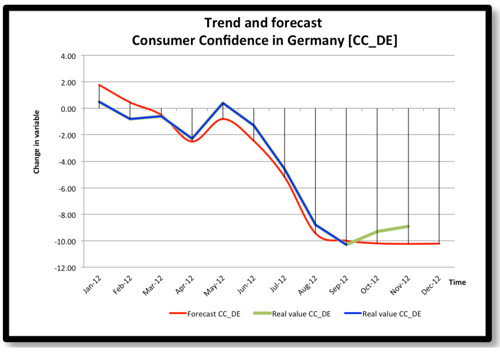
The forecasts above have been made according to the coefficients of the VAR model. As can be seen, some market variables are leading indicators for two throughput goods and show a different forecast (Consumer Confidence in the Netherlands and Iron Production in Germany). This is because the forecasts are made using all the variables in the VAR model and the coefficients of the variables are different for each model.

7.3 Validating the forecasts

To determine the accuracy of these forecasts not only based on statistical tests and validations from dry bulk experts, some leading indicator forecasts are compared to forecasts made by other companies or institutions. Many statistical database companies, such as the CBS in the Netherlands, GfK in Germany and Eurostat for the EU countries, provide some forecasts on these leading indicators in their databases.

It must be noted that there is no information on the method that these companies use to make these forecasts and whether or not their time series are based on the same information. A first indication confirms this as the scales used are different and elaboration on the indicators has revealed that these forecasts include other measurements. For example, calculating Consumer Confidence can be based on many statistics such as willingness to buy, economic expectations or consumers' assessment of their current and expected future financial situation.

The forecast for Consumer Confidence in Germany has been evaluated using multiple sources of information. Figure 7-8 shows the forecast for the coming three months made by the VAR model. The forecast shows little changes in the indicator. A forecast made by the Dow Jones & Company, reported in a press release by www.treasury.nl, also indicates unchanged expectation of the indicator as supposed to the previous month (treassury.nl, 2012). The expectation for November 2012, made by the GfK, is set to increase slightly as supposed to October (GfK, 2012). The forecast made by the VAR model indicates a very small decrease is expected (from -10.16 to -10.20 in November). Although the general trends of the forecasts are good to compare, the indicators provide a forecast based on very different information. The build up of the indicators is different, which doesn't allow a complete comparison of the two indicators. The green line indicates actual values that have been added after the forecasts have been made. This shows the forecast of the GfK is accurate as a slight increase is present. The VAR model has also produced an accurate forecast compared to the added values. Having estimated the VAR model with the same statistics as the other forecasts made would have yielded a comparable forecast, but the information that these companies use is not available for public use.




Duits consumentenvertrouwen oktober ongewijzigd

25 september, 2012 in Nieuws door onze redactie

door onze redactie

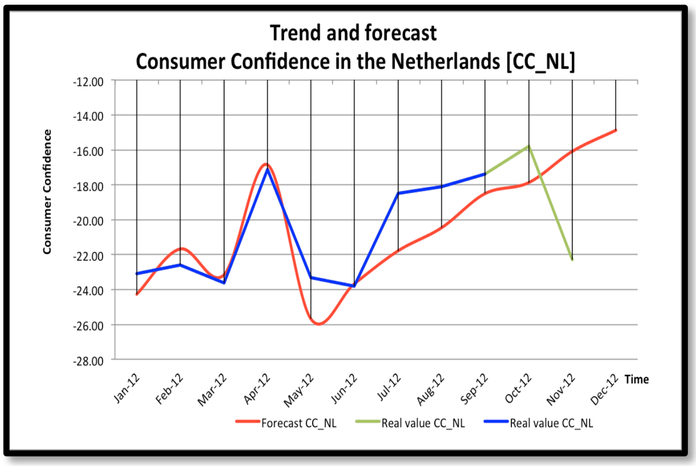
Dow Jones - Het Duitse consumentenvertrouwen is in oktober conform de verwachting ongewijzigd ten opzichte van een maand eerder, blijkt dinsdag uit de indicator van onderzoeksgroep GfK, die een vooruitblik geeft voor het Duitse consumentenvertrouwen.

Voor oktober komt de indicator uit op 5,9, gelijk aan een maand eerder. In september noteerde de index ook ongewijzigd ten opzichte van de maand ervoor.

Figure 7-8: Forecast of Consumer Confidence in Germany and corresponding press release (treassury.nl, 2012)

The real values for October have indicated that consumer climate in Germany has increased slightly in October 2012. As is concluded, every forecast can explain some of the expected trend, but a small error in the forecast is always present in quantitative forecasting. As the indicators are constructed using several consumer information sources, it is hard to exactly determine the cause of the increase and determine whether qualitative judgement would have seen the increase coming.

As described in Chapter 7.2 and shown Figure 7-1, the forecast for Consumer Confidence in the Netherlands is very volatile to the political situation in the Netherlands. A press release by the CBS indicates a sudden decline in the confidence indicator in October. The policy measures of the new government can be accounted largely for this decline. Figure 7-9 shows the line graph of Consumer Confidence in the Netherlands and the corresponding press release. The green line indicates real values after the forecast has been made.




Economie / Geldzaken

Gepubliceerd: 20 november 2012 10:20
Laatste update: 20 november 2012 10:59

Deel:

Consument nog veel somberder

DEN HAAG - Consumenten waren veel negatiever over de toekomstige economie en over hun toekomstige financiële situatie dan in oktober.

Foto: ANP

Dat blijkt uit dinsdag bekendgemaakte cijfers van het Centraal Bureau voor de Statistiek (CBS).

De indicator van het consumentenvertrouwen daalde 5 punten en kwam uit op -37. Daarmee is het vertrouwen erg laag. Het gemiddelde over de afgelopen 20 jaar komt uit op ongeveer -8.

Consumenten waren vooral over hun eigen financiële situatie in de komende 12 maanden stukken somberder dan vorige maand. Deze indicator verslechterde 12 punten en kwam uit op -32, de laagste stand ooit.

Figure 7-9: Forecast of Consumer Confidence in the Netherlands and corresponding press release (CBS, 2012)

Although the statistics used for this research come from the Eurostat database and therefore the indicator is calculated differently, the general trend is still similar. Therefore the sudden drop in Consumer Confidence is visible in both statistics. Because it concerns a sudden drop in values, this was unexpected for by the VAR model forecast. The increase in April has been correctly represented by the forecast because the Forecasting dashboard aligns previous made forecasts with previous observations. This way, previous values always align better than forecasts into the future. The coefficients that have been used for the line graphs have been verified, creating a better fit of the line.

Although not many forecasts have been made available to public information sources, based on the forecast of Consumer Confidence in Germany and in the Netherlands, the VAR model presents a good forecast that can be trusted and used for decision making processes.

7.4 Conclusion

In this Chapter, the process of forecasting the leading indicators has been discussed. Due to the fact that the VAR model requires stationary (differenced) time series to be used, the output is displayed in changes of the indicator. Graphs represented here, and that are used for the information dashboard, have been transformed to show real values of the indicators. This has been done so that forecasts and real values can be compared to other information sources such as the information that the experts retrieve from customers and news sources. Making the information comparable by providing the same scale are imperative for developing user's trust in the system, which eventually leads to them using the model regularly. To be able to implement the information into a dashboard that can support the forecasting process, the forecasts of changes need to be converted into a forecast of real values. This makes interpretation of the information easier and the information in the graphs then directly corresponds to information from the market. The transformation is done in Chapter 8, where the design of the information dashboard is accounted for.

The VAR model has proved a useful tool for trend identification and forecasting. The results show that the trend can be forecast with good accuracy, although it must be said that the trend line does sometimes not indicate sudden peaks and troughs. However, for this research, the trend that has been identified by the VAR model corresponds to market developments and is therefore a good representation of the real values of the leading indicator. A forecasting process that also include a human side to making the forecast can be considerably improved by consulting the Forecasting Support System and the information dashboard.

8. DESIGN OF AN INFORMATION DASHBOARD

The Forecasting Support System provides accurate and relevant information for supporting the forecasting process at the PoR. One of the last challenges is to display this information in a dashboard that can be used when the forecasting process is being executed. The information dashboard is available during all times and must contain data and statistics that are relevant for making forecasting decisions. This requires careful consideration for the design of the dashboard, as the information provided needs to be convincing and trustworthy for the users. Guidelines for designing a 'trustworthy' system have been discussed and attention can now be turned to specific design requirements for the information dashboard.

Basic requirements for the dashboard have been set up according to the research that has been performed and the data that has been gathered. The requirements delineate a possible dashboard design and indicate to experts what the dashboard in future might look like. Working with the dashboard proves whether or not the dashboard fits the expectations of users and therefore it might take some time before the dashboard is fully developed to the needs and wants of the users. This Chapter poses a preliminary design of the dashboard. The FSS to be designed can be characterised as a model driven FSS, visually represented in a spreadsheet based environment. A spreadsheet model has been designed for the following reasons (Power & Sharda, 2007):

- Spreadsheets are appropriate tools for building a FSS because several sub models or information pages can be presented in the worksheets
- Users of the model have knowledge about the software and can reconfigure the system if needed, to display desired information about the forecasts.

The next Chapter describes the implementation, evaluation and maintenance of the Forecasting Support System into the forecasting process and describes any changes to the dashboard after performing a first verification and validation session of the dashboard. After the design of the information dashboard, it is added to the Forecasting Support System so that it can fully support the forecasting process at the PoR.

Chapter 8.1 states the requirements for the design of an information dashboard, where the following Chapter sets out the design of the dashboard and how some features of the preliminary design (Chapter 8.2). A conclusion in Chapter 8.3 rounds up this Chapter and reiterates some important conclusions from the work performed in this section.

8.1 Design requirements

The previous Chapters have shown that when making a forecast, attention must be given to the set up and method of the analysis. When designing an information dashboard that provides data on the forecasted time series, certain design requirements must be identified so that a preliminary design can be made. The requirements posted below indicate a possible design for the dashboard. Evaluation and feedback after implementation of the dashboard state whether the design is most optimal and indicates if changes to the design are needed to provide more relevant or other information. Therefore, only preliminary design requirements are stated here. Verifying whether the requirements have been met can be done after implementation of the FSS and dashboard. This is because the verification is based on the user's experience with use of the model and the overall satisfaction.

These requirements delineate the design of the dashboard, which can be seen as a decision support tool (DSS) on its own. The fact that it is focused on forecasting and supporting a forecasting process means the information dashboard is integrated into the Forecasting Support System. Setting up design requirements for a DSS requires careful consideration and was done according to a well-known framework. Keen and Sol (2008) identify requirements for decision support systems and their framework is applied here. Three terms that a successful DSS should contain are:

- Usefulness;
- Usability;
- Usage.

Hence, the requirements that have been identified add to one of these aspects. The three terms are clarified below together with their corresponding requirements.

Usefulness

The goal of the dashboard is to provide support for the forecasting process. If the availability of the dashboard leads to better and more accurate decision-making then this adds to the usefulness of the tool. The information dashboard is primarily used for supporting decisions of the users, not to make decisions for them. Therefore, the users must get a quick overview of what leading indicators are affecting the dry bulk good being forecasted. Information such as the strength and direction of the influence, the lag period and previous errors is vital information for assessing the supporting role of leading indicators. It is vital that the DSS does not show a forecast for the dry bulk goods, as this is what the experts are responsible for. The power of this new forecasting process lies in combining qualitative and quantitative forecasts and the experts can combine the information and make a forecast. To make interpretation for the users as clear as possible, the information in the dashboard needs to be presented in its original scale. Because the VAR model has resulted in output in 'changes' in the variables, this information needs to be converted. This also makes it possible to get a richer understanding of the market developments of this leading indicator. The last two requirements state the scope of the forecasts. A three-month forecast is required, as the forecasting process is done every quarter and a twelve-month history of the forecasts made can give a good indication of the trend that is proposed by the forecast. The following requirements for the dashboard have been identified:

Requirements to add to 'Usefulness' of the dashboard
1. The user must be able to get a quick overview of the following:
– Leading indicators that have a proven statistical influence on the throughput of dry bulk goods.
– The number of leading indicators that affect a certain type of dry bulk good.
– The trend and direction of this leading indicator (forecast).
– The trend and real values of the leading indicator over the last twelve months
– The forecasting errors made by the model over the last twelve months.
2. The DSS must not include information concerning a forecast for the dry bulk good.
3. Information about the leading indicators must be provided in the original scale.
4. Forecasts for the leading indicators must concern a three-month future forecast.
5. The forecasted trend should cover at least the previous twelve months.

Table 8-1: Requirements for the Usefulness of the dashboard

Usability

The DSS is to be implemented within the process of forecasting at the PoR, but the success of this depends on the usability of the DSS. Experts are used to making a forecast based on mainly qualitative information but if the usability of the DSS is of a high standard, its use undoubtedly increases the accuracy and efficiency of decision-making at the PoR. The visual display of the dashboard is important for its usability, the aim is to provide users with a screen with information that can be understood at a glance and provide more information when studied when zooming in. An overview page can help to create a quick, complete view of the leading indicators. Other aspects that require attention are the type of information presented, especially concerning the type of graphs and information provided (Few, 2012). Using distinct colour coding, elements are quickly noticed and colours indicate the direction or expected change. For overview purposes, the amount of leading indicators for each dry bulk good is limited to four. Including more leading indicators is considered not to be orderly by the users of the information dashboard. Indication of which of these indicators benefit the most to the throughput of a dry bulk good is also vital to show in the dashboard. This has been set in requirement Uf_1. Lastly, the dashboard should be kept flexible and customisable so that users can request the information they desire. For this requirement, the use of Microsoft Excel is preferred, as users have much experience with using this software. Flexibility also add to the usability and frequency of use of the DSS (Swink, 1995); (Selby, 2005); (Benbassat & Dexter, 1982).

Requirements to add to 'Usability' of the dashboard
1. A dashboard overview page must summarise the most important information of each of the leading indicators.
2. The DSS should use colour coding for indicating direction of the forecast.
3. The number of leading indicators per type of good should be limited to 4 to maintain overview of the DSS.
4. The DSS should be customisable so that users can request specific information when desired.

Table 8-2: Requirements for the Usability of the dashboard

Usage

The third set of requirements corresponds to the usage of the dashboard, especially regarding the integration of the model into the current process. Analysis in Chapter 3.4.1 has shown that the information dashboard must be designed while keeping in mind the fact that it has to be integrated as a support to the process of exploring market developments and referencing the forecast (processes A2 and A3 in figure 3-4 on page 37). The 'Usage' requirements are set up to provide essentials for achieving successful integration and ensuring that forecasters adopt the support tool when making decisions. Although adaptation of the system is mainly dependent on organisational, social and psychological factors, certain design requirements can help to achieve this. The factors are different for every person and user must feel comfortable with using the tool. For example, one might not be very fond of graphs and might prefer tables with data. Based on these preferences, people may or may not feel comfortable with using the system. Some requirements that have been established are shown in Table 8-3.

Providing quantitative information in a way that user can 'digest' the data and use it for decision-making requires a mixed approach. Providing graphs and data table can help to ensure different preferences are accounted for. Furthermore, when users open the information dashboard, relevant information must be available first and underlying calculations and formulas can be consulted when moving down the page. This way, a quick overview is always present. Because the scope of this research is set to represent leading indicators, and the workplan forecasts concern total throughput of the dry bulk goods, a ‘bridging element’ must be designed to show the effect that the leading indicators have on the throughput goods. This information is vital for forecasters when they reference the forecasts in process A3 in figure 3-4 on page 37. Other aspects of implementing the system include using as much automatic processes as possible to make a forecast. Spreadsheet-based models are strong at automating calculations and this increases the ease of work for users. Furthermore, as the forecasting process at the PoR is conducted in Dutch and this is the predominant language used, the information dashboard also have to present information in Dutch.

Requirements to add to ‘Usage’ of the dashboard
1. The information dashboard must present quantitative information using both graphs and data tables.
2. A clear separation must be present between the output information and the underlying data and calculations.
3. An indication of the strength of the relationship between the leading indicator and the throughput good must be shown.
4. Updating the information dashboard should be automatically done when extending the time series.
5. A spreadsheet-based allows users to become familiar with the system and create understand the underlying model.
6. The information dashboard should present information in Dutch

Table 8-3: Requirements for the Usage of the dashboard

8.2 The information dashboard

The information dashboard has been designed to create a quick overview of all the leading indicators for the dry bulk goods and provide more detailed information when ‘zooming in’ on the information. A spreadsheet-based model allows several sheets to be used for

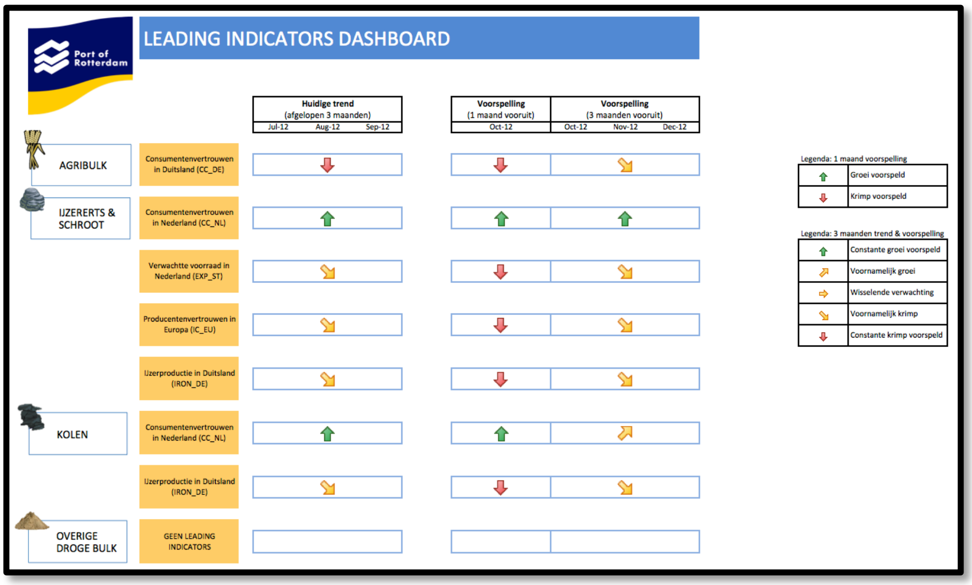


Figure 8-1: Information dashboard overview page

different representations. In this information dashboard, a main page provides a summarised representation of the three-month trend of the leading indicators, as well as a one-month and a three-month forecast. The main page is shown in Figure 8-1. The coloured arrows provide an indication of the current and expected trend of the leading indicator. The information to provide these indications comes from the forecast pages for each of the dry bulk goods, shown in Figure 8-2.

Information regarding the dry bulk goods is presented on their dedicated spreadsheet. Figure 8-2 shows the dashboard page for Coal throughput, which in design is similar to the other pages. Two leading indicators have been identified and are represented here. The information that is provided on these pages is the following:

- An indication of the magnitude that a leading indicator has on the dry bulk good, indicated on a scale from 1 to 6, whereby 6 indicates the strongest influence on the dependent good;
- A line graph showing the trend of the leading indicator over the last 9 months, together with a forecast line for the last 9 months as well as a forecast for the coming three months. A data table provides exact figures observed and forecasted. The line graphs show the original scale of the leading indicators;
- A stack chart to indicate the accuracy of forecasts over the last 9 months. The MAE is plotted in this graph. The blue and white colour stack indicates a forecast for the month turned out to be higher than observed or lower than observed;
- The gauge on the right of the screen visually represents the forecast for the coming month. A colour code shows an increase, decrease or similar trend expectation is expected. The colour gauge is divided into several scales of changes, to represent a different angle for greater changes in direction.

Figure 8-2: Information dashboard for Coal leading indicators

The forecasts and graphs that are provided in these dashboard pages are calculated in a separate spreadsheet page. This page, making the forecasts for Coal throughput, is shown in Figure 8-4. The coefficients that have been estimated by the VAR model are shown in the top part of the screen, while forecasts, real values and their deviations are shown at the bottom of the screen. This information regards the last twelve months, as this list is extended once the dashboard is updated to include new forecasts.

Updating the information dashboard

Using the information dashboard to provide accurate information requires it to be constantly updated. By adding observed values to the time series in the spreadsheet model (Figure 8-3), the data is automatically differenced or seasonally adjusted if needed. This spreadsheet collects all the information about the time series and serves as the basis for the information in the dashboard. The differencing and seasonal adjustment is done by the underlying formulas in the excel workbook. The functions are the same as the method applied in the EViews software, only this required building the equations by hand.

	A	B	C	D	E	F	G	H	I	J	K	L
1	Leading Indicators time series								Throughput series			
2	DATE	CC_DE	CC_NL	EXP BE	EXP_ST	IC_EU	IRON_DE	WORLDTRAD	AGRI	IRONORE	COAL	OTHERDB
174	Apr-11	7.9	5.7	107.4	0.7	4.9	2397.0	161.0	649.8	3263.0	1873.2	1009.3
175	May-11	9.0	2.6	107.2	1.3	3.1	2614.0	164.1	884.5	3957.6	2443.3	946.1
176	Jun-11	9.8	0.4	106.1	-1.7	2.5	2463.0	161.1	879.1	3181.8	2364.3	1109.1
177	Jul-11	8.4	1.4	104.9	-2.6	-0.2	2384.0	163.6	691.2	3463.7	2165.0	1032.9
178	Aug-11	0.2	-3.5	100.0	-1.9	-2.6	2246.0	165.9	748.0	3631.2	2091.4	1218.6
179	Sep-11	-1.9	-12.9	98.0	0.7	-5.8	2203.0	165.2	1123.5	2991.3	2343.7	1078.7
180	Oct-11	-3.3	-17.1	97.2	-1.0	-6.7	2230.0	164.0	925.3	3198.0	2762.7	1112.4
181	Nov-11	-2.9	-20.3	97.6	-0.4	-7.6	2075.0	164.8	896.1	2947.6	2282.1	1166.6
182	Dec-11	-2.2	-24.2	98.7	2.5	-7.7	1820.0	165.9	853.1	1850.3	2394.0	1268.5
183	Jan-12	0.5	-23.1	100.9	0.8	-7.2	2228.0	165.5	640.5	2890.2	2308.3	980.9
184	Feb-12	-0.8	-22.6	102.3	2.5	-5.3	2195.0	165.7	665.4	1679.9	2182.4	884.5
185	Mar-12	-0.6	-23.6	102.6	2.6	-7.1	2391.0	165.8	577.0	3151.9	2379.2	864.8
186	Apr-12	-2.3	-17.1	102.6	2.6	-7.7	2260.0	164.1	748.6	2906.9	1916.0	872.1
187	May-12	0.4	-23.3	100.7	1.2	-11.3	2385.0	168.8	880.1	3177.3	1873.7	1154.2
188	Jun-12	-1.3	-23.8	97.2	1.4	-12.0	2337.0	166.3	633.1	2633.8	2246.9	1102.9
189	Jul-12	-4.6	-18.5	95.5	-0.7	-12.8	2294.0	166.0	710.6	3540.9	1250.5	1013.9
190	Aug-12	-8.8	-18.1	94.2	-0.1	-14.6	2160.0	165.7	667.7	2090.6	1876.5	1194.7
191	Sep-12	-10.3	-17.4	93.2	-0.2	-14.5	2254.0	167.3	500.0	2800.0	2200.0	800.0
192	Oct-12											
193	Nov-12											
194	Dec-12											

Figure 8-3: Time series spreadsheet

Returning to the forecast page for Coal, the columns need to be extended downwards to automatically update the forecast. As can be seen in Figure 8-4, the forecast uses the coefficients and the other values of the indicators to make a forecast (the picture has been cropped for better viewing purposes).

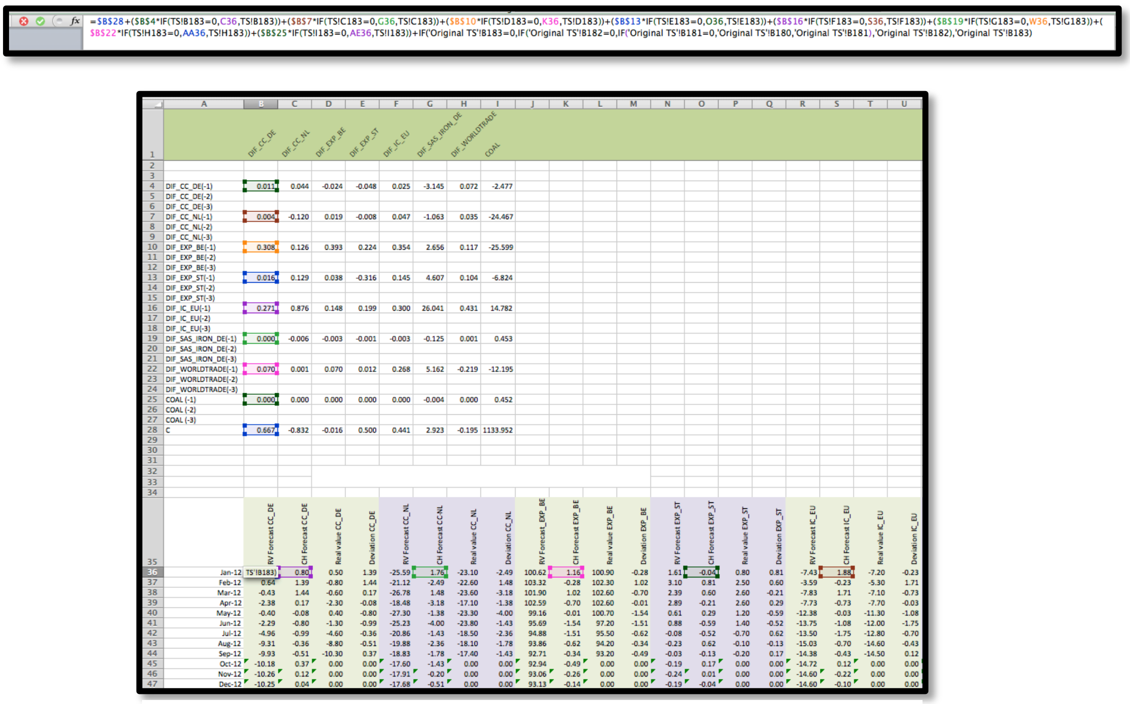


Figure 8-4: Calculations for forecasting the leading indicator for Coal

To ensure that the relationships between the leading indicators and the dry bulk goods remains present and accurate, estimating a new VAR model is required to maintain the FSS. This might also result in new leading indicators being found as a result of changing patterns in the economy, consumer spending behaviour and developments in the maritime industry. When a new VAR model is estimated, updating the information dashboard is relatively easy. The times series in Figure 8-3 would have to be changed when new leading indictors are found. If not, a newer VAR model provides new coefficients and give a more up to date estimation of the relationships. For updating this information, only the coefficients in Figure 8-4 need to be changed. The forecasts are calculated automatically, using the coefficients and the observed values in the spreadsheet named 'Original TS', which is shown in Figure 8-3. The line graphs, deviations, gauges and summary dashboard page are then automatically updated to provide the most recent information for users of the dashboard.

8.3 Conclusion

For the design of the information dashboard, several design requirements have been established in cooperation with users of the FSS. They have been categorised in three aspects, namely usefulness, usability and usage. Chapter 8.1 has shown that the requirements have been met and several work sessions with the users have confirmed this. Furthermore, the sessions have posed some important improvements to the dashboard that have been incorporated. This can be characterised as an iterative process, constantly adding quality to the information dashboard. The information dashboard, after being verified and validated, is ready to be implemented into the forecasting process at the PoR.

9. IMPLEMENTATION, EVALUATION AND MAINTENANCE OF THE FORECASTING SUPPORT SYSTEM

The forecasting process at the PoR is based on many source of information to make decisions. By implementing the FSS, forecasters can relate back to this new source of information. However, it is possible that the FSS is not used due to various reasons. This may happen because forecasters have no faith in the support system or do not understand it, it does not provide relevant information or the forecast is not accurate enough and might be overruled by the knowledge and experience that an expert may have. Therefore, carefully considering the approach to implementation is crucial, as this can have implications for the amount of use of the Forecasting Support System. This Chapter answers the implementation and maintenance part of sub question 5, defined in the first Chapter of this report:

How does the Forecasting Support System need to represent information, be implemented and be maintained to effectively support the forecasting process?

This Chapter elaborates on the implementation of a FSS into a business process in general and specifically for the PoR (9.1), the evaluation with a user of the system (9.2) and provides recommendations for maintaining and updating the information dashboard (9.3).

9.1 Implementation

After developing a Forecasting Support System, the challenge arises to implement the visual output of the system, in this case the information dashboard, into the current forecasting process. The success of implementation is determined not only by installation and deployment into the process but more important, getting users to accept the DSS as useful and reliable tool that can support their business process. Unfortunately, there are no standard steps that can be taken for the implementation of the DSS, as no two processes are the same and what works well for one process might not work for another (Sauter, 1997).

Swanson (1988) defines some key aspects that determine success or failure of implementing a DSS, and these are adapted by Sauter to create a list of nine key issues that can cause success or failure. Although these issues concern the implementation of a DSS, they are argued to be applicable for implementation of a FSS as well. This is because the spreadsheet-based model, the outcome of a DSS and FSS, is the product that gets implemented. These issues are summarised in four main principles for implementation of a FSS in a business process. By addressing these four principles, the nine key aspects are covered and these factors have to be of the DSS in a general forecasting process and at the PoR (Sauter, 1997).

Ensure that the system does what it is supposed to do, the way it is supposed to do it.

- Ensure ease and flexibility of use.
- Getting grip of the current process.
- A prototype can help to establish key issues that the user requires in the DSS.
- Interviewing users to gain information about requirements.

Keep the solution simple

- Simple information -> no ‘latest technology’ or fancy ‘Bells and Whistles’.
- Provide information to ‘get the work done’.

- Keep the operations and calculations of the system separate; decision makers need not to know every detail.

Develop a satisfactory support base
- Ensure user involvement
- Address specific concern of DSS and increase user's comfort level.
- Commit users and managers to address the added value of a DSS.
- Exemplify the need for the system in relation to a companies' strategy.

Institutionalise the system
- Create incentives for use of the DSS.
- 'Spread the word'
- Individual training for operating and maintaining the DSS.

This list of principles is applicable to implementation of a FSS in any situation and is therefore also to be considered when implementing a FSS in the forecasting process at the PoR. Alongside these principles, some other case specific principles have been identified. These ensure successful implementation of the system at the PoR.

The main threat of implementing the FSS into the forecasting process is whether or not the users will use the information provided to make their forecast. The FSS has been designed to be purely quantitative and must work alongside the qualitative process currently being employed at the PoR. Although it takes time before a thorough evaluation can be made on the success of implementation, some crucial factors need to be addressed to prevent failure of the implementation of the FSS.

It must be iterated that qualitative forecasting remains the main forecasting method for the PoR. It is argued that combining these methods allows forecasters to make a more substantiated forecast (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009). This way, the regular pattern of the trend is shown by the FSS the forecasters themselves can predict sudden peaks and troughs in the trend. As is stated by Blattberg and Hoch (1990): *"Models are consistent, but as a consequence are also rigid. Experts are inconsistent but are flexible in adapting to changing conditions"*. The FSS provides support to the process and can be consulted when forecaster have little information available or need a second opinion on their forecast. The FSS can provide them with this.

To gain the trust of forecaster in the FSS, the accuracy of the forecasts for the leading indicators must be high. The FSS shows information concerning the deviation (error) of the forecast but it is more important that the general direction and the impact that the leading indicators has on the dry bulk goods is presented. Again, time can only tell whether the forecasters are satisfied with the forecasts made by the FSS, but this aspect is considered to be decisive in the success of the FSS.

This project concerns a pilot project for the PoR and the results have shown that the FSS can represent information about the market. Investigating the limitations of this output has shown that the model is of a general level at the moment, indicating only leading indicators on a high level of abstraction. For forecaster, more insight into detailed market indicators for specific products is desired. When implementing this FSS, the forecasters need to be convinced that when more detailed information is provided on specific throughput goods, the model becomes more useful for understanding market developments, and consequently, making a more accurate forecast. Convincing the users and showing the potential of the model is essential when implementing the FSS.

9.2 Evaluation

The information dashboard is the output of the FSS that provides forecasters with information concerning the leading indicators. To evaluate the implementation of the dashboard into the current forecasting process, a work session was organised with forecasters. The display of the dashboard was examined and several questions concerning the implementation of the model were posed. The feedback that the user provided was used to make final changes to the dashboard and reiterated several important implementation aspects.

The information dashboard was presented to the forecasters and the various components of the spreadsheet were discussed. The overview page (Figure 8-1) presents a summarised overview of the leading indicators and was deemed a clear and neatly organised overview. Information concerning the current trend and forecast for the leading indicators was quickly recognisable and users indicated that the overview page invited them to learn more about the forecasts for the individual indicators.

The amount of leading indicators presented for Iron Ore & Scrap (four leading indicators) was judged as a limit in order to keep the overview page clear. A recommendation was posed that when more leading indicators are defined (for other goods), an aggregate forecast for the throughput good would provide a clearer overview. This would entail the combined effect that the leading indicators have on the throughput good, thereby reducing the amount of information on the main page. This would then increase neatness and clarity of the overview page. As the scope of this research entailed the forecasting of leading indicators individually, this recommendation must be transferred to the section discussing recommendations for further research. Furthermore, the aggregate forecast was considered to be a ‘nice to have’ feature as forecasters could themselves develop the aggregate forecast based on the strengths of the leading indicators.

The individual spreadsheet pages for the throughput goods were judged to be very informative for making a forecast. A question concerning the time span of the graphs was posed at the forecasters in order to verify if the time span for the graphs provided enough information. The response of the forecasters indicated that the time span currently provided (twelve months) is a good representation of the trend and is useful for assessing the reliability of the forecast as both the forecast and the real values are presented here. Furthermore, the accuracy graph of the forecasts (the error presented in a stack chart) was deemed very useful by the forecasters. These allow users to gain or ease off their trust in the forecasts. Other questions were aimed at getting feedback on the coloured indicators representing the one-month forecast and the strength indicated by the coloured stars. The forecasters judged this information to be very relevant for use in the forecasting process. Although this would not be a decisive factor, it would provide good support for making the forecasts.

The main contribution of the FSS, according to the forecasters, is the fact that the FSS can serve as a ‘second opinion’ tool. Users indicated that often qualitative information about market indicators is not available or little is known about the causes for a specific throughput good. When this occurs, forecaster agreed that the FSS could serve as an important decisive factor. As was indicated in Chapter three, when little information is available, forecasters often make a conservative forecast. Having the FSS, they believed the information on the leading indicators could help them to improve their forecast or at least have information to fund their decision.

A major advantage of the model is its visual representation. Forecasters agreed that the visual display is very important for creating a clear and reliable interface. The information dashboard was considered to be a well-organised dashboard that attracts attention to important aspects of the system by using colours.

The information dashboard was deemed a well-constructed and clear information screen that presents accurate and adequate information for supporting the forecasting process at the PoR. From this, it can be concluded that the FSS is considered to be 'trustworthy' system, as was aimed for when the design guidelines were set up. As was discussed, the forecasters provide the evaluation on whether or not the requirements for the dashboard have been met. During the work session, no requirements were identified as missing in the information dashboard. Forecasters were hesitant for the level of abstraction but could see the potential of the model when more throughput goods are analysed and represented. Most important is the fact that forecasters agreed upon the use of the model for the process and that the model can serve as a good 'second opinion' for their decisions. Experiencing the works of the model and gaining trust in it are major aspects that determine the eventual use of the model. It is hard to determine this at the moment, as only time can tell whether or not the forecasters gain trust in the FSS.

9.2.1 Limitations of designing a process specific support tool

The FSS and the information dashboard have been specifically designed for supporting the forecasting process at the PoR. Many DSS are designed to support various types of decisions to be made. They are often used when making financial decisions or production levels decisions. A DSS often helps in those cases, but here the FSS can only help to support the forecasting process. This has its advantages and disadvantages. The tool is custom made for the process, thereby providing the information that is required and the model is build so to deliver this information. This makes the model very applicable for supporting any forecasting process that is qualitative or quantitative (as a second quantitative forecast can be used o verify the results). Compared to the DSS, a disadvantage of the FSS as a whole is the fact that it is rigid and cannot support other decision than those concerning forecasting. The model cannot be used to, for example, support decisions concerning the decision for choosing a most appropriate contract for a build project in the port.

The forecasts of the market indicators that are made by the FSS can be used on a wider scope. Within the PoR several departments, such as the CBL and the corporate strategy department, can use the forecasts for analysis and gaining market understanding. This shows that the FSS' forecasts can help to substantiate decisions in several areas of business. Because the information dashboard is spreadsheet-based and was developed in cooperation with users, extending it can be done with relative ease. For market exploration purposes, the VAR model can be used to explain relationships between market indicators that may have an effect on the port's activities. For example, identifying a relationship between production levels and the amount of barge ships coming to Rotterdam might be useful information for evaluation of terminal usage and occupancy at various times. The VAR model can easily be made to estimate a relationship between these variables, as long as the correct information series are available.

9.3 Maintenance

After implementing, the FSS needs to be updated and maintained to be able to keep providing forecaster with up to date information. The forecasts that are made by the model require data to be up to date so that the model can use these figures. During a handover session, a run through the FSS shows forecasters how to update the model and the information dashboard. For future reference, a manual is provided to illustrate how the model can be updated.

As discussed, the time series need to be updated monthly to provide the most up to date real values. As data is often provided as preliminary data and is confirmed some time later and the forecasts are made every quarter of the year, updating the forecasts every three months ensures that at least two months are showing confirmed data. This reduces the error and decreases the workload of updating the model. The time series have been selected to be available monthly, but if for some reason no data is available of the previous month, the information dashboard uses a previous forecasted value as input fro the next forecast, rather than a real value. This allows the forecast to be made but decreases the accuracy.

The VAR model can be updated in larger time intervals, as the trend of the indicators is not a fast changing occurrence. As was discussed, creating a VAR model requires at least 100 real values in each time series (Toda & Phillips, 1994). This corresponds to roughly eight years, but this would yield a complete new VAR model. A shorter time interval is therefore advised but because the modelling is time intensive, a yearly update is too soon. For ease of use purposes and workload purposes, it is recommended to update the VAR model every three years. This yields 36 new real values in the time series, thereby creating new data points for at least a third of the time series, thereby allowing a good representation of older values and new values for use in the VAR model.

In this research, the statistical software EViews has been used to determine the leading indicators. For updating the information dashboard to provide the most up to date forecasts, the use of this software is not needed, as data preparations and forecast calculations have been integrated into the spreadsheet model. For the determination of new coefficients, and possibly the identification of new leading indicators, EViews is necessary to be used. The manual that has been developed provides information on how to perform VAR analysis in the EViews software.

Besides changes to the dashboard and the rest of the FSS, regular feedback with dry bulk experts must be performed in order to verify whether the model is providing accurate results or not. This mainly concerns the relationships between throughput goods and market indicators that are determined by the VAR model, but also the identification of market indicators that are to be used in statistical analysis. As was shown in this research, the dry bulk experts can indicate many indicators that might be relevant for analysis. This is especially important when the model is applied to other throughput goods such as containers and liquid bulk goods.

9.3.1 Manual for future reference

Besides this report, an electronic manual is provided for the PoR and the users of the FSS and information dashboard. The manual is two-folded, where one part explains the method to build a VAR model and identify the leading indicators. The other part of the manual shows how to make a forecast using the spreadsheet model that has been designed. The manuals use screenshots and video captures to describe the method and the steps that need to be taken. The manuals, along with the information dashboard are provided on the DVD on the back cover of this report.

VAR model manual
This manual describes the steps that have to be taken in EViews to identify leading indicators for specific goods. The steps that have been described in Chapter 5, are represented by a screen captures and corresponding explanation of the steps taken. Providing both visual and textual explanation can help to provide adequate support for building a VAR model.

Forecasting manual
The spreadsheet dashboard, shown in Chapter 8.2, has been build using formulas and automatic updating macro's. This allows users to make a forecast using several simple handlings within the spreadsheet. Some elements of the data preparation are included in the information dashboard, so to allow users to directly insert data from a database. The steps for making the time series stationary and removing the seasonal influences are included in the information dashboard. This allows the forecasts to be made independently of statistical software. This manual consists of a screen capture video that demonstrates how a forecast can be made within the information dashboard. This allows users to pause the video when needed and to complete the steps alongside watching the video. The steps are described in the video, whereas explanation and argumentation for the build-up of the model are provided in this report.

9.3.2 Extending the Forecasting Support System

This Chapter has provided information concerning the maintenance of the FSS and the information dashboard. The information, explained with visualisations in the manual, is vital for ensuring the status quo of the forecasting process. In the future, the FSS and information dashboard might be extended to provide other information, be applicable for other commodities or be used in another business area. A recommendation for extension is explained below.

When applying the VAR model for other commodities, an important aspect is the gathering of time series and preparing them for statistical analysis. The VAR model manual then describes the steps that have to be taken in the EViews programme. Before that, a critical evaluation has to be done on the list of variables that is to be included in the research. This research has shown that a work session with a dry bulk expert and a list of characteristics for economic indicators can yield an adequate list of variables. Furthermore, it is important to understand the market of the goods that will be forecasted, as this way it becomes clear what market developments may need more attention before selection for use in the research. The biggest challenge is selecting the variables and dry experts can help to provide this information. However, as this research has shown, selecting variables on the basis of their statistical properties is also very important.

9.4 Conclusion

The implementation of the FSS into the current forecasting process requires careful consideration of some important aspects that have been described above. The system must, above all 'do what it is supposed to do', it must be 'kept simple', a 'satisfactory support base' must be created and the system needs to be 'institutionalised' into the process. This requires commitment from the users as well as other people at the PoR who are involved in with the forecasting process.

Besides these general approaches, some specific implementation strategies for the PoR must be kept in mind. The most important aspect is for the FSS to gain trust of the forecasters, resulting in the use of the FSS for the process. A work session with users of the FSS has evaluated the system and it was agreed upon that the model provides a good 'second opinion' for when forecasters have little qualitative information. In this case, they can resort back to the FSS for information.

The maintenance of the model is kept to a minimum. Effective updating can be done as described in Chapter 8.2, and this has to be carried out every three months. Estimating a new VAR model can be done with a larger time interval. It is proposed to do this every three years, as by this time enough new observations are present to perform proper VAR analysis.

10. EVALUATION OF THE DESIGN PROCESS

This Chapter sets out a reflection on the design steps that were taken to produce a FSS and an information dashboard to be implemented in the forecasting process at the PoR. It is important to consider what elements of the design process have been executed successfully and what elements require further work. Furthermore, strengths and limitations of the artefacts can be identified by reflecting back on the design steps delineated in the beginning of this report. Chapter 10.1 reflects on the attributes of a trustworthy system, defined by Sage and Armstrong (2000) and Chapter 10.2 reflects back on the design framework by Herder & Stikkelman (2004).

10.1 Attributes of a 'trustworthy system'

In Chapter 4.1, several design guidelines for this research were developed on the basis of the framework developed by Sage & Armstrong. The elements of a 'trustworthy system' were translated to be applicable for this research. Here, the elements are reflected upon and judged whether or not the FSS has been designed according to these guidelines. The elements are discussed one by one below. The italic sentences represent the design guidelines that were translated from the framework in Chapter 4.1 to be applicable for this research.

- *Effective*
  The FSS must provide quantitative information that is relevant for making a forecast, split out per throughput good.
  The information dashboard, which is the representing output of the FSS, provides forecasters with forecasts of the leading indicators. Based on statistics, the strength of the economic variable on the throughput good is also provided. Separate spreadsheets allow a clear and effective way of using the tool.

- *Manageable*
  Users of the system must be aware of the functions and capabilities of the FSS. This allows them to effectively work with the model and use it for their support if needed.
  The design framework by Herder & Stikkelman (2004) has been applied for this research. This has been done so to keep users of the FSS involved from the beginning of the design process and thereby allow transparency to be present.

- *Cost-Efficient*
  The leading indicator FSS is a pilot project at the PoR and there is little budget reserved at this moment. Costs must be kept to a minimum.
  The FSS and the corresponding information dashboard have been designed according to a tight budget. Consequently, only a small fee was paid for acquiring the EViews 7 software. The fact that little budget was available has been a limiting factor for the research and the results.

- *Compatible and Supportive*
  A quantitative tool provides the most effective support to the current forecasting process and the focus on the quantitative nature ensures the tool is compatible with the current process.

The evaluation sessions with experts at the PoR have confirmed that the FSS provides quantitative information about the leading indicators and that this information backs up the qualitative knowledge that experts have.

- *Comprehensive and Usable*
  The FSS must be designed to provide a thorough representation of the leading indicators for each throughput good but a balance must be kept with regard to the amount of information presented.
  To be able to contain the overview of information, certain design requirements for the information dashboard have been delineated according to this design guideline. For example, the number of leading indicators defined per throughput good is limited to four, as this provides thorough information and provide overview.

- *Reliable and Verifiable*
  The FSS must provide statistics on the accuracy of the forecasts to provide forecasters with insight into how well the leading indicator can be forecasted.
  As part of the verification and validation of the model and the forecasts, several statistical accuracy measures have been applied. These accuracy measures are aslo shown in the information dashboard as to provide forecasters with accuracy information.

- *Interoperable and Integratable*
  One of the most important elements, the FSS needs to be implemented in the forecasting process without interfering with the current activities performed.
  As explained, the quantitative nature of the FSS has ensured that it can be implemented in the current forecasting process. Because forecasters have been involved in the design of the FSS from the start of the project, transparency has allowed operability issues to be included from the beginning. For example, the delineation between individual and aggregate forecasts (explained in Chapter 4.2) has ensured that the FSS is usable and can be integrated in the process in order to support it.

- *Adaptable, Evolvable and Maintainable*
  The dashboard supports the quarterly forecasting sessions and therefore needs to be regularly updated and maintained. This asks for consideration of software to be used for determining trends and making the forecasts.
  A manual and hand-over session ensures that experts at the PoR are able to update or change the information dashboard every three months. A new VAR model can be made according to the manual for estimating new coefficients for the model.

The elements described above have been addressed and included in the design of the FSS. From the design perspective of the FSS, the elements delineated above have been met and incorporated in the design. As Sage & Armstrong state that the success of a ‘trustworthy system’ depends on the interrelationship between people, technology and their environment, only time can tell whether the FSS that has been designed is a successful long-term addition to the forecasting process at the PoR. This has to be evaluated after a certain time period.

10.2 The generic conceptual design framework

The framework by Herder & Stikkelman (2004) that was applied for this research has revealed strengths and limitations for designing a FSS using this framework. The framework describes a generic design framework so it is expected to not perfectly fit the design for an FSS as described in this report. This Chapter sets out some characteristics of the framework as it currently is drawn and, according to the experience of applying it for the design of a FSS, provides a new framework and some recommendations for application in further research.

The original framework that was applied calls for close interaction with users of the system. From the beginning, users can express their needs and desires for the design that can be incorporated in the design. The framework highlights the need for users to be involved in the ‘develop goals’ phase. As was done in this research, the users have provide important aspects of the design, such as the goal of developing a quantitative tool and the need to forecast the individual leading indicators rather than forecasting throughput goods as a whole. However, the identification of the problem that needs to be addressed has not been fully explained in this framework and a proposition has been made to integrate this in the framework. Therefore, the development of a design space has been changed to identifying the design space and the problem identification, whereby focus must lie on aspects of the current forecasting process that can be improved rather than creating a new design space (in Herder & Stikkelman’s case: finding a suitable location for the chemical cluster in the Port of Rotterdam). Identifying the areas that can be improved involves the users of the system, as has been done in this research by conducting a survey amongst the users. In the new framework, stakeholders are therefore involved in identifying the design space, identifying the problem from this analysis and developing goals based on the results of the analysis as well as initial design goals. These initial design goals are related to the need for a FSS, coming from the literature or other sources. In this research, the need to integrate a qualitative and quantitative tool has been one of the design goals coming from the literature.

The framework by Herder & Stikkelman delineates between objectives and constraints. Distinguishing between these two aspects has proved to very useful in this research, as design guidelines and design requirements have been set up for the development of the FSS and information dashboard. These aspects have only been renamed in the new framework.

The importance of a design process is to create a physical artefact or service that can be used for several aspects of business activities. The framework by Herder & Stikkelman has proven to be more focused on developing several alternatives and deciding which of the alternatives is most suitable for the design space identified. By performing this research, a clear transition had to be made from a non-sequential approach in the original framework to a more step-by-step framework to actually develop and implement a FSS. The new framework therefore clearly exhibits a step-based approach whereby a step is included to ‘develop the FSS’ rather than developing a test for alternative designs. The development of the FSS refers to the execution of the VAR model and forecasts made from the output of the model. Opposite to the original framework, where a chosen design is the output of the framework, the information system (in this case a dashboard) is the result of the design process. This information system is then implemented into the process whereas the design in Herder & Stikkelman’s framework still has to be executed.

A major aspect of design is the verification and validation of the model and its output. In this research, because a test for alternatives was not applicable, the aspects have changed to 'develop the FSS' and 'verify and validate the FSS'. For the system to be a reliable system and deliver accurate forecasts, so that users adopt the system into their decision-making process, internal and external checks are very important. For this step of the design process, other forecasts have an important impact as the accuracy of the FSS can be benchmarked against these methods. In this research, an exponential smoothing method and a comparison with a forecast made by the GfK have validated the VAR model forecasts. It is important to involve this benchmarking step in the design process as to develop understanding of the FSS's ability to make an accurate forecast.

The suggested amendments, to make the framework applicable for this type of research, have been implemented into the framework in Figure 10-1.

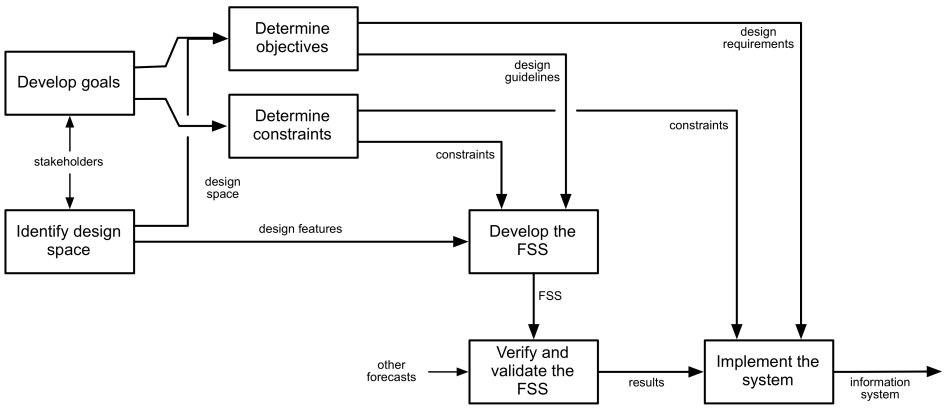


Figure 10-1: Proposed new framework for FSS design

10.3 Conclusion

This Chapter has evaluated the main theoretical aspects of the design process in this research. After establishing elements of a trustworthy system in Chapter 4.1, it is important to reflect back on these. It can be concluded that all elements of the framework have been accounted for but the main element of trust is with the users themselves. They need to use the FSS and need to trust it. Trying to map psychological and personal trust factors for trusting a system is another field of research and for this project an expectation of the success of implementation can only be provided. Besides the behaviour that humans show towards such a system, the research has shown that the FSS is considered to be a 'trustworthy system'.

The framework by Herder & Stikkelman that was used for this research has provided structure for this report. Evaluating its use, some limitations have been found concerning the design of a FSS. The main conclusion being the fact that the original framework was not set up to actually design an artefact, but selects alternatives and uses tests to choose the most appropriate alternative. During this research, the framework did not seem as applicable as though originally and as a result some amendments have been made. The framework has been converted into a step-by-step framework for the design of a FSS. Further research can now focus on applying this framework in several other fields of study, to validate it or add components that might be missing.

11. CONCLUSIONS AND RECOMMENDATIONS

Based on the results of the analysis that has been carried out, several conclusions and recommendations are stated in this Chapter. The research has provided much insight into forecasting, statistical analysis and the design of a Forecasting Support System. Although many conclusions can be drawn from here, the most important conclusions and recommendations are explained below. Chapter 11.1 focuses on providing an answer to the research question posed in Chapter 1. Chapter 11.2 provides conclusions from the research and these lead to recommendations for the Port of Rotterdam Authority and further research in Chapter 11.3.

11.1 Conclusions regarding the research questions

The research questions have provided a basis for the research as well as structure for this report. Answering them is essential for determining the conclusions of this research. Providing main conclusions for each of the sub questions creates a foundation for answering the main research question. The conclusions concerning the sub questions and the main research question verifies whether the research has performed what is was intended to do and states what the deliverables of the project are. The main research question was formulated as follows:

What should the design of a Forecasting Support System with leading indicators entail to support short-term forecasting processes for dry bulk goods throughput in seaports?

Before an answer is provided for the main research question, the sub questions are answered and conclusions are provided.

1. *What are strengths and weaknesses of short-term forecasting methods and what guidelines for the design of a FSS can be identified?*

The literature review has shown that strengths and weaknesses of forecasting methods can be best repressed by consulting both qualitative and quantitative methods for making a forecast. In forecasting, various methods can be applied to try to give an indication of future trend and developments. The effectiveness of using one of these methods depends on the time period concerned and the data available. For this research several possible short-term forecasting methods have been identified and evaluated. Both qualitative and quantitative methods have their strengths and weaknesses and a literature review has indicates that combining these methods can help forecasters to make a more substantiated forecast. The models provide constant, unbiased forecasts and it allows experts to assess the forecast and adapt it where necessary.

2. *What components of the current forecasting process indicate that a quantitative element can be added to improve the process?*

Analysis has shown that market information used for forecasting, at the moment of a qualitative nature, can be best supported by adding a quantitative element. The current forecasting process at the PoR is mainly based on qualitative information and knowledge that the forecasters have about the market, its indicators and the relationships they have with throughput in the Port of Rotterdam. Analysing the process from three perspectives has pointed out where in the process a Forecasting Support System can be added to support forecasters in their decision-making. The three perspectives that analyse the process from different angles were as follows:

1. A system of input, control, support and output;
2. A network of information exchange and collaboration between people;
3. A human steered business process.

Respectively, an IDEF0 model, a network diagram and a survey held amongst forecasters have shown that information concerning market developments is important for the whole process and that, at the moment, this information is mainly qualitative information. The Forecasting Support System, a quantitative tool, can be implemented here. The network analysis has shown that several people and teams at the PoR have to agree with the forecast output. The main strength of this set up is the fact that the forecasts are checked by several people, thereby using their knowledge to assess the validity of the forecasts before it is used for financial analysis and cash flow monitoring in other department at the PoR.

Based on the analysis of the process and the aim to design a FSS, several design guidelines, depicted by Sage and Armstrong, have been adopted. These guidelines ensure that the system becomes 'trustworthy'; an important characteristic for successful implementation of the FSS. The design guidelines have been implemented in the design and have steered the design to creating a system that was considered to be 'trustworthy'. Users of the system deemed this in the evaluation session.

3. *Which economic drivers can be identified as 'leading indicators'?*

Figure 11-1 **and** Table 11-1 **show that several leading indicators have been identified for the dry bulk goods in the Port of Rotterdam.** For the identification of leading indicators for Agribulk, Iron Ore & Scrap, Coal and Other dry bulk goods, a VAR model was selected as most promising method for statistical analysis. After variables were selected, data was prepared and CCF functions were calculated, the VAR model was estimated to provide coefficients for the leading indicators. The results show one leading indicators has been identified for Agribulk, four leading indicators for Iron Ore & Scrap and two leading indicators for Coal throughput. The analysis has not identified leading indicators for the Other dry bulk goods group. This is mainly due to the fact that Other dry bulk goods are a aggregation of several products, as is Agribulk. Iron Ore & Scrap and Coal consist of only a few products, therefore leading indicators are recognised quicker. The results of the VAR model are shown in Figure 11-1, where the yellow boxes show the significant leading indicators among the other indicators from the VAR model. Table 11-1 shows the leading indicators.

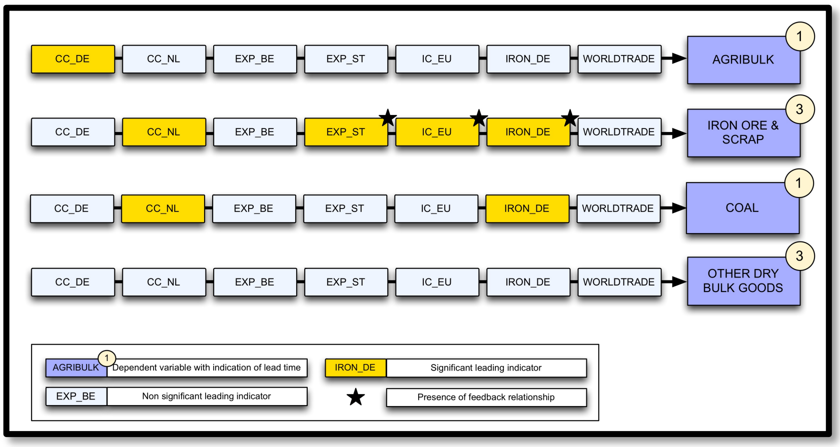


Figure 11-1: Leading indicators identified by the VAR model

Throughput good	Leading indicators
Agribulk	1. Consumer Confidence in Germany
Iron Ore & Scrap	1. Consumer Confidence in the Netherlands 2. Expected Stock levels in the Netherlands 3. Industrial Confidence in Europe 4. Iron Production in Germany
Coal	1. Consumer Confidence in the Netherlands 2. Iron Production in Germany
Other dry bulk goods	No leading indicators have been identified

Table 11-1: Leading indicators per throughput good

4. *Is the quantitative forecasting tool a reliable and accurate source of information to support the forecasting process?*

Statistical accuracy measures (MAE and MRAE) indicated the VAR to be more accurate than the exponential smoothing method and work sessions with users of the model have judged the model to meet expectations and requirements. Consulting experts who have experience with VAR model building carried out verification of the VAR model. This has resulted in a confirmation that the model was correctly build and could be used for further analysis. Validation sessions with dry bulk experts at the PoR have shown that the output of the model provides a good representation of the market for dry bulk goods. This model has confirmed the knowledge concerning the leading indicators that the experts have for Iron Ore & Scrap and Coal throughput and the model can be extended to a more specific level for other goods. The forecasts, by means of ex post forecasting, have provided good insight into the trend of the leading indicators and this information is vital for use in the information dashboard. One of the main conclusions from the verification and validation sessions is the fact that the forecasts are accurate at representing a general trend of a leading indicator but that sudden peaks and troughs, such as the collapse of Dutch cabinet, JPMorgan's financial loss or the ECB's lending rate decrease, have been hard to forecast. These decisive moments in the corresponding time period have affected the leading indicators significantly, especially the Consumer Confidence time series.

The VAR model has proven to be a good method for both identification and forecasting the leading indicators. Compared to the exponential smoothing method, the VAR model shows lower Mean Absolute Errors (MAE) and Mean Relative Absolute Errors (MRAE) results, as is shown in Table 11-2. Iron Production in Germany is better forecasted with an exponential smoothing method when analysing these figures. However, form the line graphs of the forecasts, it is clearly visible that the VAR model is far superior in forecasting changes in the trend than the smoothing method. Validating the forecasts was a last step before the information dashboard could be build.

		MAE		MRAE	
		VAR model	Exp. Smoothing	VAR model	Exp. Smoothing
Agribulk	CC_DE	0.74	2.87	0.53	1.19
Iron Ore & Scrap	CC_NL	1.57	5.83	0.02	0.55
	EXP_ST	1.26	2.12	0.80	0.84
	IC_EU	0.83	3.13	0.15	1.34
	IRON_DE	155.69	130.39	0.06	0.02
Coal	CC_NL	1.81	5.83	0.16	0.55
	IRON_DE	38.57	130.39	0.01	0.02

Table 11-2: MAE and MRAE test results

The focus of the verification and validation has been on the statistical part of this research. Much attention has been spent on correct identification of the leading indicators and producing accurate forecasts for these variables. Statistical verification and validation of the information dashboard was not possible. Therefore, future users of the tool were consulted and they confirmed the dashboard could help to substantiate the process. However, verification and validation of the dashboard is less extensive than the leading indicators because the phase described here is an explanatory phase. Monitoring of the systems' use helps to to provide further verification and validation, possibly leading to further development of the information dashboard.

5. *How does the Forecasting Support System need to represent information, be implemented and be maintained to effectively support the forecasting process?*

The requirements for the design of the dashboard have been met and users of the FSS have verified that the model is likely to have a beneficial impact on the forecasting process, while updating the dashboard is easily done by standard spreadsheet actions. The information dashboard that is part of the Forecasting Support System has been designed according to preliminary requirements, determined in cooperation with users of the dashboard. Several implementation success factors, defined by Swanson and Sauters, have called for this approach and it has shown to be beneficial. The information dashboard was evaluated with users of the model in a work session. Here, the FSS and the information dashboard were confirmed to be a good tool for serving as a 'second opinion' tool. As was identified in Chapter 3, when forecasters have little available information about the market, the forecast is often made too conservative. Consulting the information dashboard helps to forecasters to establish a more substantiated decision. The main goal for successful implementation and use of the FSS still remains with trust in the model. At the moment, this is hard to analyse, but time can only tell whether the model has been beneficial to supporting the forecasting process at the PoR.

The information dashboard provides many automatic calculations to ensure that performing maintaining on the system is easy. Adding new observations and extending the columns in the spreadsheet model updates the model to provide new forecasts. Determining new leading indicators or updating the coefficients requires the estimation of a new VAR model in the EViews software package. A manual is provided to show the steps that have to be taken.

Now that clarification has been provided or each of the sub questions of this research, an answer can be given to the main research question:

What should the design of a Forecasting Support System with leading indicators entail to support short-term forecasting processes for dry bulk goods throughput in seaports?

The design of the FSS has incorporated many technical, societal and scientific aspects and a clear structure has been set out that focuses on providing a quantitative forecasting tool for supporting the forecasting process at the PoR. It can be concluded that much attention has been spent on the determination of the leading indicators, but that the research provides a good basis for the FSS to be implemented and extended in further research. The sub questions have addressed the development of the FSS and the information dashboard for supporting the forecasting process at the PoR. Some important aspects have been investigated which influence the outcome of the research.

The framework that has been developed shows some changes to the original framework by Herder & Stikkelman, thereby providing the framework to be specifically applicable for the design of a FSS to be implemented in a forecasting process. The changes that have been made can be concluded as follows:

- The design space for the FSS is not being developed for the case of a forecasting process, but it is to be identified. This is because the FSS supports an already existing forecasting process. Analysing the current process and identifying a design space yields important objectives and creates design features for the FSS. In this case, one of the design features is the pure quantitative nature that the FSS must exhibit;
- Stakeholders or users of the FSS should not only be involved when setting goals but also for the identification of the design space. Forecasters are well aware of possible drawbacks of the current process that can be overcome by implementing the FSS;
- The framework has been adapted to include design guidelines and design requirements for the FSS rather than performance indicators, objectives and constraints;
- The development of a test is no longer applicable; the focus has been turned to developing a FSS. The framework has been transformed from a non-sequential framework to a step-by-step framework to develop an FSS;
- Rather than executing multiple tests that are to be developed when following Herder & Stikkelman's original framework, verifying and validating the model and the results is important for building an effective FSS.

Because the framework delineates the most important steps that need to be taken when designing a FSS, applying it in other sectors is possible and can provide evaluation of general applicability of the framework. For example, applying the framework in the design of a FSS for supporting production company forecasts can help to develop the framework further. Here, the support tool supports a decision-making process concerning production levels to cope with forecasted demand. The identification of the design space and the implementation of the system are likely to have a much greater impact on the company, as machinery and job orders may need to be changed to be able to produce the desired amount of products. Furthermore, because changing machinery takes a long time, it is interesting to see if the framework is applicable for developing a long term forecast as well.

More importantly, further research provides confirmation on whether or not the framework is too general or too vague for application in other domains. The structure that is provided guides researchers to creating a FSS, based on experiences from this research. The framework also notifies researchers to take into account important aspects of FSS design, ensuring a complete analysis is delivered. Testing the framework is an important feedback process and can determine whether or not further amendments have to be made.

11.2 Conclusions regarding the Port of Rotterdam

Besides answering the research questions it is important to consider the conclusions of this research regarding the Port of Rotterdam. Below, some of the main conclusions are elaborated on.

The goal of this research was to design a Forecasting Support System that can support the forecasting process at the PoR. A FSS consists of the following elements (Fildes & Goodwin, 2003):

- Database with multiple time series;

- Quantitative forecasting tool;
- Application of managerial decisions.

Based on the identification of market variables, several time series were selected to build the FSS. The FSS provides forecasters at the PoR with a quantitative tool for making a more substantiated forecasting decision. This is important in order to provide accurate forecasts that are being used throughout the PoR. Higher accuracy of the forecasts develops a more accurate workplan for the coming year, as these are based on the Q3 forecasts for throughput and price per tonne. Based on the workplan, port dues are calculated (by multiplying the expected throughput with the price per tonne) and insight is provided into expected income for the PoR for the coming year. Therefore, accurate forecasts results in accurately determined port dues and income and lost income due to forecasts being off target are minimised. Income for the PoR is used for future development of the port, in order to remain competitive amongst other ports in North Western Europe and the world.

The determination of leading indicators and their relationship with throughput goods in the port has provided more insight into market developments. For the long term, monitoring developing trends of significant leading indicators for throughput goods can help to better develop the facilities and terminals in the port. If leading indicators are having an increasing effect on throughput goods and it is due to this relationship that throughput is growing in size, port development can focus on providing facilities to accommodate the expected increase in throughput. This specifically aims at allocating land for specific goods and services, for example adding new facilities in the 'Botlek' area if dry bulk goods or chemical products' throughput is showing a continuous growing trend due to the leading indicators having an advance effect on them. New facilities and terminals can be built or re-organised as a result of developments in market conditions.

The main conclusion for the PoR is that the leading indicators dashboard is a 'trustworthy' system that may have a contributing role in the forecasting process at the PoR. The tool allows forecasters to base their decision not only on qualitative information, but also on quantitative data provided by the FSS. This allows forecasters to make more substantiated decisions that concern forecasts for dry bulk goods. The tool has been designed not to interfere with work performed by the forecasters as so to provide a solid base for supporting the forecasting process.

11.3 Recommendations

To provide the Port of Rotterdam Authority and future researchers with some reflections on this research, certain recommendations have been set out. The recommendations are applicable for the Port of Rotterdam (PoR), for further scientific research (SR), or both (PoR + SR).

PoR: The FSS has shown to provide relevant information for supporting the forecasting process, but more specific information, possibly for other throughput goods, is desired. Splitting up the Agribulk group and the Other dry bulk goods into specific products creates more detailed research and the identification of leading indicators for specific groups. For the Agribulk group, at the moment, this is restricted due to the fact that customs duties in the Netherlands do not provide data on specific Agribulk goods. For the category Other dry bulk goods, it is recommended to define more specific product types. For example, taking bauxite and alumina, two products used in the production of aluminium, and determining leading indicators for these products. This could involve market indicators such as selling prices in Europe or other parts of the world, aluminium production or the extraction and production quantities in countries such as Australia and various South American countries.

PoR: Considering this research has used free and publically available data for use in the statistical models, the results are accurate compared to other forecasting methods. To identify more accurate leading indicators for specific goods, access to more statistical databases is needed. The PoR, especially the BAI department, is closely linked to the CBS in the Netherlands and this institution can provide relevant statistics concerning market developments that have an effect on port activity. The Dutch and German market indicators have proven to be important indicators for throughput in the Port of Rotterdam. Another recommendation for the BAI department is to strengthen its ties with the 'Nederlands-Duitse Handelskamer' in The Hague. The Germany Desk at the PoR is already closely connected to this institute and they might be able to provide new sources of German market statistics. Furthermore, once a decision by the MT has been made to continue the project and budget is made available for it, consideration can be given to purchasing a subscription to data that is available monthly and might be influential on the throughput of goods in the port.

PoR: As it is difficult to assess the success of implementation of the FSS at the moment, it is recommended to keep monitoring the use and effectiveness of the model. As time can only tell whether or not the users adopt the model into their decision-making process, this is an important aspect of the FSS. Monitoring the implementation involves getting feedback from the users and can be done individually or as a group. It is vital to gain insight into specific factors that influence the decision of a user to use which proportion of qualitative and quantitative information but also how the decision is made. This can be based on logical argumentation using the information provided or on intuition. The factors influencing the decision can be a minor detail in the information dashboard but can be a deciding factor for a user deciding not to use the system. For example, the visual representation of data, whether this is using points or commas for decimal indication or even the amount of decimal points indicated can set of people. If necessary, changes to the information dashboard are easily applied and can help forecasters with the information they desire for making a forecast. However, it is important to identify these minor glitches at an early stage and repair them if necessary. Once users have decided not to use the model anymore, it is harder to convince them to start using the model again.

SR: The proposed framework for the development of a FSS can be applied and tested in other fields of study. Evaluating its use may provide essential improvements to the model for it to become a framework that can be used more often. The application of the framework can be combined with research into different commodities, for example the throughput of containers, so to evaluate also the applicability of the VAR model for other goods. For example, the forecasters for container throughput in the port might desire a different information dashboard layout, resulting in other information having to be presented. It could be the case that more focus must be turned to creating several forecasts and plotting these to provide different scenario's for expected market development and throughput. The framework would then have to include an element where the forecasts are compared and several scenarios can be built to assist in decision-making. This process would have to be added in or around the verification and validation step.

PoR + SR: Further research can also be done on the exact flows of good being transported through the port. For this research, throughput has been defined as the combined total of imports and export through the port. Further research can focus on one of these flows, and possibly be allocated to a specific geographical area. For example, research into leading indicators that cause more dry bulk goods to be transported from Germany to Rotterdam for transport to the rest of the world can provide relevant information concerning throughput in the port. A risk associated with this is the fact that no or very little statistical information may be available and that logistics companies are not willing to provide these statistics very easily.

REFLECTION

This section provides some of the most important reflections on the research performed. It reflects back on the scope of the research, the theories and methods used and the results of the research. A personal reflection evaluates the personal experiences of performing this research.

Scope

The scope of this research has been delineated by several boundaries, the most important being the choice to include indicators from key markets for the Port of Rotterdam. Statistics from the Netherlands, Germany, Europe, China and the world were included as these are the most important areas that import and export to and from the Port of Rotterdam. This has reduced the set of information to identify leading indicators from but the focus has remained on the most relevant markets. Adding more indicators most likely adds some leading indicators, but their explanatory power may not be significant or indicators would have had to be removed due to statistical data preparation rules (correlations >0.8 were removed to avoid multicollinearity). Estimating multiple VAR models, one for each geographical area, can deal with a larger amount of indicators but would remove the 'holistic' view of several market indicators that the VAR model has at the moment.

A second limitation of this research concerns the scope around the forecasts. In forecasting throughput goods, a total throughput figure is forecasted and used in decision-making processes. Often this forecast is evaluated and adapted is forecasters feel this is necessary. In this research, forecasts have been made for the leading indicators, not for the total throughput goods. This important scope delineation was set from the start of this research (Chapter 4.2) and was requested for by the users of the process. When the information dashboard gets implemented, a translating step needs to be made by the user of the model. This concerns the effect that the leading indicators have on the throughput good. The information dashboard accounts for this and users feel this is an effective presentation of information without interfering with their business activities.

Another aspect of this research that is worth reflecting upon is the data that has been used for statistical analysis. This has furthermore reduced the scope of the research as well as the results. The fact that this project concerns a pilot project meant that only free and publically available data was used for analysis. Once the management team approves the project, budget is made available and statistics can be purchased for use in statistical analysis. This would have significantly increased the scope and may have identified more leading indicators for the throughput goods. Many statistics that describe the Chinese economy were not available, as well as electricity production figures. The Chinese indicators are especially important to include when applying this model for use in determining leading indicators for container throughput, as many assembled consumer goods are transported from China to Rotterdam. The dry bulk experts consider electricity production a leading indicator for Coal throughput, but this would have to be statistically proved for it to be included in the FSS.

Theory and methods

Using a theoretical framework was important to provide a basis for this research and, after some amendments, provides a clear structure for further research on this topic. It would have been better to use a specific FSS design framework but the literature review has not provided one. However, a preliminary framework has now been established and can be used in the future. Hopefully, future research provides an evaluation of its use and researchers provide improvements for the model if they feel it is necessary.

The use of the CCF functions was less effective as expected before. The results of the CCF do indicate a relationship between the variables but the method does not provide any extra information that is required to perform a VAR analysis. For this research, only estimating the VAR model would have yielded the same results as the CCF only provides a confirmation of a correlation between the time series. As we are interested in leading indicators, the VAR model is much more effective in determining this relationship. The CCF's were calculated as many researchers have argued them to be beneficial for their research. In this research, the CCF did not show to be a decisive factor in determining the leading indicators.

The choice for estimating a VAR model has been very satisfying, as the method has identified several leading indicators and has provided accurate forecasts. The process of selecting time series and performing various preliminary tests before conducting the VAR model proved to be a challenge, as there exist many methods for preparing the data. The methods that have been used in this research can be easily executed in the EViews software, thereby lowering the barrier for people at the PoR to start building a new VAR model for other goods. An important aspect here has been the switch in software from SPSS to EViews, as explained in appendix 2. Although similar software packages, the EViews software is much more powerful in performing econometric analysis, whereas SPSS is more appropriate for use in statistical analysis in social sciences.

Results

The results from the VAR model are very promising and this creates incentive to extract the method to other throughput goods and other fields of study. The verification and validation sessions have confirmed that the model gives an accurate representation of reality, thereby gaining trust in the model from the forecasters at the PoR. This is an important aspect of creating a 'trustworthy' system, among with other key attributes that determine the success of implementing a FSS.

Setting the requirements for the information dashboard was done in cooperation with users of the information dashboard but it was expected to have produced a more complete list of requirements. Although, this left room for creativity in the design of the dashboard, an increased risk was present of the information dashboard not being designed as expected by the users. To reduce this risk, a work session with the users of the dashboard was organised to show the preliminary design of the dashboard. As a result, several small changes to the layout of the dashboard where made before implementation. As the project is still awaiting approval by the management team, another work session can be organised to further improve the information dashboard. During the research, a choice was made to implement a spreadsheet-based model, as supposed to a web-based model. This has provided transparency in the model as people at the PoR have experience with working with spreadsheets, which allows them to change the information dashboard if desired. Thereby, the dashboard is made independent from input from the designer. Furthermore, the forecasts that are made for the leading indicators are automatically estimated as more data is added to the spreadsheet. This allows for an easier way of working while achieving accurate results.

Personal reflection

Looking back at the research project, some reflections can be made concerning my own experiences of the work performed. The concept of leading indicators and forecasting practise was relatively new for me so the project provided a steep learning curve in the first few weeks. Although the goal of the research, to design an information dashboard to support the current process, was clear from the start, finding an appropriate design approach was harder than expected. The statistical analysis that had to be performed turned out to be way beyond my prior knowledge of statistics. This was frustrating at times during the research, as the master thesis project is aimed at using knowledge gained from the master programme and applying it in a real life situation. By digging in, keeping disciplined and consulting various econometrics books, papers and experts I have managed to acquire a good amount of knowledge concerning VAR modelling and time series forecasting. Conquering this new subject for me has made me appreciate the results that have been achieved even more. Therefore, the research has been a great learning experience for myself to touch upon a new subject, include this in the research and combining this with knowledge gained from the System Engineering, Policy Analysis and Management master programme at the TU Delft.

The fact that I was given the opportunity to perform this research at the Port of Rotterdam authority, allowed me to get a feeling for doing a project in a dynamic business environment. Working together with people from the PoR has provided many insights for this research and most importantly, has provided vital information for the analysis and design of the FSS. Although expectations for the research can sometimes be high, it was important for me to find a balance between the scientific contribution of this research and providing a valuable contribution to business processes at the PoR. In my opinion, a good balance between the two aspects has been achieved, resulting in the successful completion of the project.

LITERATURE

ABN AMRO. (2012). *Zakendoen met Duitsland.* Retrieved 07 30, 2012 from Duits-Nederlandse HandelsKamer (DNSK): http://www.dnhk.org/fileadmin/ahk_niederlande/Downloads/ABN_AMRO_Landenboekje_Duitsland_online.pdf

Aburto, L., & Weber, R. (2007). A sequential hybrid forecasting system for demand prediction. In P. Perner (Ed.), *International conference on machine learning and data mining* (pp. 518-532). Berlin: Springer_verlag.

Advameg, Inc. (2012). *Forecasting*. Retrieved 05 16, 2012 from Reference for Business: http://www.referenceforbusiness.com/small/Eq-Inc/Forecasting.html#b

Aiolfi, M., Capistrán, C., & Timmermann, A. (2010). Forecast combinations. In *Oxford handbook of economic forecasting.* Banco de México.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control , 19* (6), 716-723.

Ashton, A., & Ahston, R. (1985). Aggregating subjective forecasts: some empirical evidence. *Management Science , 31* (12), 1499-1508.

Atan, M., & Wu, S. (2010). A generalized leading indicator forecasting framework. Bethlehem, Pennsylvania, U.S.A.: Lehigh University.

Aytac, B., & Wu, S. (2010). *Characterization of demand for short life-cycle technology products.* Lehigh University, Department of Industrial and Systems Engineering. Springer.

Azis, I. (2010). Predicting a recovery date of the economic crisis of 2008. *Social-Economic Planning Sciences , 44*, 122-129.

Bain, A. (1873). *Mind and body. The theories of their relation.* New York, NY, U.S.S: D. Appleton and Company.

Benbassat, I., & Dexter, A. (1982). Individual differences in the use of decision support aids. *Journal of Accounting Research , 20* (1), 1-11.

Black, J., & Randow, J. (2012). *ECB cuts main rate to record low, deposit rate to zero*. Retrieved 10 4, 2012 from Bloomberg: http://www.bloomberg.com/news/2012-07-05/ecb-cuts-benchmark-rate-to-record-low-of-0-75-deposit-to-zero.html

Blattberg, R., & Hoch, S. (1990). Database models and managerial intuition: 50% model + 50% manager. *Management Science , 36* (8), 887-899.

Boehm, E., & Summers, P. (1999). *Analysing and Forecasting Business Cycles with the Aid of Economic Indicators .* The University of Melbourne, Melbourne Institue of Applied Economics and Social Research. Parkvile: The University of Melbourne.

Box, G., Jenkins, G., & Reinsel, G. (1994). *Time Series Analysis. Forecasting and control* (Vol. 3). San Fransisco, CA, U.S.A.: Wiley & Sons.

Brodie, R., & De Kluyver, C. (1987). A comparison of the short term forecasting accuracy if econometric and naive extrapolation models of market share. *International Journal of Forecasting , 3* (3-4), 423-437.

Bunn, D., & Wright, G. (1991). Interaction of judgemental and statistical methods: issues and analysis. *Management Science , 37* (5), 501-518.

Caldwell, J. (2006). *The Box-Jenkins Forecasting Technique*. Retrieved 06 26, 2012 from Foundation website: http://www.foundationwebsite.org/BoxJenkins.htm#_Toc145736392

CBS. (2012, 11 20). *Consument nog veel somberder*. Retrieved 11 21, 2012 from Nu.nl: http://www.nu.nl/geldzaken/2962720/consument-nog-veel-somberder.html

CBS. (2012, 05 22). *Consument pessimistischer*. Retrieved 10 23, 2012 from Inkomen en Bestedingen: http://www.cbs.nl/nl-NL/menu/themas/inkomen-bestedingen/publicaties/artikelen/archief/2012/2012-05-22-m10.htm

Chase, R., Jacobs, F., & Aquilano, N. (2005). *Operations management for competitive advantage.* McGraw-Hill Higher Education.

Chou, C., Chu, C., & Liang, G. (2008). A modified regression model for forecasting the volumes of Taiwan's import containers. *Mathematical and Computer Modelling , 47*, 797-807.

Chu, F. (2009). Forecasting tourism demand with ARMA-based methods. *Tourism Management , 30*, 740-751.

Chung, Y. (2005). *Identification of economic value drivers impacting operational cash flows in the casual theme restaurant industry.* Faculty of the Virgnia Polytechnic Institute and State University, Hospitality and Tourism Management. Blacksburg: University of Virginia.

Clemen, R. (1990). Combining forecasts: A review and annotated bibliography. *International journey of forecasting , 5*, 559-583.

CNN Money. (2012). *JPMorgan's trading loss: $5.8 billion*. Retrieved 10 4, 2012 from CNN Money: http://money.cnn.com/2012/07/13/investing/jpmorgan-earnings/index.htm

Creative Research Systems. (2012). *Survey Design*. Retrieved 07 11, 2012 from The Survey System: http://www.surveysystem.com/sdesign.htm

Crone, S. (2005). Forecasting with Artificial Neural Networks. Santiago de Chile, Chile: Centre for Forecasting, Department of Management Science, Lancaster University Management School.

de Gooijer, J., & Hyndman, R. (2006). 25 years of time series forecasting. *International journey of forecasting , 22*, 443-473.

de Langen, P., van Meijeren, J., & Tavasszy, L. (2012). Combining Models and commodity chain research for making long-term projections of port throughput: An application to the Hamburg-Le Havre range. *International Journal of Transport Infrastructure Research* (12), 310-331.

Diamantopoulos, A., & Mathews, B. (1989). Judgemental revision of sales forecasts: a longitudinal extension. *Journal of Forecasting* , 129-140.

Draghi, M. (2008). Deep interdependence - the transatlantic economy and its poropects. Rome, Italy.

Duke Education. (2011). *Introduction to ARIMA: nonseasonal models*. Retrieved 06 26, 2012 from Duke University: http://www.duke.edu/rnau/411rim.htm

Duke Education. (2012). *Stationarity and differencing*. Retrieved 09 24, 2012 from Duke education: http://www.duke.edu/~rnau/411diff.htm

Engle, R., Granger, C., & Kraft, D. (1984). Combining competing forecasts of inflation using a bivariate ARCH model. *Journal of economic dynamics and control , 8*, 151-165.

Feige, E., & Pearce, D. (1979). The Casual Causal Relationship Between Money and Income: Some Caveats for Time Series Analysis. *The Review of Economics and Statistics , 61* (4), 521-533.

Few, S. (2004). Dashboard Confusion. *Intelligent Enterprise* .

Few, S. (2012). *Information Dashboard Design.* Retrieved 09 21, 2012 from Perceptal Edge: www.perceptualedge.com

Fildes, R., & Goodwin, P. (2003). *The Design Features of Forecasting Support Systems and their Effectiveness.* Lancaster University Management School, The Department of Management Science. Lancaster: LUMS.

Fildes, R., Goodwin, P., & Lawrence, M. (2006). The design features of Forecasting Support Systems and their effectiveness. *Decision Support Systems , 42*, 351-361.

Fildes, R., Goodwin, P., Lawrence, M., & Nikolopoulos, K. (2009). Effective forecasting and judgmental adjustments: an empirical evaluation and strategies for improvement in supply-chain planning. *International journal of forecasting , 25* (1), 3-23.

Frank, R., Davey, N., & Hunt, S. (2010). Time Series Prediction and Neural Networks. Hatfield, HRT, U.K.: University of Hertfordshire.

Frankel, J., & Saravelos, G. (2010). Are leading indicators of financial crises useful for assessing country vulnerability? Evidence from the 2008-09 global crisis. Cambridge, MA, U.S.A.: NBER.

Franses, P. (2008). Merging models and experts. *International journal of forecasting , 24*, 31-33.

Freeman, J. (1983). Granger Causality and the Time Series Analysis of Political relationships. *American Journal of Political Science , 27* (2), 327-358.

Freeman, J. (1983). Granger Causality and the Time Series Analysis of Political Relationships. *American Journal of Political Science , 27* (2), 327-358.

FSB. (2009). *Foundation for Small Businesses.* Retrieved 05 10, 2012 from UK Policy Issue: http://www.fsb.org.uk/policy/images/impact%20of%20the%20financial%20crisis%20on%20small%20businesses.pdf

Gates, K., Molenaar, P., Hillary, F., Ram, N., & Rovine, M. (2010). Automatic search for fMRI connectivity mapping: An alternative to Granger causality testing using fornal equivalences among SEM path modeling, VAR, and unified SEM. *NeuroImage , 50*, 1118-1125.

GfK. (2012, 10 26). *German consumer climate slightly brighter*. Retrieved 10 28, 2012 from GfK Press releases: http://www.gfk.com/news-and-events/press-room/press-releases/pages/german-consumer-climate-slightly-brighter.aspx

Granger, C. (2001). *Essays in Econometrics, Collected Papers of Clive W.J. Granger. Volume II: Causality, Integration and Cointegration, and Long Memory* (Vol. 2). (E. Ghysels, N. Swanson, & M. Watson, Eds.) New York, NY, U.S.A.: Cambridge University Press.

Granger, C., & Bates, J. (1969). The combination of forecasts. *Operational research quarterly , 20* (4), 451-468.

Granger, C., & Ramanathan, R. (1984). Improved methods of combining forecasts. *Journal of Forecasting , 3* (2), 197-204.

Guerts, M., & Reinmuth, J. (1972). A Bayesian approach to forecasting efforts of atypical situations. *Journal of marketing research , 9*, 292-297.

Gujarati, D. (2003). *Basic Econometrics.* West Point, NY, U.S.A.: McGraw Hill.

Hassler, U., & Wolters, J. (1994). On the power of unit root tests against fractional alternatives. *Economics Letters , 45* (1), 1-5.

Havenbedrijf Rotterdam N.V. (2010, 12 30). Eindejaarsbijeenkomst 2010. Rotterdam, Zuid-Holland, Nederland.

Havenbedrijf Rotterdam N.V. (2010). European Gateway for dry bulk. Rotterdam, Zuid-Holland, NL: Havenbedrijf Rotterdam.

Havenbedrijf Rotterdam N.V. (2011). *Jaarverslag 2011.* Corporate Finance & Control. Rotterdam: Havenbedrijf Rotterdam.

Havenbedrijf Rotterdam N.V. (2011). *Key Figures*. Retrieved 05 21, 2012 from Financieel - omzet in miljoenen: http://jaarverslag.portofrotterdam.com/key-figures/ons-bedrijf/financieel/1662?id=g24

Havenbedrijf Rotterdam N.V. (2012). Minerals and construction materials. Rotterdam, Zuid-Holland, NL: Havenbedrijf Rotterdam N.V.

Havenbedrijf Rotterdam N.V. (2012). *Ons Bedrijf*. Retrieved 06 18, 2012 from Havenbedrijf Rotterdam: http://www.portofrotterdam.com/nl/Havenbedrijf/ons-bedrijf/Pages/default.aspx

Havenbedrijf Rotterdam N.V. (2012). *Port Statistics 2009-2010-2011.* Rotterdam: Havenbedrijf Rotterdam N.V.

Havenbedrijf Rotterdam N.V. (2011). *Port Visie 2030.* Rotterdam: HbR.

Havenbedrijf Rotterdam N.V. (2012). Rotterdam your world-class agri-port. Rotterdam, Zuid-Holland, NL: Havenbedrijf Rotterdam N.V.

Havenbedrijf Rotterdam N.V. (2012). Rotterdam your world-class coal port. Rotterdam, Zuid-Holland, NL: Havenbedrijf Rotterdam N.V.

Havenbedrijf Rotterdam N.V. (2012). Rotterdam your world-class Iron Ore & Scrap port. Rotterdam, Zuid-Holland, NL: Havenbedrijf Rotterdam N.V.

Havenbedrijf Rotterdam N.V. (2012). World top 20 ports. *Total throughput 2011 in million metric tonnes* . Rotterdam, Zuid-Holland, NL: Business Analysis & Intelligence.

Heij, C., van Dijk, D., & Groenen, P. (2011). Real-time macroeconomic forecasting with leading indicators: An empirical comparison. *International Journal of Forecasting , 27*, 466-481.

Herder, P., & Stikkelman, R. (2004). Methanol-Based Industrial Cluster Design: A Study of Design options and the Design Process. *Industrial & Engineering Chemical Research* , 3879-3885.

Hogarth, R., & Makridakis, S. (1981). Forecasting and planning: an evaluation. *Management Science , 27* (2), 115-138.

Honig, J., Kolfschoten, G., & Warnier, M. (2012). Anaylse van bedrijfssystemen. *SPM1121* . Delft, ZH, NL: TU Delft.

Huang, H., & Lee, T. (2007). To combine forecasts or to combine information? Riverside, California, U.S.A.: University of California.

Hyndman, R., & Koehler, A. (2005). *Another look at measures of forecast accuracy.* Monash University.

IMF. (2012). *World Economic Outlook - April 2012.* Washington: IMF Publication Services.

James, W. (1890). *The principles of psychology.* New York, NY, U.S.A.: H. Holt and company.

Keen, P., & Sol, H. (2008). *Decision Enhancement Services. Rehearsing the future for decisions that matter.* Amsterdam, NH, NL: IOS Press BV.

Kyd, C. (2012). *How to analyse seasonal sales in Excel*. Retrieved 09 24, 2012 from Exceluser: http://www.exceluser.com/solutions/seasonality-sales.htm

Lüktepohl, H. (2007). *New Introduction to Multiple Time Series Analysis.* Berlin, Germany: Springer.

Linde, P. (2005). *Seasonal Adjustment.* Statistics Denmark. Copenhagen: Statistics Denmark.

Long, K. (2003). Process Modeling, Today & Tomorrow. Vancouver, BC, Canada: Process Renewal Consulting Group Inc.
MacLennan, J. (2011). *Jamie's Blogspot*. Retrieved 10 15, 2012 from Azure Marketplace Data with PowerPivot and Predixion: http://jamiemaclennan.blogspot.nl/2011/02/azure-marketplace-data-with-powerpivot.html
Makridakis, S., & Wheelwright, S. (1989). *Forecasting methods for management.* New York, U.S.A.: Wiley.
Marcellino, M. (2006). *Handbook of Economic Forecasting* (Vol. 1). (G. Elliot, C. Granger, & A. Timmermann, Eds.) North Holland.
McCulloch, W., & Pitts, W. (1943). A Logical Calculus of Ideas Immanent in Nervous Activity. *Bulletin of Mathematical Biophysics , 5*, 115-133.
Meko, D. (2011). Autocorrelation. *Applied time series analysis* . Tucson, AZ, U.S.A.
Meyler, A., Kenny, G., & Quinn, T. (1998). *Forecasting Irish infation using ARIMA models.* Central Bank of Ireland, Economic analysis, Research and Development department. Dublin: Central Bank of Ireland.
Mushtaq, R. (2011). *Augmented Dickey Fuller test.* Retrieved 10 18, 2012 from Social Science Research Network: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1911068
OECD. (2012). Composite Leading Indicators. Paris, France: OECD.
OECD. (2006). *Composite leading indicators for major OECD non-member economies.* OECD, Short-term Economic Statistic Division. Paris: OECD.
Pindyck, R., & Rubinfield, D. (1998). *Econometric models and economic forecasts* (Vol. 4). Columbus, OH, U.S.A.: McGraw-Hill Publishers.
Power, D., & Sharda, R. (2007). Model-driven decision support systems: Concepts and research directions. *Decision Support Systems , 43*, 1044-1061.
Rekowski, M. (2003). *Leading indicators as a forecasting method of the economic situation in Poland - a summary of the research results.* Poznan, Wydaw, Poland: Akademia Ekonomiczna w Poznaniu.
Root, E. (2011). Time Series analysis lectures on ACF, PACF, Cross correlations and Leading indicators for time series. Boulder, CO, U.S.A.: University of Colorado.
Ross, D. (1985). Application and Extensions of SADT. *Computer , 18* (4), 25-34.
Sage, A., & Armstrong, J. (2000). *Introduction to Systems Engineering.* Hoboken, NJ, U.S.A.: Wiley.
Sauter, V. (1997). *Decision support systems.* Hoboken, NJ, U.S.A.: John Wiley & Sons, Inc.
Scocco, D. (2012). *Cuasation vs. Correlation*. Retrieved 09 24, 2012 from DailyBlogTips: http://www.dailyblogtips.com/causation-vs-correlation/
Selby, R. (2005). Measurement-driven dashboards enable leading indicators for requirements and design of large-scale systems. *11th IEEE International Software Metrics Symposium.* Como: IEEE.
Slovik, P. (2011). Market uncertainty and market instability. *Irving Fishing Committee Bulletin , 34*, 430-435.
Smith, H., & Fingar, P. (2003). *Business Process Management (BPM): The Third Wave* (Vol. 1). Tampa, FL, U.S.A.: Meghan-Kiffer Press.
Stock, J., & Watson, M. (1992). A procedure for predicting recessions with leaing indicators: Economic issues and recent experiences.
Stopford, M. (2009). *Maritime Economics.* Abingdon: Routledge.
Swanson, E. (1988). *Information System Impementation.* Homewood, IL, U.S.A.: Irwin.
Swink, M. (1995). The influences of user characteristics on performance in a logistics DSS application. *Decision Sciences , 26*, 503-530.
Tabachnick, B., & Fidell, L. (2007). *Using Multivariate Statistics.* Boston, MA, U.S.A.: Pearson Education Inc.
Taleb, N. (2010). *The Black Swan: The Impact of the Highly Improbable.* New York, NY, U.S.A.: Random House Publishing Group.
The Economist. (2006). *Guide to economic indicators: making sence of economics.* London, United Kingdom: Profile Books Ltd.
Thomson Reuters. (2012). World Equities & G7 + E7 Leading Indicator. New York, NY, U.S.A.
Toda, H., & Phillips, P. (1994). Vector autoregression and causality: a theoretical overview and simulation study. *Econometric Reviews , 13* (2), 259-285.
treassury.nl. (2012, 09 25). *Duits consumentenvertrouwen oktober ongewijzigd*. Retrieved 10 12, 2012 from treasury.nl: http://www.treasury.nl/blog/duits-consumentenvertrouwen-oktober-ongewijzigd/

Valenzuala, O., Rojas, I., Rojas, F., Pomares, H., Herrera, L., Guillen, A., et al. (2008). Hybridization of intelligent techniques and ARIMA models for time series prediction. *Fuzzy sets and systems , 159* (7), 821-845.

van Dorsser, C., Wolters, M., & van Wee, B. (2012). A very long term forecast of the port throughput in the Le Havre - Hamburg range up to 2100. *European Journal of Transport and Infrastructure Research , 1* (12), 88-110.

Veenstra, A., & Franses, P. (1997). A co-integration approach to forecasting freight rates in the dry bulk shipping sector. *Transportation Research Part A: Policy and Practice , 31* (6), 447-458.

Waddell, D., & Sohal, A. (1994). Forecasting: The key to managerial decision making. *Management Decision , 32* (1), 41-49.

Walker, W. (2011, 10 19). Policy Analysis, 1962-2012: From Predict And Act To Monitor And Adapt. Delft, ZH, the Netherlands: TU Delft.

WebFinance Inc. (2012). *Business Dictionary*. Retrieved 05 13, 2012 from Forecasting: http://www.businessdictionary.com/definition/forecasting.html

Whiteside, J. (2008). A practical application of Monte Carlo simulation in forecasting. *AACE International Transactions* (pp. 408-419). Toronto: Curran Associates, Inc.

Wilson, J. (2010). *Essentials of business research methods: A Guide to doing your research project.* Thousand Oaks, CA, U.S.A.: SAGE Publications Ltd.

WSA. (2012). *World Steel Association*. Retrieved 11 19, 2012 from Iron Production 2011: http://www.worldsteel.org/statistics/statistics-archive/2011-iron-production.html

WTO. (2012, 05 10). World Trade Organisation. Geneve, Switserland. From WTO Statitics database: http://stat.wto.org/StatisticalProgram/WSDBStatProgramHome.aspx?Language=E

Yanovitzky, I., & Van Lear, A. (2007). Time Series Analysis. Traditional and Contemporary approaches. In M. Slater, A. Hayes, & L. Snyder, *Advanced data analysis methods for communication research.* Thousand Oaks, CA, U.S.A.: SAGE publishing.

Z24. (2010, 08 12). *z24.nl*. Retrieved 05 10, 2012 from Zakelijks nieuws regio Rotterdam: http://www.z24.nl/speciaal/feeds/anp/artikel_163715.z24/Crisis_Havenbedrijf_Rotterdam_voorbij.html

Zhang, G., Patuwo, E., & Hu, M. (1998). Forecasting with artificial neural networks: The state of the art. *International journal of forecasting , 14*, 35-62.

Zhu, H. (2010). *Three essays on updating forecasts in vector autoregression models.* Queen's University, Department of Economics. Kingston: Queen's University Press.

APPENDICES

Appendix 1: Survey and results

ENQUÊTE KORTE-TERMIJN PROGNOSE PROCES

Afstudeeronderzoek naar 'leading indicators' voor droge massagoederen in de haven van Rotterdam

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ALGEMENE INDRUK VAN PROCES

De volgende vragen hebben betrekking op het proces als geheel, daarmee wordt bedoeld de prognose sessie waarin wordt gekeken naar aangeleverde informatie, recente trends en ontwikkelingen in de markt enz. en op basis hiervan een gezamenlijk prognosecijfer wordt gemaakt.

Context

- In hoeverre levert de prognose een bijdrage/toegevoegde waarde aan andere bedrijfsprocessen van CBL&PIM?

  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

weinig bijdrage <--> *veel bijdrage*

Format

- In hoeverre is de huidige manier van werken (gezamenlijke overeenstemming over prognoses) een prettige manier van werken?

  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

onprettig <--> *zeer prettig*

- In hoeverre is dit de meest efficiënte manier van werken?

  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

inefficiënt <--> *zeer efficiënt*

Methode

- In hoeverre is de huidige manier van werken de meest praktische manier om gewenste resultaten te bereiken?

  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

onpraktisch <--> *zeer praktisch*

INPUT VAN INFORMATIE

Deze vragen hebben betrekking op de input van informatie in het proces. Met input van het proces wordt bedoeld de informatie die aangeleverd wordt door Frank, waaronder realisaties van overslag vergeleken met voorgaande prognoses en vergelijkingen van data. De kwaliteit van informatie heeft betrekking op de betrouwbaarheid en nauwkeurigheid van informatie. De kwantiteit betreft de hoeveelheid van informatie die wordt voorzien.

Kwaliteit van de input informatie

- In hoeverre is de kwaliteit van de input van belang voor de uitkomsten van het proces?

  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

gering belang <---> *groot belang*

- In hoeverre is de kwaliteit van de input van een geschikt niveau om een nauwkeurige prognose te maken?
  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

ongeschikt <--> *zeer geschikt*

Kwantiteit van de input informatie

- In hoeverre is de kwantiteit van de input van belang voor de uitkomsten van het proces?
  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

gering belang <---> *groot belang*

- In hoeverre is de kwantiteit van de input van een geschikt niveau om een nauwkeurige prognose te maken?
  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

ongeschikt <--> *zeer geschikt*

ONDERSTEUNING VAN HET PROGNOSE PROCES

Deze vragen hebben betrekking op de middelen die worden ingezet om te assisteren bij het maken van een prognose. Op dit moment is dat informatie afkomstig van bijv. CPB, OECD, kranten, bedrijven die uitbreiden/krimpen en andere relevante markt informatie.
Als u meer informatie kon gebruiken voor het maken van een prognose, kunt u dan aangeven in hoeverre informatie over/van de volgende gebieden en bedrijven bij kunnen dragen aan het verbeteren van het prognose proces en de uitkomsten:

- Stuwadoors en hun bedrijvigheid (uitbreidingen, sluitingen van terminals etc.):
  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

weinig bijdrage <---> *veel bijdrage*

- Bedrijven die goederen kopen/verkopen en deze transporteren via Rotterdam (m.b.t. hun capaciteit):
  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

weinig bijdrage <---> *veel bijdrage*

- Markt bewegingen, trends en de ontwikkelingen van belangrijke statistieken van de economie:
  1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

weinig bijdrage <---> *veel bijdrage*

DASHBOARD MET ‘LEADING INDICATORS’

Dit ‘dashboard’ zal middels verschillende tellers aangeven hoe belangrijke bepalende factoren voor de overslag van goederen in Rotterdam zich ontwikkeld hebben en er op het moment voor staan. Het gaat dan bijvoorbeeld over statistieken van de economie zoals de industriële productie van Duitsland, wat waarschijnlijk een effect zal hebben op de doorvoer van staal in Rotterdam.

Dashboard met 'leading indicators'

- Denkt u dat het een waardevolle toevoeging aan het proces is om een zogenaamd 'dashboard' met 'leading indicators' beschikbaar te stellen bij de besluitvorming?

1:☐ 2:☐ 3:☐ 4:☐ 5:☐ 6:☐ 7:☐ 8:☐ 9:☐ 10:☐

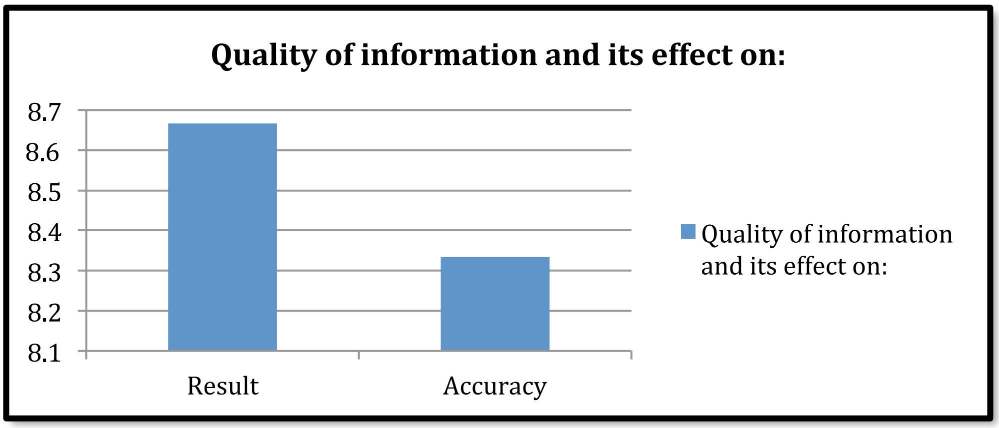
niet waardevol <---> *zeer waardevol*

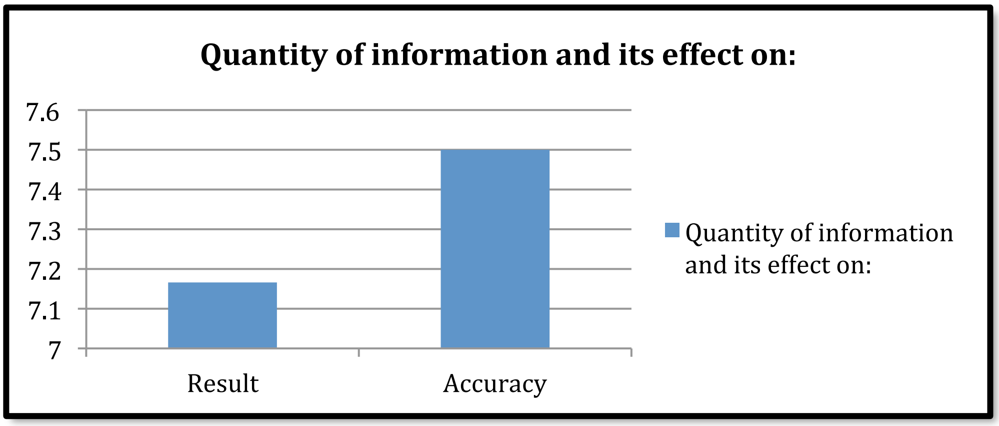
OVERIGE OPMERKINGEN OVER HET PROCES

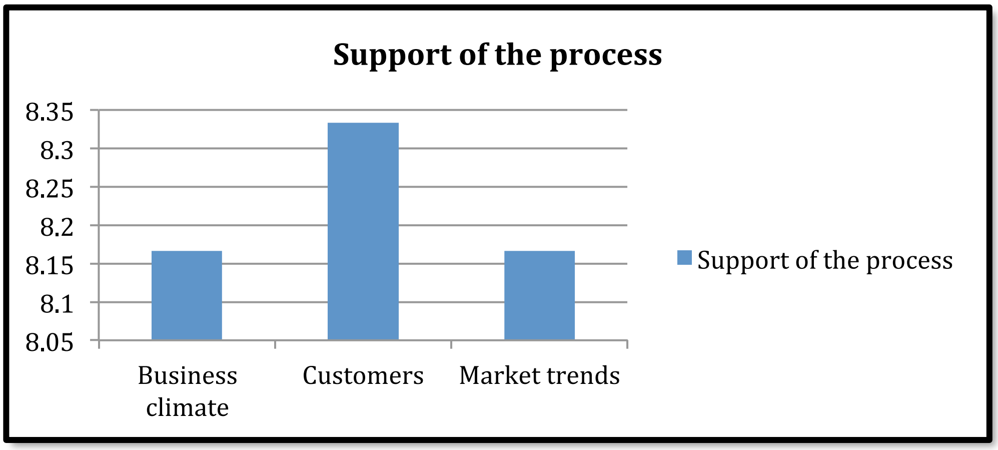
Gebruik de ruimte hieronder om eventuele antwoorden verder toe te lichten of voor eventuele op- en aanmerkingen. Hartelijk dank voor u medewerking! De resultaten van deze enquête en mijn afstudeeronderzoek zullen bij u kenbaar gemaakt worden!

Results of the survey

The survey posed to experts at the PoR has delivered various results concerning the forecasting process at the moment. In appendix 1, the survey is shown and the results are displayed below.







Appendix 2: The Eviews software package

For this research, the use of statistical analysis software is of high importance for accurately and efficiently determining the leading indicators. The software allows statistical analysis to be performed much quicker and more accurate than when doing the calculations by hand. Furthermore, the software is able to provide graphical results of the analysis that can be used to interpret the relationships between the variables. For this research, a decision was made to use SPSS as software package for doing the statistical analysis. This software is used worldwide and is a very user-friendly package. This software is also used and taught in several courses at the faculty of Industrial Engineering at the TU Delft. Furthermore, the decision to use this software was made because the business manager at the PoR who is responsible for updating and maintaining the model is familiar with working with SPSS.

However, during the course of this research project, an important decision was made to switch to another statistical software package, EViews. This is a similar software package to SPSS but focuses more on time series analysis, rather than basic statistical analysis in SPSS. The software SPSS is often used for analysing relationships between variables based on preferences of respondents, such as research concerning whether a price change in fuel affects the people's choice for taking the car or the train. Although SPSS offers a purchasable extension for forecasting, EViews already incorporates these techniques along with more options and configurable items. This allows EViews to be much more powerful for analysing time series, as well as making forecasts with the software. Furthermore, EViews offers a comparable user interface to SPSS but is, concluding after using it during this research, much easier to work with and interpret the results. This also has benefits for when the system is implemented into the PoR business activities.

Appendix 3: Composition of the economic indicators

Real GDP

In many statistical analyses GDP is included as economic variable because it gives a good reflection of the overall status of the economy. Gross Domestic Product is a monetary value of all goods and services produced within a country in a specific time period. GDP is often used as a comparing measure between countries and reflects well how an economy is behaving. For this research, yearly real GDP prices were extracted from the International Monetary Fund's (IMF) database. The values were extracted in billions of U.S. dollars, as to make the time series comparable.

Variable	Unit	Value	Time frame	Source
Real GDP the Netherlands	Current prices	x1.000.000.000 U.S. $	Per year	IMF
Real GDP Germany	Current prices	x1.000.000.000 U.S. $	Per year	IMF
Real GDP EU	Current prices	x1.000.000.000 U.S. $	Per year	IMF
Real GDP China	Current prices	x1.000.000.000 U.S. $	Per year	IMF
Real GDP World	Current prices	x1.000.000.000 U.S. $	Per year	IMF

Industrial Production

Another commonly used statistic, but a good indicator for the wellbeing of an economy. Where Real GDP includes also services (intangible products) the industrial production index of a country can give a good indication of the amount of output from manufacturing companies, public utilities and mining operations. Industrial production is indexed and the data is updated monthly. The OECD, MBS and CPB provide data for this indicator.

Variable	Unit	Value	Time frame	Source
IP the Netherlands	index	2005=100	Per month	OECD
IP Germany	index	2005=100	Per month	OECD
IP EU	index	2005=100	Per month	OECD
IP China	index	2005=100	Per month	MBS
IP World	index	2000=100	Per month	CPB

(Relevant) World Trade

Although a very general and hard to measure figure, world trade is a good indicator for business around the world. For the Port of Rotterdam, it is important to monitor this statistic because shipping transport is a worldwide business and Rotterdam receives ships from all continents. Relevant world trade is specifically focused on the Netherlands and states what proportion the Netherlands contributes to world trade. Both data series are indexed, world trade is available monthly and relevant world trade is only yearly. The CBP provides these figures.

Variable	Unit	Value	Time frame	Source
World Trade	index	2000=100	Per month	CPB
Relevant World Trade	index	2000=100	Per year	CPB

Industrial Confidence

The industrial confidence is a measure of confidence that producers and manufactures have in the economy, politics and the general state of the country. The indicator, which gathers data by questionnaires, asks respondents to answer about their own business as well. This creates reliable information as producers are close to the business. Past performance and future performance are indicated, creating a reliable and accurate indicator for economic activity. Industrial Confidence in the Netherlands and Germany has been decomposed to create better insight into the market. The expected business activity, the expected ordering position and the expected stock that companies have are measured by survey but have not been indexed. This allows analysts to give monthly updates based on deviations from the zero line. The CBS provides this data, whereas in Germany, the IFO is a reliable source for providing business indicators. Based on the same data gathering method, information about the climate, situation and expectations are collected and indexed. For China and the world, no data is available. Industrial confidence data for China had to be purchased and world data was not found in any publically accessible database.

Variable	Unit	Value	Time frame	Source
IC the Netherlands	index	no base year	Per month	Eurostat
- Expected Business Activity	Survey	% deviation from zero line	Per month	CBS
- Expected Ordering Position	Survey	% deviation from zero line	Per month	CBS
- Expected Stock	Survey	% deviation from zero line	Per month	CBS
IC Germany	index	no base year	Per month	Eurostat
- Business Climate	index	2005=100	Per month	IFO
- Business Situation	index	2005=100	Per month	IFO
- Business Expectations	index	2005=100	Per month	IFO
IC EU	index	no base year	Per month	Eurostat
IC China	NO DATA			
IC World	NO DATA			

Consumer Confidence

Similar to industrial confidence, consumer confidence is an important measure of the other side of the economy and is the driving force behind trade worldwide. The indicators assess the current financial situation of consumers, as well as their willingness to buy new household applications, e.g. TV's and fridges. Coming from the Eurostat database, this indicator is available monthly and is indexed. Although consumer goods are transported in high quantities through the port, the focus lies on dry bulk goods that are often transported through the port by manufacturing companies and heavy industry. Therefore, it is not necessary to decompose this indicator, as was done with the industrial confidence indicator.

Variable	Unit	Value	Time frame	Source
CC the Netherlands	index	no base year	Per month	Eurostat
CC Germany	index	no base year	Per month	Eurostat
CC EU	index	no base year	Per month	Eurostat
CC China	NO DATA			
CC World	NO DATA			

Purchasing Power Parity

A measure of a countries' currency value is interesting to consider as the value of money is determined by demand and supply of goods in that country. Therefore including the PPP in several countries might have a leading effect on dry bulk throughput in the Port of Rotterdam. Valued in the same unit as real GDP (in billions of U.S. dollars), the PPP is also corrected for inflation and presents a current day price. The data is available yearly and is provided by the United Nations data department.

Variable	Unit	Value	Time frame	Source
PPP the Netherlands	Current prices	x1.000.000.000 U.S. $	Per year	UNData
PPP Germany	Current prices	x1.000.000.000 U.S. $	Per year	UNData
PPP EU	Current prices	x1.000.000.000 U.S. $	Per year	UNData
PPP China	Current prices	x1.000.000.000 U.S. $	Per year	UNData
PPP World	Current prices	x1.000.000.000 U.S. $	Per year	UNData

Market specific indicators

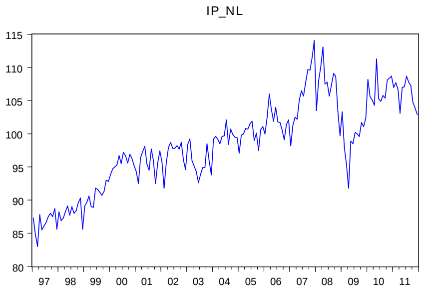
After verification and validation of the economic indicators with a dry bulk expert at the PoR, several specific market indicators were added to the list. They are listed below and can be used in the analysis for specific dry bulk goods. For example, the iron and steel production in Germany is expected to have some explanatory power of iron ore and Coal throughput in the port. Electricity production in the Netherlands and Germany can also have an influence on the amount of coal being transported through the port. Harvest yield and commodity prices are expected to have some relationship with Agribulk throughput but no data was found in databases, so for this reason they cannot be included in the rest of the research. Iron and steel production are the only monthly data available and is therefore the most suitable out of this list for statistical analysis. Another important statistic is the Baltic Dry Index; an indicator of prices for transporting dry bulk via sea routes by evaluating demand and supply of vessels. Unfortunately, data for this index is not (fully) available for free and requires a payable subscription, and the index therefore cannot be further used in this research.

Variable	Unit	Value	Time frame	Source
Baltic Dry Index	NO DATA			
Spark/dark spread	NO DATA			
Iron Production in Germany	amount	x1000 tonnes	Per month	WSA
Steel production in Germany	amount	x1000 tonnes	Per month	WSA
Automotive industry in Germany	amount	number of cars	Per year	OICA
Cokesimport Germany	amount	x1000 tonnes	Per year	EuroStat
Electricity production in the Netherlands	amount	Terajoule	Per year	EuroStat
Electricity production in Germany	amount	Terajoule	Per year	EuroStat
Harvest yield	NO DATA			
Commodity prices	NO DATA			
Mining yield Germany	amount	x1000 tonnes	Per year	EuroStat

Appendix 4: Line graphs and ACF-PACF graphs of initial variables

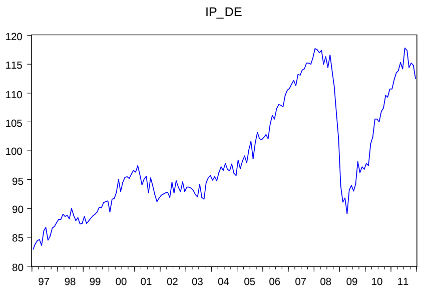
Line graphs	ACF-PACF graphs

Industrial Production NL



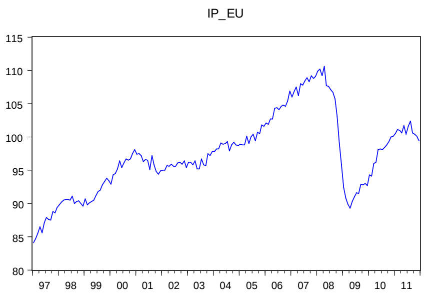
Lag	AC	PAC	Q-Stat	Prob
1	0.928	0.928	157.63	0.000
2	0.887	0.187	302.51	0.000
3	0.861	0.133	439.65	0.000
4	0.843	0.109	571.84	0.000
5	0.800	-0.136	691.67	0.000
6	0.762	-0.039	801.03	0.000
7	0.728	-0.028	901.26	0.000
8	0.698	-0.001	993.96	0.000
9	0.682	0.133	1083.0	0.000
10	0.642	-0.126	1162.4	0.000
11	0.609	-0.006	1234.3	0.000
12	0.590	0.071	1302.2	0.000

Industrial Production DE



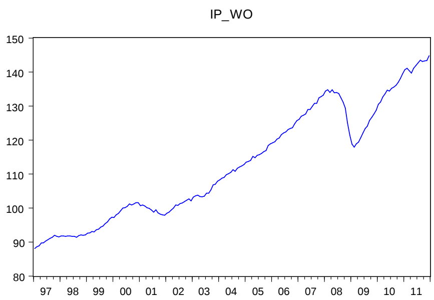
Lag	AC	PAC	Q-Stat	Prob
1	0.972	0.972	172.92	0.000
2	0.943	-0.036	336.53	0.000
3	0.909	-0.099	489.48	0.000
4	0.867	-0.157	629.54	0.000
5	0.821	-0.098	755.83	0.000
6	0.779	0.058	869.95	0.000
7	0.735	-0.003	972.31	0.000
8	0.688	-0.080	1062.6	0.000
9	0.645	0.019	1142.3	0.000
10	0.601	-0.046	1211.8	0.000
11	0.558	0.019	1272.1	0.000
12	0.518	0.019	1324.5	0.000

Industrial Production EU



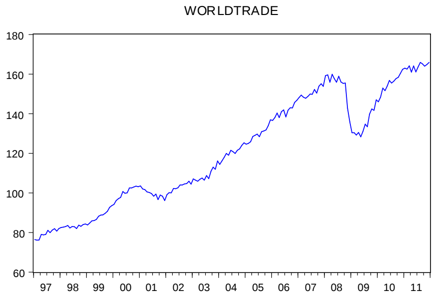
Lag	AC	PAC	Q-Stat	Prob
1	0.973	0.973	173.27	0.000
2	0.945	-0.041	337.47	0.000
3	0.909	-0.142	490.51	0.000
4	0.867	-0.143	630.52	0.000
5	0.821	-0.086	756.73	0.000
6	0.776	0.029	870.15	0.000
7	0.728	-0.051	970.58	0.000
8	0.680	-0.033	1058.6	0.000
9	0.629	-0.063	1134.5	0.000
10	0.580	-0.001	1199.3	0.000
11	0.533	0.022	1254.4	0.000
12	0.488	0.015	1300.9	0.000

Industrial Production WO



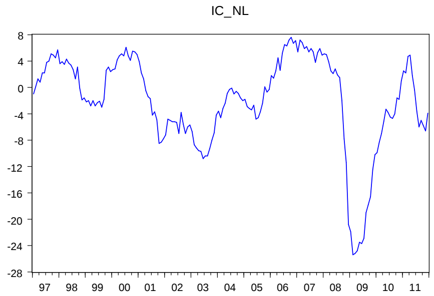
Lag	AC	PAC	Q-Stat	Prob
1	0.982	0.982	176.50	0.000
2	0.964	-0.021	347.41	0.000
3	0.944	-0.044	512.35	0.000
4	0.924	-0.028	671.18	0.000
5	0.902	-0.036	823.65	0.000
6	0.881	-0.005	969.91	0.000
7	0.860	-0.007	1110.1	0.000
8	0.840	0.002	1244.4	0.000
9	0.820	0.009	1373.1	0.000
10	0.800	-0.025	1496.3	0.000
11	0.779	-0.028	1613.9	0.000
12	0.758	-0.009	1725.9	0.000

World Trade



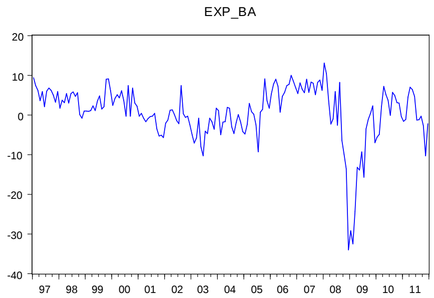
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.982	0.982	176.62	0.000
		2	0.965	-0.003	347.97	0.000
		3	0.947	-0.037	513.78	0.000
		4	0.926	-0.072	673.36	0.000
		5	0.906	0.001	826.94	0.000
		6	0.885	-0.013	974.53	0.000
		7	0.865	-0.010	1116.2	0.000
		8	0.844	-0.022	1251.9	0.000
		9	0.824	0.010	1382.0	0.000
		10	0.803	-0.055	1506.1	0.000
		11	0.783	0.037	1624.9	0.000
		12	0.763	-0.012	1738.3	0.000

Industrial Confidence NL



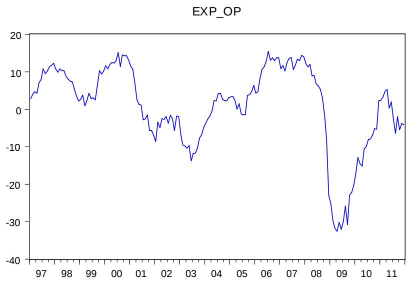
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.972	0.972	173.04	0.000
		2	0.928	-0.320	331.55	0.000
		3	0.867	-0.271	470.60	0.000
		4	0.788	-0.264	586.08	0.000
		5	0.705	0.066	679.01	0.000
		6	0.617	-0.018	750.67	0.000
		7	0.527	-0.038	803.23	0.000
		8	0.440	0.003	840.10	0.000
		9	0.356	-0.010	864.39	0.000
		10	0.273	-0.103	878.74	0.000
		11	0.197	0.040	886.28	0.000
		12	0.129	0.054	889.55	0.000

- Expected Business Activity



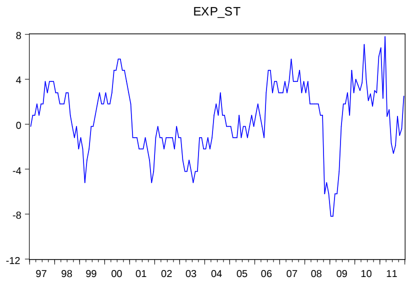
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.806	0.806	118.98	0.000
		2	0.697	0.134	208.38	0.000
		3	0.569	-0.075	268.25	0.000
		4	0.470	-0.007	309.30	0.000
		5	0.457	0.211	348.34	0.000
		6	0.354	-0.196	371.90	0.000
		7	0.302	-0.001	389.14	0.000
		8	0.209	-0.082	397.46	0.000
		9	0.149	0.022	401.73	0.000
		10	0.121	-0.000	404.56	0.000
		11	0.055	-0.077	405.14	0.000
		12	0.043	0.038	405.51	0.000

- Expected Ordering Position



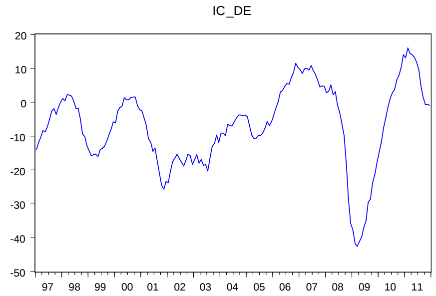
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.973	0.973	173.20	0.000
		2	0.941	-0.106	336.05	0.000
		3	0.894	-0.274	484.12	0.000
		4	0.834	-0.278	613.52	0.000
		5	0.768	-0.065	723.87	0.000
		6	0.699	0.036	815.86	0.000
		7	0.625	-0.045	889.94	0.000
		8	0.549	-0.085	947.38	0.000
		9	0.479	0.097	991.34	0.000
		10	0.403	-0.136	1022.6	0.000
		11	0.334	0.065	1044.3	0.000
		12	0.269	-0.002	1058.4	0.000

- Expected Stock



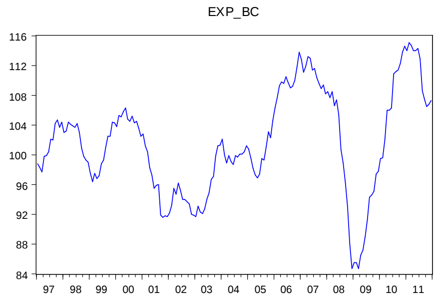
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.851	0.851	132.47	0.000
		2	0.772	0.174	242.10	0.000
		3	0.655	-0.130	321.61	0.000
		4	0.543	-0.101	376.47	0.000
		5	0.428	-0.079	410.74	0.000
		6	0.329	-0.019	431.09	0.000
		7	0.239	-0.016	441.86	0.000
		8	0.152	-0.050	446.29	0.000
		9	0.098	0.040	448.12	0.000
		10	0.029	-0.071	448.28	0.000
		11	-0.022	-0.037	448.37	0.000
		12	-0.103	-0.156	450.44	0.000

Industrial Confidence DE



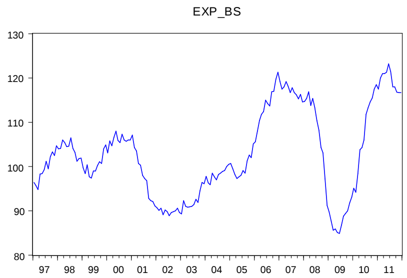
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.980	0.980	175.72	0.000
		2	0.940	-0.513	338.23	0.000
		3	0.880	-0.360	481.50	0.000
		4	0.805	-0.156	602.00	0.000
		5	0.717	-0.102	698.15	0.000
		6	0.618	-0.121	770.01	0.000
		7	0.516	0.120	820.38	0.000
		8	0.410	-0.059	852.43	0.000
		9	0.306	-0.004	870.31	0.000
		10	0.202	-0.057	878.20	0.000
		11	0.104	0.005	880.29	0.000
		12	0.011	-0.054	880.32	0.000

- Business Climate



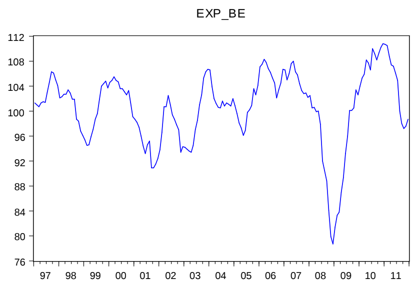
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.977	0.977	174.61	0.000
		2	0.939	-0.337	336.73	0.000
		3	0.889	-0.190	482.94	0.000
		4	0.823	-0.307	608.92	0.000
		5	0.747	-0.075	713.51	0.000
		6	0.662	-0.169	795.99	0.000
		7	0.574	0.093	858.44	0.000
		8	0.486	0.016	903.51	0.000
		9	0.399	0.032	934.02	0.000
		10	0.315	-0.023	953.11	0.000
		11	0.232	-0.076	963.55	0.000
		12	0.151	-0.129	967.98	0.000

- Business Situation



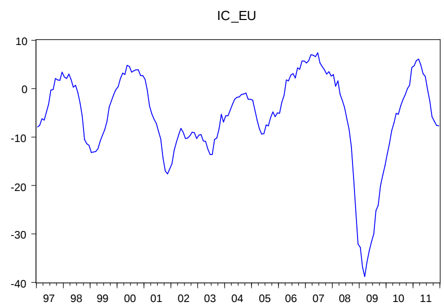
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.977	0.977	174.71	0.000
		2	0.947	-0.165	339.79	0.000
		3	0.909	-0.171	492.79	0.000
		4	0.856	-0.333	629.16	0.000
		5	0.796	-0.112	747.70	0.000
		6	0.726	-0.182	846.87	0.000
		7	0.649	-0.077	926.61	0.000
		8	0.571	0.032	988.74	0.000
		9	0.489	-0.026	1034.6	0.000
		10	0.406	-0.013	1066.5	0.000
		11	0.327	0.055	1087.2	0.000
		12	0.247	-0.034	1099.1	0.000

- Business Expectations



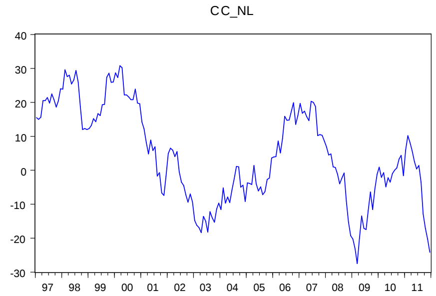
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.962	0.962	169.32	0.000
		2	0.890	-0.466	315.19	0.000
		3	0.797	-0.173	432.74	0.000
		4	0.684	-0.201	519.82	0.000
		5	0.563	-0.013	579.11	0.000
		6	0.436	-0.089	614.97	0.000
		7	0.317	0.103	634.06	0.000
		8	0.209	-0.016	642.35	0.000
		9	0.114	0.047	644.84	0.000
		10	0.032	-0.074	645.04	0.000
		11	-0.040	-0.084	645.36	0.000
		12	-0.101	-0.024	647.35	0.000

Industrial Confidence EU



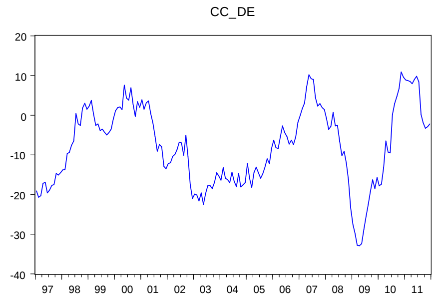
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.979	0.979	175.52	0.000
		2	0.935	-0.590	336.39	0.000
		3	0.868	-0.382	475.77	0.000
		4	0.782	-0.163	589.71	0.000
		5	0.686	0.078	677.79	0.000
		6	0.582	0.018	741.63	0.000
		7	0.475	-0.054	784.32	0.000
		8	0.365	-0.156	809.63	0.000
		9	0.258	0.094	822.35	0.000
		10	0.152	-0.136	826.80	0.000
		11	0.053	0.097	827.35	0.000
		12	-0.037	-0.002	827.61	0.000

Consumer Confidence NL



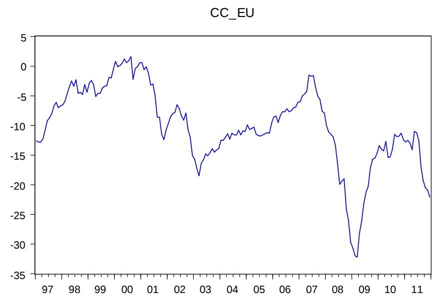
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.953	0.953	166.32	0.000
		2	0.908	-0.013	317.93	0.000
		3	0.863	-0.015	455.70	0.000
		4	0.812	-0.086	578.48	0.000
		5	0.766	0.020	688.33	0.000
		6	0.726	0.040	787.53	0.000
		7	0.681	-0.072	875.30	0.000
		8	0.634	-0.049	951.92	0.000
		9	0.588	-0.034	1018.1	0.000
		10	0.544	0.012	1075.1	0.000
		11	0.507	0.047	1124.9	0.000
		12	0.470	-0.028	1167.9	0.000

Consumer Confidence DE



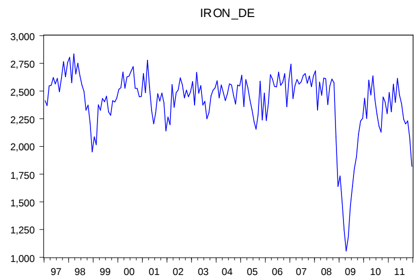
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.959	0.959	168.25	0.000
		2	0.906	-0.163	319.38	0.000
		3	0.853	-0.012	454.14	0.000
		4	0.785	-0.222	568.96	0.000
		5	0.703	-0.184	661.38	0.000
		6	0.616	-0.075	732.84	0.000
		7	0.532	0.009	786.50	0.000
		8	0.444	-0.071	824.12	0.000
		9	0.364	0.083	849.45	0.000
		10	0.293	0.048	865.98	0.000
		11	0.225	-0.040	875.75	0.000
		12	0.152	-0.141	880.26	0.000

Consumer Confidence EU



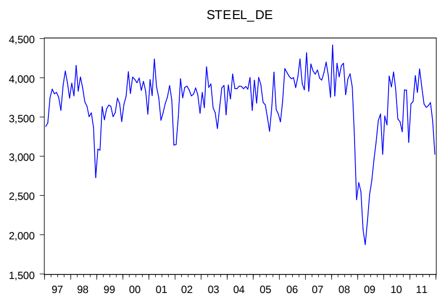
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.969	0.969	171.90	0.000
		2	0.928	-0.179	330.51	0.000
		3	0.877	-0.182	472.71	0.000
		4	0.818	-0.096	597.25	0.000
		5	0.758	-0.001	704.89	0.000
		6	0.702	0.056	797.74	0.000
		7	0.651	0.036	877.93	0.000
		8	0.599	-0.082	946.24	0.000
		9	0.544	-0.115	1003.0	0.000
		10	0.494	0.054	1050.0	0.000
		11	0.446	0.014	1088.6	0.000
		12	0.399	-0.008	1119.7	0.000

Iron Production DE



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.824	0.824	124.18	0.000
		2	0.748	0.216	227.12	0.000
		3	0.620	-0.132	298.35	0.000
		4	0.508	-0.089	346.39	0.000
		5	0.412	-0.005	378.10	0.000
		6	0.269	-0.194	391.75	0.000
		7	0.183	0.003	398.10	0.000
		8	0.093	0.007	399.76	0.000
		9	0.039	0.028	400.06	0.000
		10	0.002	0.030	400.06	0.000
		11	-0.085	-0.188	401.46	0.000
		12	-0.045	0.246	401.85	0.000

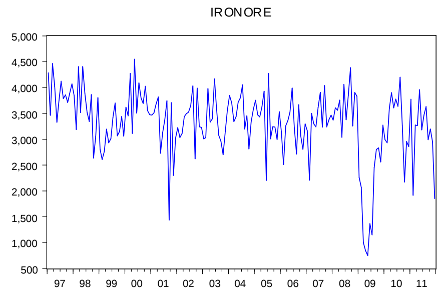
Steel Production DE



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.763	0.763	106.62	0.000
		2	0.660	0.186	186.80	0.000
		3	0.522	-0.074	237.21	0.000
		4	0.465	0.093	277.52	0.000
		5	0.387	-0.012	305.55	0.000
		6	0.269	-0.166	319.19	0.000
		7	0.191	-0.011	326.11	0.000
		8	0.097	-0.072	327.89	0.000
		9	-0.015	-0.179	327.93	0.000
		10	-0.034	0.132	328.16	0.000
		11	-0.079	-0.010	329.38	0.000
		12	0.010	0.245	329.40	0.000

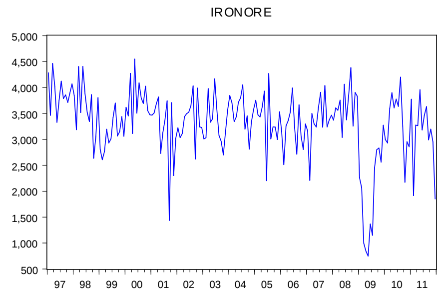
Line graphs	ACF-PACF graphs

Agribulk



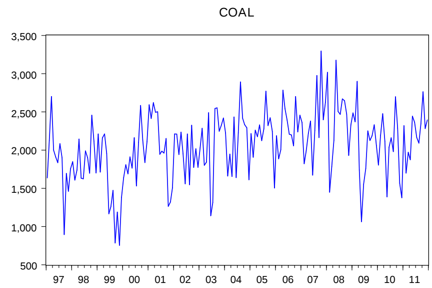
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.434	0.434	34.429	0.000
		2	0.497	0.380	79.807	0.000
		3	0.378	0.115	106.30	0.000
		4	0.265	-0.063	119.39	0.000
		5	0.126	-0.166	122.34	0.000
		6	0.091	-0.043	123.91	0.000
		7	-0.022	-0.067	124.01	0.000
		8	-0.010	0.039	124.03	0.000
		9	-0.032	0.050	124.22	0.000
		10	-0.059	-0.020	124.89	0.000
		11	-0.112	-0.111	127.31	0.000
		12	-0.031	0.047	127.50	0.000

Iron Ore & Scrap



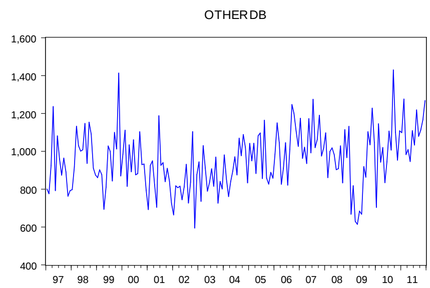
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.434	0.434	34.429	0.000
		2	0.497	0.380	79.807	0.000
		3	0.378	0.115	106.30	0.000
		4	0.265	-0.063	119.39	0.000
		5	0.126	-0.166	122.34	0.000
		6	0.091	-0.043	123.91	0.000
		7	-0.022	-0.067	124.01	0.000
		8	-0.010	0.039	124.03	0.000
		9	-0.032	0.050	124.22	0.000
		10	-0.059	-0.020	124.89	0.000
		11	-0.112	-0.111	127.31	0.000
		12	-0.031	0.047	127.50	0.000

Coal



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.404	0.404	29.839	0.000
		2	0.255	0.110	41.840	0.000
		3	0.250	0.138	53.446	0.000
		4	0.160	0.004	58.229	0.000
		5	0.145	0.047	62.139	0.000
		6	0.091	-0.021	63.682	0.000
		7	0.145	0.100	67.640	0.000
		8	0.155	0.057	72.199	0.000
		9	0.127	0.028	75.303	0.000
		10	0.091	-0.021	76.914	0.000
		11	0.046	-0.037	77.330	0.000
		12	0.184	0.171	83.898	0.000

Other dry bulk goods

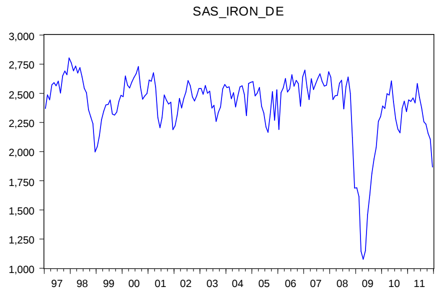


Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.288	0.288	15.205	0.000
		2	0.337	0.277	36.122	0.000
		3	0.279	0.152	50.535	0.000
		4	0.184	0.013	56.830	0.000
		5	0.172	0.023	62.339	0.000
		6	0.040	-0.099	62.647	0.000
		7	0.120	0.060	65.370	0.000
		8	0.051	0.003	65.869	0.000
		9	0.170	0.156	71.383	0.000
		10	0.162	0.097	76.437	0.000
		11	0.166	0.062	81.787	0.000
		12	0.202	0.051	89.763	0.000

Appendix 5: Line graphs and ACF-PACF graphs of deseasonalised variables

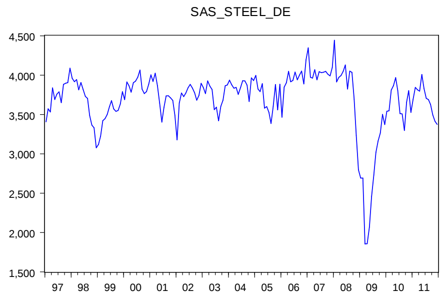
Line graphs	ACF-PACF graphs

Iron Production DE



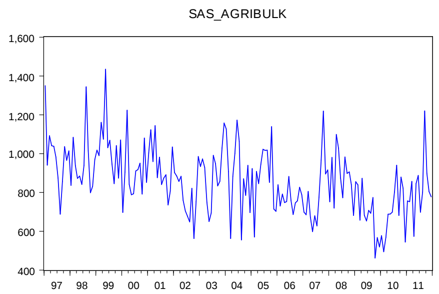
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.883	0.883	142.84	0.000
		2	0.770	-0.046	252.09	0.000
		3	0.646	-0.116	329.32	0.000
		4	0.540	0.006	383.53	0.000
		5	0.420	-0.128	416.51	0.000
		6	0.289	-0.146	432.19	0.000
		7	0.181	0.023	438.43	0.000
		8	0.107	0.066	440.62	0.000
		9	0.042	-0.043	440.96	0.000
		10	-0.013	-0.018	441.00	0.000
		11	-0.064	-0.033	441.78	0.000
		12	-0.086	0.037	443.22	0.000

Steel Production DE



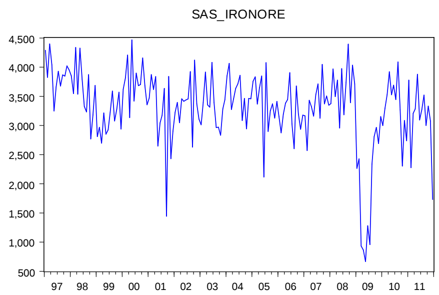
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.880	0.880	141.75	0.000
		2	0.776	0.008	252.68	0.000
		3	0.662	-0.103	333.71	0.000
		4	0.541	-0.100	388.26	0.000
		5	0.427	-0.051	422.45	0.000
		6	0.306	-0.110	440.04	0.000
		7	0.204	-0.007	447.91	0.000
		8	0.123	0.024	450.80	0.000
		9	0.045	-0.059	451.18	0.000
		10	-0.035	-0.095	451.41	0.000
		11	-0.096	-0.006	453.19	0.000
		12	-0.127	0.067	456.34	0.000

Agribulk



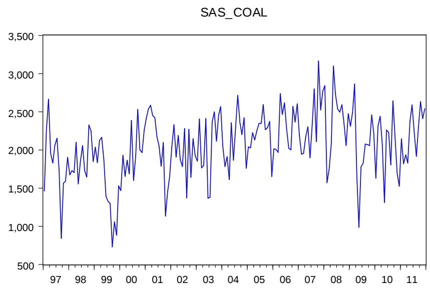
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.426	0.426	33.186	0.000
		2	0.340	0.194	54.481	0.000
		3	0.246	0.059	65.694	0.000
		4	0.274	0.138	79.678	0.000
		5	0.276	0.113	93.942	0.000
		6	0.212	0.006	102.42	0.000
		7	0.189	0.025	109.20	0.000
		8	0.127	-0.032	112.28	0.000
		9	0.213	0.119	120.99	0.000
		10	0.233	0.095	131.45	0.000
		11	0.260	0.094	144.54	0.000
		12	0.089	-0.145	146.07	0.000

Iron Ore & Scrap



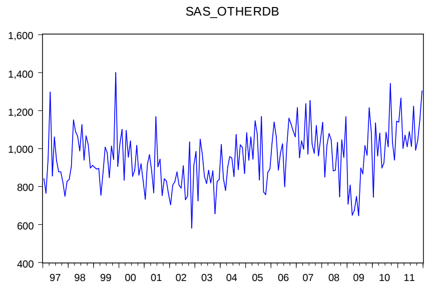
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.883	0.883	142.84	0.000
		2	0.770	-0.046	252.09	0.000
		3	0.646	-0.116	329.32	0.000
		4	0.540	0.006	383.53	0.000
		5	0.420	-0.128	416.51	0.000
		6	0.289	-0.146	432.19	0.000
		7	0.181	0.023	438.43	0.000
		8	0.107	0.066	440.62	0.000
		9	0.042	-0.043	440.96	0.000
		10	-0.013	-0.018	441.00	0.000
		11	-0.064	-0.033	441.78	0.000
		12	-0.086	0.037	443.22	0.000

Coal



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.453	0.453	37.521	0.000
		2	0.296	0.114	53.602	0.000
		3	0.283	0.144	68.447	0.000
		4	0.184	-0.009	74.762	0.000
		5	0.135	0.010	78.164	0.000
		6	0.099	-0.007	80.022	0.000
		7	0.139	0.090	83.705	0.000
		8	0.175	0.091	89.546	0.000
		9	0.151	0.029	93.925	0.000
		10	0.132	0.006	97.261	0.000
		11	0.068	-0.064	98.158	0.000
		12	0.115	0.075	100.75	0.000

Other dry bulk goods

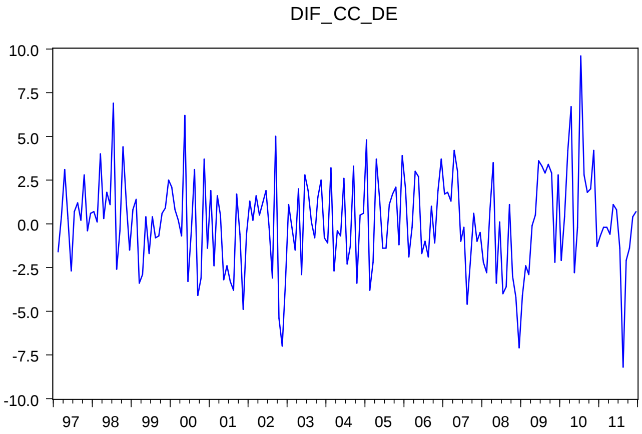


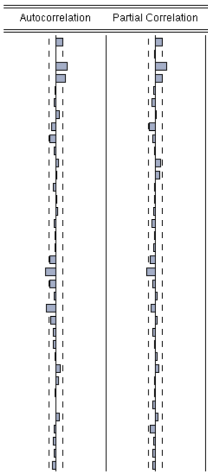
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.267	0.267	13.077	0.000
		2	0.356	0.306	36.394	0.000
		3	0.298	0.178	52.804	0.000
		4	0.208	0.029	60.824	0.000
		5	0.217	0.052	69.662	0.000
		6	0.101	-0.060	71.596	0.000
		7	0.175	0.068	77.419	0.000
		8	0.076	-0.026	78.508	0.000
		9	0.194	0.134	85.746	0.000
		10	0.179	0.098	91.886	0.000
		11	0.134	0.010	95.384	0.000
		12	0.130	-0.033	98.701	0.000

Appendix 6: Line graphs and ACF-PACF graphs of final variables

Line graphs	ACF-PACF graphs

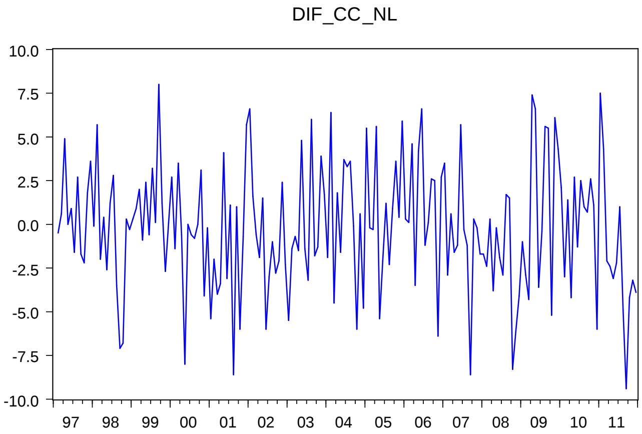
Consumer Confidence DE

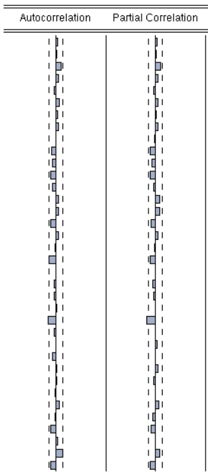




	AC	PAC	Q-Stat	Prob
1	0.144	0.144	3.7784	0.052
2	0.007	-0.014	3.7884	0.150
3	0.224	0.230	13.056	0.005
4	0.194	0.138	20.039	0.000
5	-0.008	-0.048	20.053	0.001
6	-0.041	-0.082	20.362	0.002
7	0.068	0.010	21.226	0.003
8	-0.091	-0.130	22.799	0.004
9	-0.118	-0.063	25.474	0.002
10	-0.038	-0.019	25.748	0.004
11	0.059	0.106	26.413	0.006
12	0.020	0.087	26.490	0.009
13	-0.053	-0.015	27.033	0.012
14	0.015	-0.017	27.075	0.019
15	0.030	-0.026	27.254	0.027
16	-0.043	-0.069	27.615	0.035
17	-0.023	-0.018	27.721	0.048
18	-0.023	-0.047	27.824	0.065
19	-0.118	-0.101	30.660	0.044
20	-0.228	-0.177	41.265	0.003
21	-0.117	-0.063	44.087	0.002
22	-0.028	0.036	44.243	0.003
23	-0.192	-0.089	51.868	0.001
24	-0.100	0.029	53.965	0.000
25	-0.063	-0.052	54.810	0.001
26	-0.055	-0.019	55.439	0.001
27	-0.018	0.028	55.506	0.001
28	0.086	0.075	57.092	0.001
29	0.043	-0.016	57.486	0.001
30	-0.012	-0.013	57.519	0.002
31	-0.004	-0.057	57.523	0.003
32	0.071	0.043	58.641	0.003
33	-0.042	-0.100	59.034	0.004
34	-0.062	-0.042	59.879	0.004
35	-0.040	-0.053	60.246	0.005
36	-0.072	-0.058	61.424	0.005

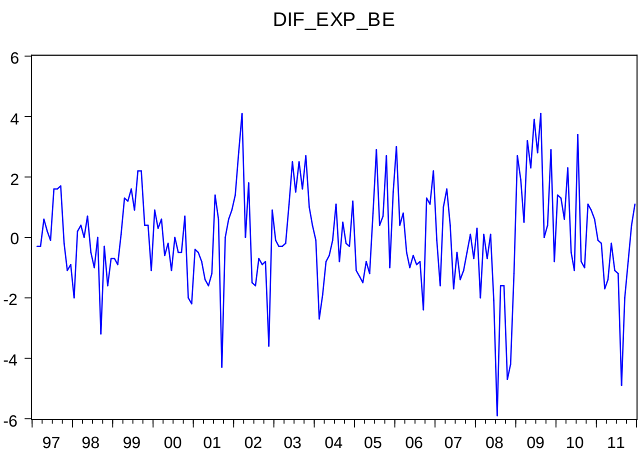
Consumer Confidence NL

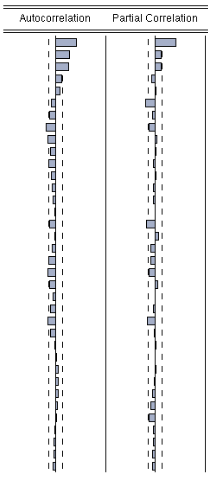




	AC	PAC	Q-Stat	Prob
1	0.032	0.032	0.1918	0.661
2	0.021	0.020	0.2764	0.871
3	0.112	0.111	2.6003	0.457
4	0.048	0.041	3.0289	0.553
5	-0.036	-0.043	3.2668	0.659
6	0.068	0.057	4.1209	0.660
7	0.035	0.023	4.3486	0.739
8	0.044	0.048	4.7140	0.788
9	-0.001	-0.015	4.7143	0.858
10	-0.082	-0.099	6.0171	0.814
11	-0.077	-0.082	7.1668	0.785
12	-0.107	-0.107	9.3788	0.670
13	-0.070	-0.046	10.338	0.666
14	0.062	0.089	11.089	0.679
15	0.065	0.092	11.931	0.684
16	-0.108	-0.091	14.228	0.582
17	0.053	0.051	14.782	0.611
18	-0.016	-0.017	14.832	0.673
19	-0.142	-0.111	18.942	0.461
20	-0.000	0.007	18.942	0.526
21	-0.033	-0.065	19.161	0.575
22	-0.047	-0.043	19.623	0.607
23	0.020	0.002	19.706	0.660
24	-0.165	-0.179	25.364	0.386
25	-0.041	0.002	25.720	0.423
26	0.007	0.038	25.730	0.478
27	-0.067	-0.006	26.701	0.480
28	0.014	0.047	26.741	0.532
29	0.009	-0.035	26.757	0.585
30	-0.016	-0.006	26.815	0.633
31	0.078	0.077	28.137	0.614
32	-0.010	-0.055	28.158	0.662
33	-0.104	-0.096	30.577	0.588
34	0.031	-0.004	30.786	0.626
35	0.136	0.090	34.933	0.471
36	-0.101	-0.101	37.240	0.412

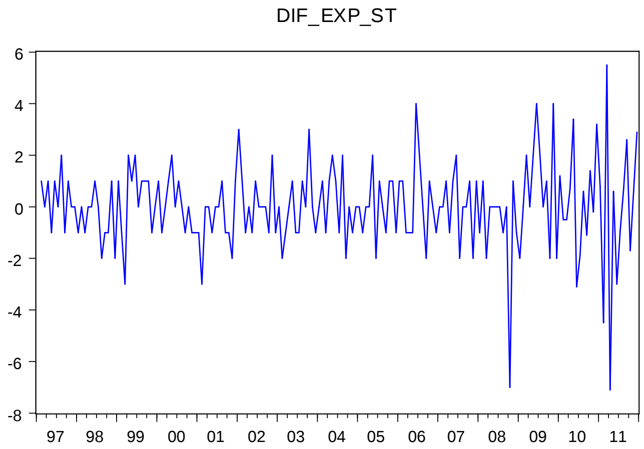
Business Expectations





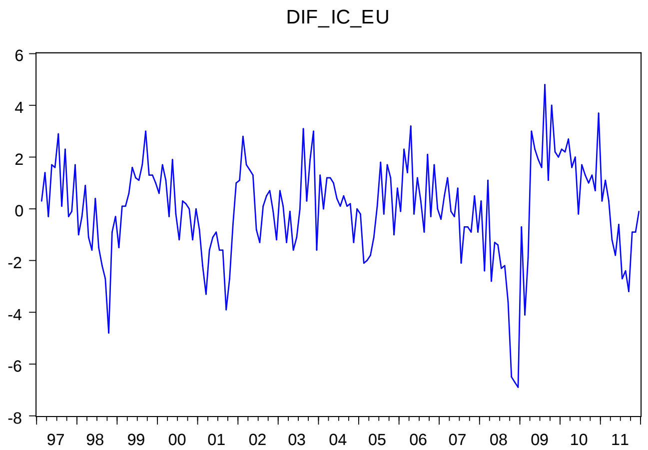
	AC	PAC	Q-Stat	Prob
1	0.438	0.438	34.899	0.000
2	0.286	0.116	49.856	0.000
3	0.263	0.127	62.542	0.000
4	0.116	-0.072	65.047	0.000
5	0.087	0.014	66.448	0.000
6	-0.094	-0.204	68.101	0.000
7	-0.132	-0.057	71.384	0.000
8	-0.189	-0.122	78.124	0.000
9	-0.165	0.029	83.324	0.000
10	-0.112	0.021	85.734	0.000
11	-0.154	-0.039	90.336	0.000
12	-0.087	0.014	91.811	0.000
13	-0.075	-0.031	92.912	0.000
14	-0.060	-0.033	93.614	0.000
15	-0.010	0.000	93.632	0.000
16	-0.133	-0.176	97.166	0.000
17	-0.021	0.080	97.250	0.000
18	-0.066	-0.094	98.138	0.000
19	-0.142	-0.090	102.22	0.000
20	-0.157	-0.130	107.26	0.000
21	-0.123	0.044	110.36	0.000
22	-0.053	-0.002	110.94	0.000
23	-0.104	-0.047	113.17	0.000
24	-0.157	-0.172	118.34	0.000
25	-0.102	-0.014	120.53	0.000
26	-0.020	0.024	120.61	0.000
27	0.022	-0.003	120.71	0.000
28	0.049	0.016	121.23	0.000
29	0.054	-0.009	121.86	0.000
30	0.053	-0.057	122.48	0.000
31	0.029	-0.082	122.66	0.000
32	0.015	-0.121	122.71	0.000
33	-0.020	-0.037	122.80	0.000
34	-0.028	-0.030	122.97	0.000
35	-0.046	-0.051	123.45	0.000
36	-0.053	-0.059	124.10	0.000

Expected Stock



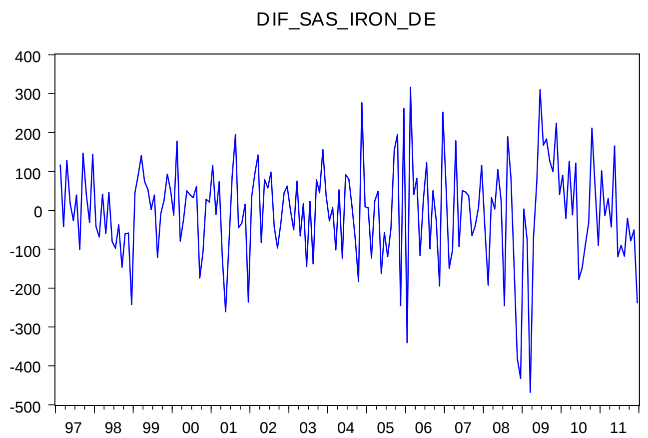
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.224	-0.224	9.1697	0.002
		2	0.129	0.083	12.207	0.002
		3	-0.018	0.029	12.266	0.007
		4	0.017	0.009	12.320	0.015
		5	-0.050	-0.049	12.777	0.026
		6	-0.033	-0.059	12.984	0.043
		7	-0.022	-0.033	13.079	0.070
		8	-0.105	-0.112	15.153	0.056
		9	0.021	-0.018	15.234	0.085
		10	-0.038	-0.018	15.515	0.114
		11	0.082	0.074	16.820	0.113
		12	-0.027	0.007	16.962	0.151
		13	-0.144	-0.193	21.026	0.072
		14	0.011	-0.079	21.050	0.100
		15	-0.056	-0.051	21.670	0.117
		16	0.016	-0.000	21.719	0.153
		17	-0.159	-0.159	26.747	0.062
		18	0.081	-0.009	28.055	0.061
		19	-0.096	-0.061	29.913	0.053
		20	0.015	-0.060	29.958	0.071
		21	0.043	-0.002	30.329	0.086
		22	-0.024	-0.061	30.446	0.108
		23	-0.060	-0.128	31.192	0.118
		24	-0.017	-0.067	31.252	0.147
		25	0.076	0.028	32.481	0.145
		26	-0.045	-0.059	32.917	0.165
		27	0.007	-0.088	32.929	0.199
		28	0.045	0.020	33.372	0.222
		29	-0.017	-0.045	33.436	0.260
		30	0.140	0.066	37.714	0.157
		31	-0.048	-0.037	38.217	0.174
		32	0.066	-0.038	39.187	0.179
		33	0.020	0.032	39.279	0.209
		34	0.019	0.014	39.359	0.242
		35	-0.058	-0.070	40.120	0.254
		36	0.014	-0.093	40.161	0.291

Industrial Confidence EU



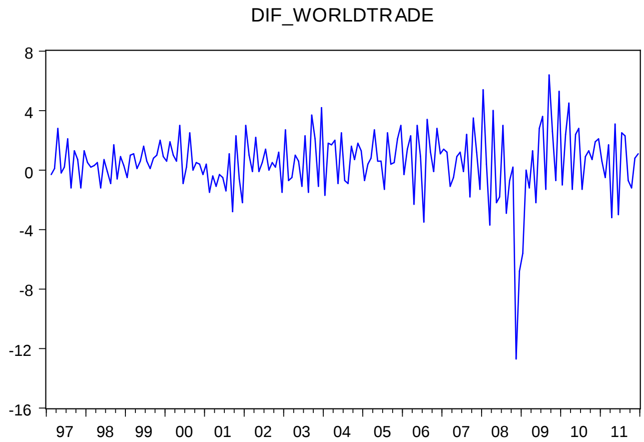
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.584	0.584	62.150	0.000
		2	0.567	0.343	121.01	0.000
		3	0.452	0.058	158.59	0.000
		4	0.287	-0.161	173.85	0.000
		5	0.193	-0.097	180.77	0.000
		6	0.115	-0.010	183.26	0.000
		7	0.071	0.044	184.20	0.000
		8	-0.068	-0.168	185.08	0.000
		9	-0.026	0.054	185.21	0.000
		10	-0.179	-0.174	191.36	0.000
		11	-0.202	-0.070	199.22	0.000
		12	-0.218	-0.011	208.40	0.000
		13	-0.283	-0.072	224.05	0.000
		14	-0.201	0.102	231.97	0.000
		15	-0.248	-0.074	244.17	0.000
		16	-0.237	-0.111	255.36	0.000
		17	-0.240	-0.042	266.90	0.000
		18	-0.217	-0.031	276.36	0.000
		19	-0.234	-0.038	287.42	0.000
		20	-0.173	0.039	293.49	0.000
		21	-0.174	-0.103	299.72	0.000
		22	-0.234	-0.167	311.04	0.000
		23	-0.139	0.004	315.02	0.000
		24	-0.236	-0.154	326.65	0.000
		25	-0.197	-0.021	334.78	0.000
		26	-0.096	0.143	336.74	0.000
		27	-0.098	-0.028	338.77	0.000
		28	-0.042	-0.040	339.16	0.000
		29	0.037	0.009	339.46	0.000
		30	0.050	-0.050	339.99	0.000
		31	0.035	-0.019	340.26	0.000
		32	0.073	-0.087	341.45	0.000
		33	0.079	0.029	342.83	0.000
		34	0.070	-0.039	343.93	0.000
		35	0.123	-0.044	347.36	0.000
		36	0.046	-0.127	347.83	0.000

Iron Production DE



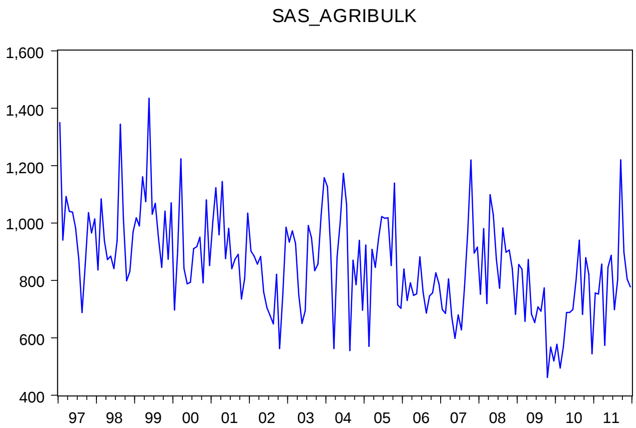
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.029	0.029	0.1513	0.697
		2	0.063	0.062	0.8750	0.646
		3	-0.069	-0.073	1.7606	0.624
		4	0.068	0.069	2.6182	0.624
		5	0.074	0.079	3.6258	0.604
		6	-0.095	-0.116	5.3163	0.504
		7	-0.135	-0.132	8.7531	0.271
		8	-0.072	-0.044	9.7375	0.284
		9	-0.037	-0.043	9.9945	0.351
		10	-0.031	-0.035	10.177	0.425
		11	-0.129	-0.103	13.407	0.268
		12	-0.104	-0.089	15.520	0.214
		13	-0.019	-0.020	15.594	0.272
		14	-0.022	-0.051	15.691	0.333
		15	0.029	0.011	15.857	0.392
		16	0.094	0.112	17.617	0.347
		17	-0.093	-0.133	19.342	0.309
		18	0.049	-0.006	19.817	0.343
		19	-0.136	-0.161	23.589	0.212
		20	0.088	0.025	25.174	0.195
		21	0.038	0.039	25.476	0.227
		22	-0.071	-0.105	26.528	0.230
		23	-0.123	-0.143	29.661	0.159
		24	-0.030	-0.031	29.852	0.190
		25	0.078	0.023	31.124	0.185
		26	-0.094	-0.161	32.993	0.162
		27	-0.050	-0.018	33.520	0.180
		28	-0.030	-0.017	33.708	0.211
		29	0.107	0.028	36.196	0.168
		30	-0.028	-0.135	36.369	0.196
		31	-0.003	-0.060	36.372	0.233
		32	0.019	0.034	36.451	0.269
		33	0.050	-0.022	36.996	0.290
		34	0.022	-0.104	37.105	0.328
		35	0.051	0.058	37.682	0.348
		36	0.016	-0.041	37.743	0.390

World Trade



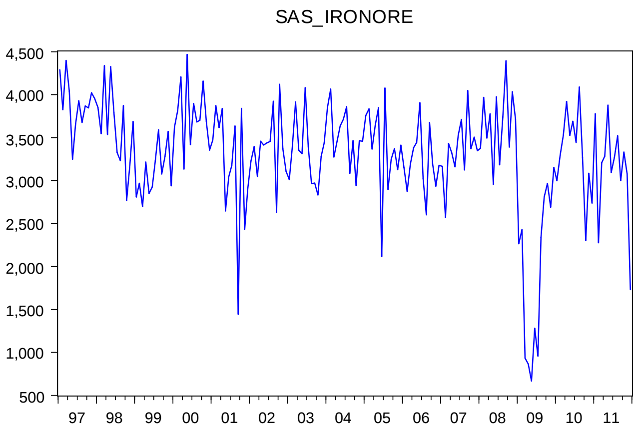
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.044	-0.044	0.3525	0.553
		2	0.162	0.160	5.1392	0.077
		3	0.405	0.430	35.360	0.000
		4	-0.177	-0.182	41.183	0.000
		5	0.123	-0.053	43.989	0.000
		6	0.217	0.155	52.816	0.000
		7	-0.234	-0.124	63.098	0.000
		8	0.070	-0.113	64.017	0.000
		9	0.069	0.045	64.928	0.000
		10	-0.318	-0.162	84.299	0.000
		11	-0.005	-0.160	84.304	0.000
		12	0.009	0.094	84.319	0.000
		13	-0.290	-0.031	100.78	0.000
		14	0.100	0.003	102.75	0.000
		15	-0.074	-0.033	103.82	0.000
		16	-0.313	-0.172	123.29	0.000
		17	0.200	0.108	131.31	0.000
		18	-0.132	0.016	134.83	0.000
		19	-0.212	-0.142	143.96	0.000
		20	0.323	0.180	165.27	0.000
		21	-0.200	-0.038	173.45	0.000
		22	-0.084	-0.151	174.89	0.000
		23	0.204	-0.035	183.56	0.000
		24	-0.315	-0.116	204.25	0.000
		25	0.028	-0.007	204.41	0.000
		26	0.125	-0.024	207.74	0.000
		27	-0.181	0.088	214.73	0.000
		28	0.056	-0.034	215.40	0.000
		29	0.134	0.019	219.30	0.000
		30	-0.147	0.072	224.00	0.000
		31	0.043	-0.120	224.40	0.000
		32	0.066	-0.101	225.35	0.000
		33	-0.141	0.069	229.79	0.000
		34	0.097	-0.076	231.90	0.000
		35	0.053	-0.029	232.53	0.000
		36	-0.209	-0.038	242.43	0.000

Agribulk



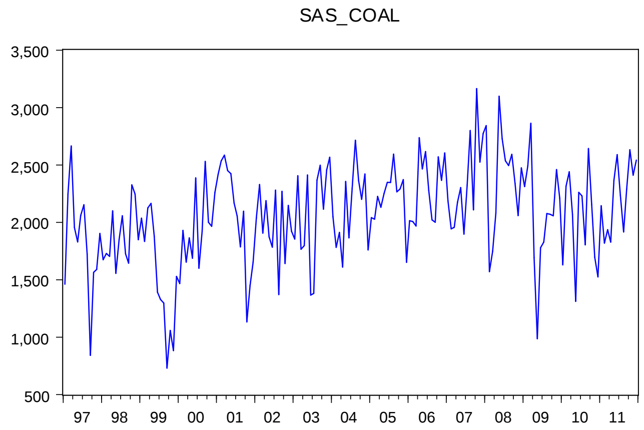
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.426	0.426	33.197	0.000
		2	0.340	0.193	54.414	0.000
		3	0.246	0.060	65.608	0.000
		4	0.274	0.138	79.577	0.000
		5	0.276	0.114	93.859	0.000
		6	0.212	0.006	102.30	0.000
		7	0.190	0.026	109.10	0.000
		8	0.127	-0.032	112.19	0.000
		9	0.213	0.119	120.91	0.000
		10	0.233	0.095	131.38	0.000
		11	0.260	0.094	144.48	0.000
		12	0.089	-0.145	146.01	0.000
		13	0.083	-0.031	147.38	0.000
		14	0.069	-0.028	148.32	0.000
		15	0.092	0.000	150.01	0.000
		16	0.099	0.019	151.95	0.000
		17	0.038	-0.027	152.24	0.000
		18	0.072	0.043	153.28	0.000
		19	0.062	0.015	154.07	0.000
		20	0.026	-0.098	154.21	0.000
		21	0.033	-0.005	154.44	0.000
		22	0.048	0.041	154.93	0.000
		23	0.064	0.073	155.78	0.000
		24	0.106	0.089	158.15	0.000
		25	0.095	0.023	160.08	0.000
		26	0.078	-0.011	161.37	0.000
		27	0.054	-0.028	162.00	0.000
		28	0.132	0.098	165.73	0.000
		29	0.125	0.019	169.14	0.000
		30	0.154	0.087	174.31	0.000
		31	0.084	-0.015	175.86	0.000
		32	0.051	-0.068	176.44	0.000
		33	0.147	0.086	181.28	0.000
		34	0.106	-0.058	183.80	0.000
		35	0.112	-0.020	186.64	0.000
		36	-0.002	-0.085	186.64	0.000

Iron Ore & Scrap



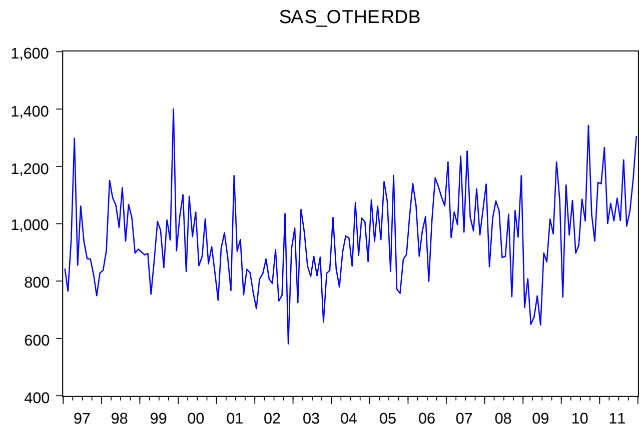
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.453	0.453	37.584	0.000
		2	0.525	0.402	88.306	0.000
		3	0.395	0.106	117.19	0.000
		4	0.277	-0.087	131.49	0.000
		5	0.144	-0.167	135.35	0.000
		6	0.114	-0.020	137.78	0.000
		7	-0.009	-0.064	137.80	0.000
		8	-0.008	0.018	137.81	0.000
		9	-0.035	0.036	138.05	0.000
		10	-0.057	-0.008	138.66	0.000
		11	-0.118	-0.111	141.37	0.000
		12	-0.072	-0.003	142.37	0.000
		13	-0.150	-0.069	146.81	0.000
		14	-0.075	0.061	147.91	0.000
		15	-0.076	0.059	149.05	0.000
		16	-0.150	-0.144	153.54	0.000
		17	-0.020	0.087	153.61	0.000
		18	-0.086	-0.041	155.12	0.000
		19	-0.061	-0.023	155.87	0.000
		20	0.014	0.096	155.91	0.000
		21	-0.019	-0.016	155.99	0.000
		22	-0.049	-0.098	156.49	0.000
		23	0.053	0.072	157.07	0.000
		24	-0.007	-0.014	157.08	0.000
		25	-0.012	-0.037	157.11	0.000
		26	0.069	0.104	158.12	0.000
		27	0.057	0.041	158.82	0.000
		28	0.116	0.116	161.71	0.000
		29	0.171	0.047	168.03	0.000
		30	0.138	-0.028	172.17	0.000
		31	0.153	-0.014	177.29	0.000
		32	0.095	-0.129	179.27	0.000
		33	0.146	0.138	184.01	0.000
		34	0.028	-0.066	184.19	0.000
		35	0.147	0.144	189.06	0.000
		36	-0.017	-0.081	189.12	0.000

Coal



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.453	0.453	37.513	0.000
		2	0.295	0.114	53.576	0.000
		3	0.283	0.144	68.411	0.000
		4	0.184	-0.009	74.723	0.000
		5	0.135	0.010	78.122	0.000
		6	0.099	-0.007	79.977	0.000
		7	0.139	0.090	83.662	0.000
		8	0.175	0.091	89.505	0.000
		9	0.151	0.029	93.883	0.000
		10	0.131	0.006	97.215	0.000
		11	0.068	-0.064	98.109	0.000
		12	0.115	0.075	100.70	0.000
		13	0.055	-0.047	101.29	0.000
		14	0.051	0.028	101.81	0.000
		15	0.101	0.052	103.83	0.000
		16	-0.019	-0.134	103.91	0.000
		17	0.022	0.035	104.01	0.000
		18	0.100	0.093	106.04	0.000
		19	0.104	0.063	108.24	0.000
		20	0.144	0.078	112.48	0.000
		21	0.094	-0.040	114.31	0.000
		22	0.139	0.055	118.31	0.000
		23	0.178	0.089	124.91	0.000
		24	0.117	-0.005	127.79	0.000
		25	0.174	0.114	134.16	0.000
		26	0.216	0.092	144.13	0.000
		27	0.163	-0.057	149.84	0.000
		28	0.112	-0.030	152.54	0.000
		29	0.058	-0.072	153.28	0.000
		30	0.028	-0.059	153.45	0.000
		31	-0.021	-0.035	153.55	0.000
		32	0.113	0.145	156.38	0.000
		33	0.080	-0.039	157.82	0.000
		34	0.018	-0.072	157.89	0.000
		35	0.110	0.065	160.62	0.000
		36	-0.008	-0.103	160.63	0.000

Other dry bulk goods

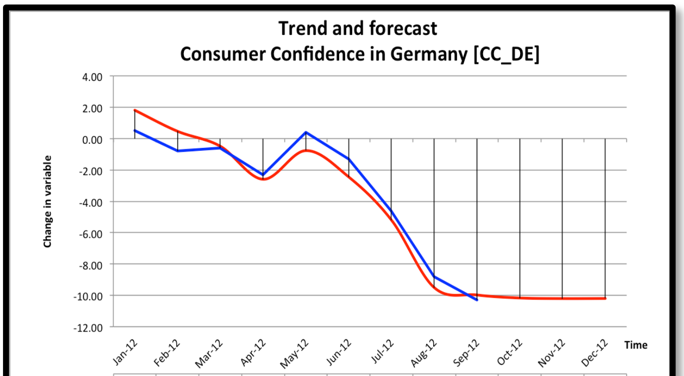


Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.267	0.267	13.029	0.000
		2	0.356	0.307	36.380	0.000
		3	0.297	0.178	52.722	0.000
		4	0.207	0.029	60.735	0.000
		5	0.217	0.052	69.560	0.000
		6	0.102	-0.059	71.504	0.000
		7	0.175	0.068	77.333	0.000
		8	0.076	-0.026	78.424	0.000
		9	0.194	0.133	85.663	0.000
		10	0.179	0.098	91.805	0.000
		11	0.134	0.010	95.301	0.000
		12	0.130	-0.033	98.617	0.000
		13	0.027	-0.112	98.757	0.000
		14	0.072	-0.027	99.768	0.000
		15	0.048	0.031	100.23	0.000
		16	0.153	0.167	104.91	0.000
		17	0.019	-0.042	104.98	0.000
		18	-0.024	-0.141	105.09	0.000
		19	0.105	0.040	107.33	0.000
		20	-0.060	-0.106	108.07	0.000
		21	0.027	-0.003	108.22	0.000
		22	-0.059	-0.020	108.94	0.000
		23	-0.023	0.031	109.06	0.000
		24	-0.099	-0.084	111.13	0.000
		25	0.009	0.061	111.15	0.000
		26	-0.020	-0.037	111.24	0.000
		27	-0.125	-0.109	114.58	0.000
		28	-0.087	-0.085	116.21	0.000
		29	-0.086	0.059	117.82	0.000
		30	-0.144	-0.069	122.38	0.000
		31	-0.085	0.024	123.98	0.000
		32	-0.035	0.088	124.26	0.000
		33	-0.044	0.058	124.69	0.000
		34	-0.003	0.054	124.69	0.000
		35	0.075	0.067	125.97	0.000
		36	-0.027	-0.058	126.14	0.000

Appendix 7: Forecasting the leading indicators

The leading indicators that have been forecasted are shown below in line graphs. They have been discussed in Chapter 7.2. Corresponding coefficients for making the forecasts are shown below the graphs.

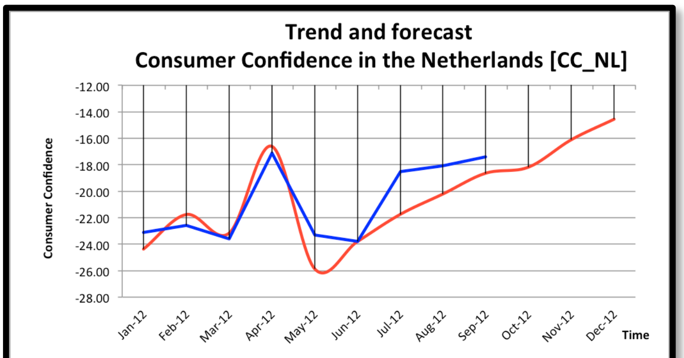
Consumer Confidence in Germany – Agribulk model



	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12
Forecast CC_DE	1.80	0.47	-0.49	-2.59	-0.77	-2.44	-5.19	-9.50	-9.97	-10.16	-10.20	-10.19
Real value CC_DE	0.50	-0.80	-0.60	-2.30	0.40	-1.30	-4.60	-8.80	-10.30	0.00	0.00	0.00

CC_DE = 0.01404*cc_de(-1) + 0.0059*cc_nl(-1) + 0.3133*exp_be(-1) + 0.0214*exp_st(-1) + 0.2638*ic_eu(-1) + 0.0004*iron_de(-1) + 0.06407*worldtrade(-1) - 0.0011*Agribulk(-1) + 1.0802

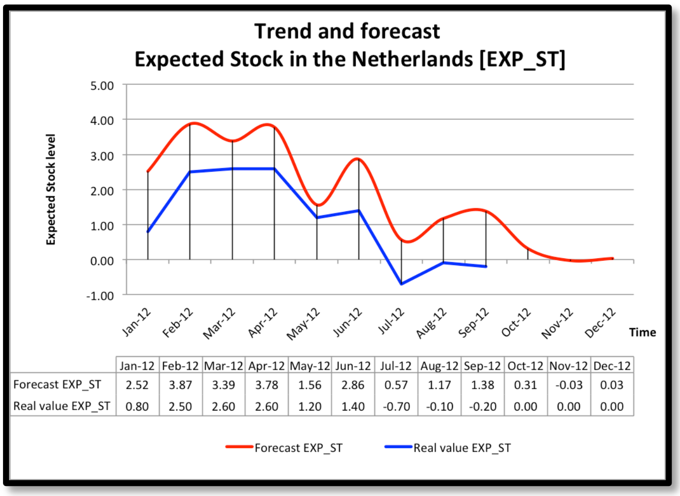
Consumer Confidence in the Netherlands – Iron Ore & Scrap model



	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12
Forecast CC_NL	-24.37	-21.76	-23.16	-16.61	-25.86	-23.80	-21.75	-20.20	-18.64	-18.18	-16.11	-14.56
Real value CC_NL	-23.10	-22.60	-23.60	-17.10	-23.30	-23.80	-18.50	-18.10	-17.40	0.00	0.00	0.00

CC_NL = 0.0874*cc_de(-1) + 0.1056*cc_de(-2) + 0.1175*cc_de(-3) - 0.126*cc_nl(-1) - 0.1233*cc_nl(-2) - 0.0313*cc_nl(-3) + 0.2354*exp_be(-1) + 0.0937*exp_be(-2) - 0.0136*exp_be(-3) + 0.2796*exp_st(-1) + 0.2540*exp_st(-2) + 0.0176*exp_st(-3) + 0.7143*ic_eu(-1) - 0.1204*ic_eu(-2) + 0.0824*ic_eu(-3) - 0.0053*iron_de(-1) + 0.00037*iron_de(-2) + 0.0043*iron_de(-3) - 0.01810*worldtrade(-1) - 0.04808*worldtrade(-2) - 0.3058*worldtrade(-3) - 9.5902e-06*ironore(-1) + 0.0001*ironore(-2) - 0.0002*ironore(-3) + 0.2987

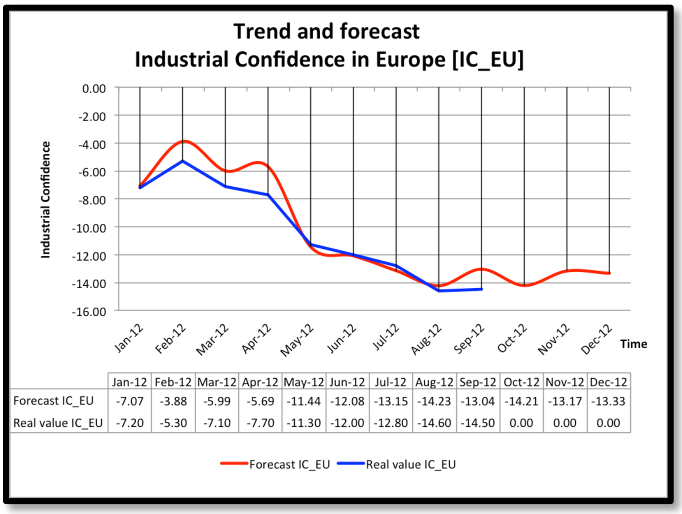
Expected Stock in the Netherlands – Iron Ore & Scrap model



	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12
Forecast EXP_ST	2.52	3.87	3.39	3.78	1.56	2.86	0.57	1.17	1.38	0.31	-0.03	0.03
Real value EXP_ST	0.80	2.50	2.60	2.60	1.20	1.40	-0.70	-0.10	-0.20	0.00	0.00	0.00

EXP_ST = - 0.0397*cc_de(-1) - 0.0008*cc_de(-2) - 0.0071*cc_de(-3) - 0.0131*cc_nl(-1) + 0.030*cc_nl(-2) - 0.0760*cc_nl(-3) + 0.1863*exp_be(-1) - 0.0981*exp_be(-2) + 0.1288*exp_be(-3) - 0.3181*exp_st(-1) - 0.1500*exp_st(-2) - 0.1358*exp_st(-3) + 0.1659*ic_eu(-1) + 0.0706*ic_eu(-2) + 0.0772*ic_eu(-3) - 0.0009*iron_de(-1) - 0.0006*iron_de(-2) - 0.0013*iron_de(-3) + 0.0448*worldtrade(-1) + 0.0997*worldtrade(-2) - 0.0413*worldtrade(-3) - 0.0005*ironore(-1) + 0.0001*ironore(-2) - 0.0001*ironore(-3) + 1.8089

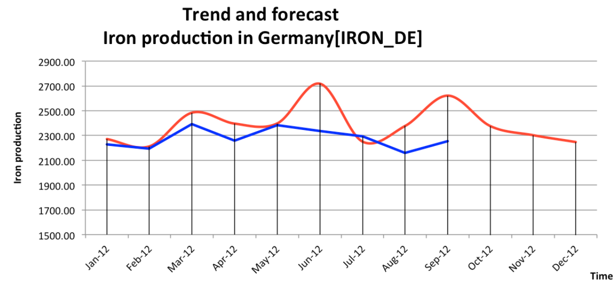
Industrial Confidence in Europe – Iron Ore & Scrap model



	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12
Forecast IC_EU	-7.07	-3.88	-5.99	-5.69	-11.44	-12.08	-13.15	-14.23	-13.04	-14.21	-13.17	-13.33
Real value IC_EU	-7.20	-5.30	-7.10	-7.70	-11.30	-12.00	-12.80	-14.60	-14.50	0.00	0.00	0.00

IC_EU = 0.0123*cc_de(-1) - 0.0137*cc_de(-2) - 0.0189*cc_de(-3) + 0.0260*cc_nl(-1) - 0.0003*cc_nl(-2) - 0.0049*cc_nl(-3) + 0.3456*exp_be(-1) - 0.0621*exp_be(-2) + 0.0607*exp_be(-3) + 0.1508*exp_st(-1) + 0.0905*exp_st(-2) - 0.0066*exp_st(-3) + 0.1179*ic_eu(-1) + 0.1995*ic_eu(-2) + 0.1437*ic_eu(-3) - 0.0037*iron_de(-1) - 0.0004*iron_de(-2) + 4.8434e-05*iron_de(-3) + 0.2136*worldtrade(-1) + 0.0469*worldtrade(-2) + 0.0694*worldtrade(-3) - 0.0005*ironore(-1) + 0.0001*ironore(-2) - 2.73306e-05*ironore(-3) + 1.4991

Iron Production in Germany – Iron Ore & Scrap model

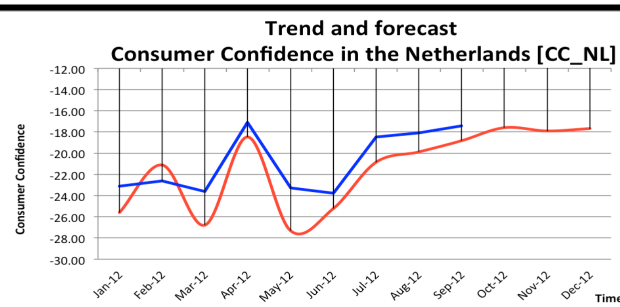


	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12
Forecast IRON_DE	2269.63	2212.25	2484.35	2396.15	2397.65	2718.47	2250.85	2377.26	2622.07	2375.95	2302.74	2247.46
Real value IRON_DE	2228.00	2195.00	2391.00	2260.00	2385.00	2337.00	2294.00	2160.00	2254.00	0.00	0.00	0.00

Forecast IRON_DE   Real value IRON_DE

IRON_DE = - 2.1989*cc_de(-1) + 3.1171*cc_de(-2) - 0.6066*cc_de(-3) - 1.5451*cc_nl(-1) - 1.0861*cc_nl(-2) - 1.6603*cc_nl(-3) - 3.9758*exp_be(-1) - 11.9665*exp_be(-2) - 3.7326*exp_be(-3) + 7.0317*exp_st(-1) + 7.8754*exp_st(-2) - 4.0697*exp_st(-3) + 7.17804*ic_eu(-1) + 20.1668*ic_eu(-2) + 35.0045*ic_eu(-3) - 0.2453*iron_de(-1) - 0.20072*iron_de(-2) - 0.2503*iron_de(-3) - 0.3789*worldtrade(-1) + 1.2703*worldtrade(-2) - 4.00621*worldtrade(-3) - 0.0173*ironore(-1) - 0.02677*ironore(-2) - 0.0267*ironore(-3) + 227.7818

Consumer Confidence in the Netherlands – Coal model

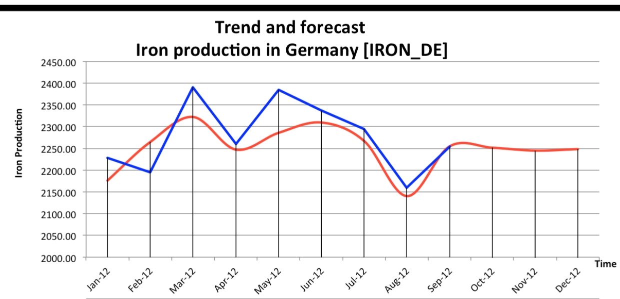


	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12
Forecast CC_NL	-25.59	-21.12	-26.78	-18.48	-27.30	-25.23	-20.86	-19.88	-18.83	-17.60	-17.91	-17.68
Real value CC_NL	-23.10	-22.60	-23.60	-17.10	-23.30	-23.80	-18.50	-18.10	-17.40	0.00	0.00	0.00

Forecast CC_NL   Real value CC_NL

CC_DE = 0.0106*cc_de(-1) + 0.0039*cc_nl(-1) + 0.3075*exp_be(-1) + 0.0157*exp_st(-1) + 0.2712*ic_eu(-1) + 0.0002*iron_de(-1) + 0.0695*worldtrade(-1) - 0.0002*coal(-1) + 0.6665

Iron Production in Germany – Coal model



	Jan-12	Feb-12	Mar-12	Apr-12	May-12	Jun-12	Jul-12	Aug-12	Sep-12	Oct-12	Nov-12	Dec-12
Forecast IRON_DE	2176.54	2264.75	2322.24	2247.24	2285.75	2309.49	2267.06	2140.37	2254.73	2251.54	2244.91	2248.35
Real value IRON_DE	2228.00	2195.00	2391.00	2260.00	2385.00	2337.00	2294.00	2160.00	2254.00	0.00	0.00	0.00

Forecast IRON_DE   Real value IRON_DE

IRON_DE = - 3.1447*cc_de(-1) - 1.0629*cc_nl(-1) + 2.6561*exp_be(-1) + 4.6074*exp_st(-1) + 26.04131*ic_eu(-1) - 0.1247*iron_de(-1) + 5.1621*worldtrade(-1) - 0.0043*coal(-1) + 2.9233