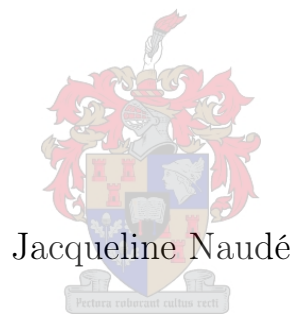


A Multi-Phase Model to Forecast Congestion at Brazilian Grain Ports: a Case Study at the Port of Paranagua



Thesis presented for the degree of
Master of Commerce
in the Faculty of Economic and Management Sciences at Stellenbosch University

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March 2016

Declaration

By submitting this dissertation electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the sole author thereof (save to the extent explicitly otherwise stated), that reproduction and publication thereof by Stellenbosch University will not infringe any third party rights and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

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Abstract

Port congestion occurs when the number of vessels arriving at a port within a given time frame exceeds the number of vessels that can be served during that time frame. At Brazilian grain ports, congestion has increased over the past decade due to an acceleration in trade volumes amidst limited expansion in port infrastructure. Extensive and unforeseen delays have highlighted the need to develop a forecasting model to estimate future levels of congestion in terms of queue lengths and waiting times based on the anticipated volume of grains to be exported. The complexity of the required model is intensified by the seasonal variation in the grain trade, the evolution of port capacity, and external events such as weather related delays.

The Port of Paranaguá is chosen as case study. A multi-phase congestion model (MPCM) is proposed comprising five individual yet interdependent phases. This step-wise approach translates the forecasted volume of annual Brazilian grain exports into the anticipated monthly number of vessels waiting at the Port of Paranaguá, as well as the corresponding average duration of the waiting periods. The methods applied by the MPCM to achieve these outcomes include linear programming, time-series forecasting, Monte Carlo simulation and multiple regression.

Input data between January 2011 and December 2013 are used to forecast monthly congestion for a hold-out period ranging from January to December 2014, as well as a long term forecast period ranging between January 2015 and December 2016. For the Port of Paranaguá, the results generated by the MPCM indicate an overall decline in congestion levels for 2015 and 2016. The performance of the MPCM is validated by comparing the estimated values of the hold-out period to actual recorded congestion levels, and by applying the methodology to another port in the Brazilian grain network. The results obtained would be of value to both vessel owners and charterers to hedge their positions, and would give owners the opportunity to strategically position their vessels for optimal utilisation. The proposed methodology can serve as basis for future development to generate a conglomerate view of congestion levels in the Brazilian port network.

Uittreksel

Hawekongestie vind plaas wanneer die aantal aankomste oor 'n gespesifiseerde tydperk die dienskapasiteit van die tydperk oorskry. Brasiliaanse graanuitvoere het drasties oor die afgelope dekade toegeneem terwyl hawe kapasiteit nie teen dieselfde tempo uitgebrei het nie. Die wanbalans het ernstige bottelnekke veroorsaak wat tot langdurige en onverwagse wagperiodes gelei het. 'n Vooruitskattingsmodel is dus nodig wat toekomstige toue en wagtye by die relevante hawens kan bereken met behulp van die verwagte volumes wat uitgevoer gaan word. Die kompleksiteit van die vereiste model lê in die seisoenale variasie in graanuitvoere, veranderinge in handelspatrone, uitbreidings in hawe infrastruktuur en onverwagse eksterne gebeurtenisse soos weerverwante vertraginge.

Paranagua is gekies as gevallestudie. In hierdie tesis word 'n Multi-fase kongestiemodel (MFKM) voorgestel wat uit vyf individuele, maar tog interafhanklike fases bestaan. Die MFKM neem die totale van die verwagte jaarlikse graanuitvoere vanuit Brasilië, en transformeer dit stapsgewys na die verwagte aantal skepe wat per maand by Paranagua wag, asook die gemiddelde wagtyd van hierdie skepe. Ten einde hierdie doel te bereik, word liniêre programmering, 'n tydreeks vooruitskattingsmetode, meervoudige regressie en Monte Carlo simulاسie in verskillende fases aangewend.

Invoerdata tussen Januarie 2011 en Desember 2013 is gebruik om maanderlikse kongestie vanaf Januarie tot Desember 2014 vooruit te skat. Die resultate van die MFKM wys op 'n algehele daling in kongestievlakke by Paranagua vir 2015 en 2016. Die akkuraatheid van die resultate word gevalideer deur die berekende waardes te vergelyk met die werklike gepubliseerde waardes in 2014, asook deur die model op 'n alternatiewe hawe in the Brasiliaanse graanhawenetwerk toe te pas. Die resultate is van waarde vir skeepseienaars en skeepshuurders omdat dit insig verleen tot die verwagte beskikbaarheid van skepe in die relevante area asook die verwagte tyd wat die skepe gaan moet wag om 'n vrag te laai. Die model kan gebruik word as basis vir verdere ontwikkeling deur die metodologie te dupliseer op ander hawens in die Brasiliaanse graannetwerk en sodoende 'n oorkoepelende kongestievooruitskating te verwesenlik.

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Table of Contents

List of Reserved Symbols	13
List of Acronyms	15
List of Figures	17
List of Tables	19
1 Introduction	1
1.1 Background	1
1.2 Problem description	3
1.3 Objectives	3
1.4 Scope	4
1.5 Relevance of the study	4
1.6 Thesis organisation	5
2 Dry bulk shipping and Brazilian grain trade	7
2.1 Dry bulk shipping	7
2.1.1 Terminology and policies	8
2.1.2 Congestion at dry bulk ports	8
2.1.3 Dry bulk grain trade	9
2.2 Brazilian grain industry	10
2.2.1 Trade and seasonality	10
2.2.2 Congestion at Brazilian grain ports	13
2.2.3 Port of Paranagua	15
2.3 Chapter summary	17
3 Literature Review	19
3.1 Queuing theory	19

3.1.1	Brief introduction to queuing theory	19
3.1.2	Literature review of port queuing models	20
3.2	Simulation	22
3.2.1	Brief introduction to simulation	22
3.2.2	Literature review of port simulation studies	23
3.3	Time-series analysis	25
3.3.1	Brief introduction to multiple regression	25
3.3.2	Literature review of time-series based port analysis	26
3.4	Chapter summary	26
4	Multi-Phase Congestion Model	27
4.1	Data	27
4.1.1	Historical Brazilian grain exports	28
4.1.2	Brazilian grain export forecasts	31
4.1.3	Brazilian grain port schedules	32
4.1.4	Congestion at Brazilian grain ports	33
4.1.5	Data quality assurance and limitations	33
4.1.6	Summary of datasets	34
4.2	Model assumptions	34
4.3	Modelling approach	35
4.3.1	Phase 1: Export volume allocation per port	39
4.3.2	Phase 2: Estimate monthly arrivals at port	40
4.3.3	Phase 3: Estimate monthly export capacity	41
4.3.4	Phase 4: Conversion of queue length	43
4.3.5	Phase 5: Conversion from queue length to waiting time	44
4.4	Validity and reliability of the MPCM	45
4.5	Implementation and revision	46
4.6	Chapter summary	46
5	Results	47
5.1	Brief review of MPCM methodology	47
5.2	Phase 1: Results	48
5.3	Phase 2: Results	51
5.4	Phase 3: Results	53
5.4.1	Regression coefficients	54
5.4.2	Evaluation of regression results	54

5.4.3	Tested assumptions	55
5.4.4	Predicted monthly export capacity	57
5.5	Phase 4: Results	58
5.6	Phase 5: Results	60
5.6.1	Long term outlook generated by the MPCM	63
5.7	Validity of the MPCM	65
5.8	Chapter summary	66
6	Discussion	67
6.1	Discussion and evaluation of the MPCM	67
6.1.1	Model strengths	68
6.1.2	Model weaknesses	68
6.2	Comparison to previous studies	69
6.3	Contributions of the study	71
6.4	Chapter summary	71
7	Conclusion	73
7.1	Thesis summary	73
7.2	Potential future work	74
7.2.1	Financial analysis of the migration to the northern ports	74
7.2.2	Sensitivity analysis of a change in queuing discipline	74
7.2.3	Impact of market conditions on arrival rates	74
8	Appendix A	79

List of Reserved Symbols

Symbol	Meaning
A_j	Port network containing port system j .
b_j	Historical maximum capacity of port system j .
C_j	Export capacity parameter of port system j .
d_{ij}	Change in volume of commodity i exported from port system j .
δ_j	Change in export capacity at port system j .
I	Commodity type
J	Port system
L_{jt}	Length of queue at port system j at time t .
M_{jt}	Seasonal dummy variables at port system j at time t .
Q_{jt}	Volume equivalent of queue at port system j at time t .
V_i	Exportable supplies of commodity i .
x_{ij}	Allocated volumes of commodity i to port system j .
W_{jt}	Waiting time in queue at port system j at time t .
Y_{jt}	Monthly vessel arrivals at port system j at time t .
Z_{jt}	Monthly export capacity at port system j at time t .

List of Acronyms

CE	Congestion equation
dwt	dead weight tonnes
ETA	Expected time of arrival
ETB	Expected time of berth
ETS	Expected time of sailing
GTIS	Global Trade Information System
HVCCC	Hunter Valley Coal Chain Coordinator
MPCM	Multi-Phase Congestion Model
USDA	United States Department of Agriculture
WMO	World Meteorological Organization

List of Figures

1.1	Satellite images of dry bulk vessels queuing at Paranagua and Santos.	1
1.2	Congestion levels at Brazilian grain terminals.	2
1.3	An illustrated breakdown of the voyage duration between Paranagua and Qingdao.	2
2.1	The main types of dry bulk vessels.	8
2.2	Monthly vessel arrivals and departures at the Port of Paranagua.	11
2.3	A map of Brazil's major grain exporting ports.	13
2.4	The average monthly rainfall in Paranagua.	14
2.5	An aerial view of the Port of Paranagua.	16
3.1	Step-wise approach to simulation modelling.	22
3.2	Step-wise approach to Monte Carlo simulation	23
4.1	Brazilian grain exports from the major ports.	28
4.2	Distribution of grain export market share per Brazilian grain port.	29
4.3	Maize, soybean and soybean meal exports from the Port of Paranagua.	29
4.4	The autocorrelation function of maize exports from the Port of Paranagua.	30
4.5	The autocorrelation function of soybean exports from the Port of Paranagua.	30
4.6	The autocorrelation function of soybean meal exports from the Port of Paranagua.	31
4.7	Brazilian grain export forecasts.	32
4.8	An illustration of the required model.	35
4.9	An illustration of the Multi-Phase Congestion Model.	38
4.10	An illustration of the Export Allocation Linear Program.	39
4.11	The historical distribution of stem sizes at Paranagua.	44
4.12	The actual cumulative distribution of stem sizes at the Port of Paranagua.	45
4.13	An example of the application of the inverse cumulative probability distribution.	46
5.1	Actual vs estimated exports per port in 2013.	49
5.2	Export allocation per port as calculated by the Export Allocation Linear Program.	50

5.3	Illustration of seasonal indices of maize, soybean and soybean meal arrivals at the Port of Paranagua.	51
5.4	Actual vs estimated maize arrivals at the Port of Paranagua.	52
5.5	Actual vs estimated soybean arrivals at the Port of Paranagua.	52
5.6	Actual vs estimated soybean meal arrivals at the Port of Paranagua.	53
5.7	Predicted value vs residual scatter plot to test for homoscedasticity.	55
5.8	Lagged residual vs residual scatterplot to test for autocorrelation.	56
5.9	Residual vs time scatterplot to test for autocorrelation.	56
5.10	Actual vs estimated monthly departures from the Port of Paranagua.	57
5.11	Actual vs estimated output of Phase 4.	58
5.12	A comparison of trend directions in queues at the Port of Paranagua.	59
5.13	Actual and estimated values for the output produced during Phase 5 for the model fit and the hold-out period.	61
5.14	A comparison of trend directions in waiting times at the Port of Paranagua.	62
5.15	Base scenario: Long term outlook of congestion levels at the Port of Paranagua.	63
5.16	Scenario of limited expansions: Long term outlook of congestion levels at the Port of Paranagua.	64
5.17	Scenario of no expansions: Long term outlook of congestion levels at the Port of Paranagua.	64
5.18	Model output of queues at Sao Francisco do Sul.	65
5.19	Model output of waiting times at Sao Francisco do Sul.	65
6.1	A demonstration of consequentiality in the model.	69

List of Tables

2.1	Grain berths at the Port of Paranagua.	15
4.1	Historical maximum volumes exported per Brazilian grain port.	28
4.2	January 2011 vessel line-up at the Port of Paranagua.	32
4.3	A snapshot of a vessel line-up to illustrate the calculation of waiting time.	33
4.4	A summary of the available input data.	34
4.5	The categorisation of queues and waiting times into quintiles.	38
5.1	Input to the Export Allocation Linear Program for 2013.	48
5.2	Output of the Wilcoxon Signed Rank test, the Sign test, and the Student's t test.	49
5.3	Projected exports per commodity per port as generated by the Export Allocation Linear Program	50
5.4	Seasonal indices of maize, soybean and soybean meal arrivals at the Port of Paranagua.	51
5.5	Coefficients and statistics of the monthly export capacity at the Port of Paranagua.	54
5.6	Regression results of monthly export capacity at the Port of Paranagua.	54
5.7	Incorporation of capacity expansions at the Port of Paranagua.	57
5.8	Goodness-of-fit measurements of the periodic reviews for queues.	58
5.9	Coefficients and statistics of the regression model used to convert queue lengths to waiting time.	60
5.10	Goodness-of-fit measurements of the regression model used to convert queue lengths to waiting time.	60
5.11	Goodness-of-fit measurements of the periodic reviews for waiting times.	61
5.12	Categorisation of congestion outlook for the Port of Paranagua in 2015 and 2016.	63
6.1	The key differences between the HVCCC model and the MPCM model.	70
8.1	Input data to the Wilcoxon signed rank test.	79
8.2	The regression results calculated during Phase 3.	80
8.3	Input data to the Durbin Watson test.	81

CHAPTER 1

Introduction

Contents

1.1	Background	1
1.2	Problem description	3
1.3	Objectives	3
1.4	Scope	4
1.5	Relevance of the study	4
1.6	Thesis organisation	5

1.1 Background

Restricted capacity at Brazilian grain ports continues to hinder trade flows. According to Global Trade Information Systems (GTIS) [7], Brazilian grain exports¹ quadrupled from 21 million tonnes to 84 million tonnes between 2000 and 2013 while the corresponding port capacity did not expand at a similar pace. The imbalance caused bottlenecks at the major grain ports, necessitating vessels to queue for prolonged periods whilst awaiting berth availability. Congestion levels reportedly reached record highs in April 2013 when a total of 199 vessels queued at Brazilian grain ports for more than a month on average [4]. Satellite images of Brazil's two largest grain ports, Paranaguá and Santos in Figure 1.1 illustrate the high levels of congestion experienced during this peak period.

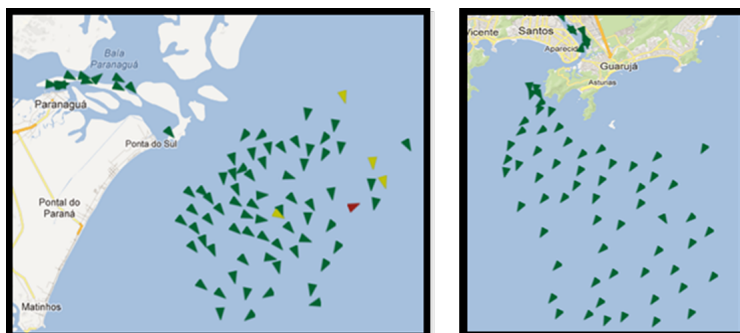


FIGURE 1.1: *Satellite images of dry bulk vessels queuing at Paranaguá (left) and Santos (right) [4].*

¹Brazilian grain exports comprise of maize, soybeans and soybean meals.

Port congestion is formed when the number of vessels arriving at a port within a given time frame exceeds the number of vessels that can be served by the port during that time frame. A review of Brazilian grain port congestion between January 2013 and July 2014 is presented in Figure 1.2 [4]. The lines represent the two key indicators used to quantify port congestion: 1) the number of vessels waiting at anchorage at a specified time; and 2) the average duration spent at anchorage. The interrelation between these two indicators is evident in Figure 1.2, implying that a change in the number of queuing vessels incurs change in the corresponding average waiting time.

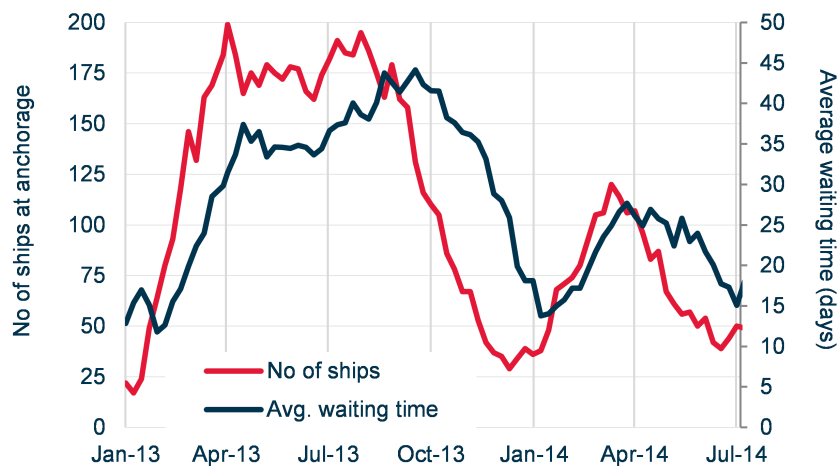


FIGURE 1.2: The number of vessels at anchorage and average waiting time at Brazilian grain ports [4].

Extensive variation in congestion levels is observed in Figure 1.2 as well as a lag between the number of vessels waiting at anchorage and the average waiting time. The varying nature of congestion levels adds uncertainty to the duration of future shipments. To illustrate, two contrasting scenarios are provided in Figure 1.3.

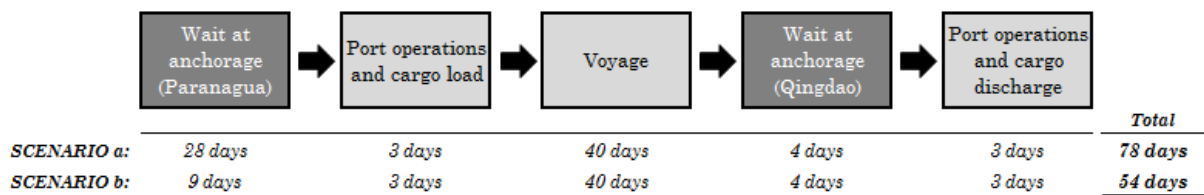


FIGURE 1.3: An illustrated breakdown of the voyage duration between Paranagua and Qingdao.

In scenario a^2 , the average duration of a bulk grain shipment from Paranagua to Qingdao in China was 78 days, of which 41% was spent waiting at anchorage. In scenario b^3 , the average waiting time at Paranagua was 9 days [4]. Suppose *ceteris paribus*, the total voyage duration would have been 54 days, of which only 24% is spent waiting in queues. The total voyage duration in scenario a is 44% longer than scenario b .

²Scenario a reflects the situation on 14 May 2014.

³Scenario b reflects the situation on 30 November 2012.

The financial implications of high congestion levels are far reaching. Extensive and unexpected waiting times at anchorage may inflict demurrage⁴ costs if the chartered vessel fails to load or discharge its cargo within the contractually agreed window of hire time. In January 2013, Reuters [20] reported demurrage costs of \$15 000 to \$20 000 per day at Brazilian grain ports. Given the reported average waiting time of 11 days at the time, load delays costs ranged between \$165 000 to \$220 000 per shipment. On a macro level, since congestion affects the overall availability of vessels in the market, the level of congestion has an indirect impact on freight rates.

1.2 Problem description

A ship broking firm, referred to as Brokerage A, provides strategic shipping information to clients, specifically referring to vessel owners and charterers. The information of relevance includes indications of freight rates, projections of vessels' availability in the market, advice on strategic positioning of vessels, and regular updates of the stance of congestion at the major bulk ports.

On the back of the high levels of congestion reached at Brazilian grain ports in 2013 and the subsequent financial implications, Brokerage A identified the need for a forecasting model to estimate future levels of congestion based on the anticipated volumes of grains to be exported. The results obtained could be of value to both ship owners and charterers as it provides guidance to the anticipated availability of vessels in the relevant area as well as the extent of future waiting times, both of which being of critical importance in negotiating freight rates of future shipments. These projections could also give owners the opportunity to strategically position their vessels for optimal utilisation.

For the purpose of this study, an applicable forecasting model needs to be identified and tested to serve as basis for future development. Brokerage A has already contracted Consultant A to perform the technical development of the identified model if it proves to be a feasible solution to the problem at hand. The required forecasting model needs to translate annual Brazilian grain export forecasts into monthly congestion levels at the respective ports whilst taking both seasonal and annual variation in grain trade into account. The problem considered in this thesis aims to provide an answer to the following research question:

Given the anticipated annual grain export volumes from Brazil, is it possible to estimate both trend and level of fluctuation of future monthly congestion levels at a port in the Brazilian port network within reasonable deviation of actual congestion levels?

1.3 Objectives

Given the research question stipulated in §1.2, the main objective of this study is to identify and develop a forecasting model to predict both trend and fluctuation in congestion at a port in the Brazilian grain port network given the annual tonnage of grains to be exported from Brazil. In order to achieve that, the following sub-objectives are pursued:

1. To *perform* a comprehensive study of the environment where the forecasting model will be implemented, including
 - (a) an introduction to the dry bulk sector with specific focus on port congestion and grain trade within the sector;

⁴Demurrage is either a lump sum or a rate paid for every workable day exceeding lay time [26].

- (b) an overview of the Brazilian grain industry; and
 - (c) an introduction to Brazilian grain ports with emphasis on the Port of Paranagua;
2. To *undertake* a literature review of models previously designed for port congestion analysis to serve as basis for the identification of an applicable modelling technique;
 3. To *propose* a suitable model to be implemented for the problem at hand by
 - (a) identifying a model that accommodates the unique characteristics of the Brazilian grain trade;
 - (b) providing a structural breakdown of the model components;
 - (c) testing the validity and reliability of the model; and
 - (d) providing guidance to the application and revision of the model;
 4. To *illustrate* the application of the proposed model by
 - (a) providing the results generated by the model;
 - (b) showing the results of the validity and reliability tests;
 5. To *evaluate* the results of the proposed model by
 - (a) discussing the accuracy of the results; and
 - (b) comparing the study to other studies with similar characteristics.

1.4 Scope

The scope of the grain volumes to be analysed includes all bulk cargoes of maize, soybeans and soybean meals exported from Brazil. Given the negligible volumes of other types of bulk grain exports such as wheat and barley [7], these commodities are excluded from the analysis.

The types of vessels of relevance exclusively refer to bulk carriers with minimum carrying capacity of 10 000 dead weight tonnes (dwt) and maximum carrying capacity subject to the draft and berth restrictions at the port. The small volume of grain exported in container vessels are beyond the scope of the study as container vessels are operated from separate terminals and have no influence on bulk operations.

The port network of relevance in this study includes all Brazilian ports where the aforementioned grains are exported. The application of the proposed model, however, is exclusively demonstrated on the port selected for this case study, the Port of Paranagua, as well as the port selected to test the repeatability of the model, Sao Francisco do Sul.

1.5 Relevance of the study

The relevance of the study is captured in the following contributions:

1. The proposed methodology forms the basis for future development as it can be applied to the other bulk grain ports in the Brazilian grain network to form a conglomerate view of congestion levels in the named sector. The generated forecasts would be of value to both vessel owners and charterers for strategic decision making;

2. The study provides insight to the complexity of port congestion modelling in the event of seasonal variation, which is complicated further by the evolving nature of the shipping industry, as well as the fluctuating influence of external events; and
3. The model can be applied to perform sensitivity analysis of the potential impact of physical expansions or efficiency improvements on congestion levels at the Port of Parangua and the Port of Sao Francisco do Sul.

1.6 Thesis organisation

This thesis comprises seven chapters, including the introductory chapter. The purpose of Chapter 2 is to provide the reader with the necessary background to the shipping industry. The chapter starts with an introduction to dry bulk shipping with particular focus on port congestion and bulk grain trade. That is followed by an overview of the Brazilian grain industry by providing insight to trade flows of the different types of grain, the ports of relevance and the factors influencing congestion levels at these ports.

Chapter 3 provides information on port congestion modelling obtained from the literature. This includes a discussion of a number of studies in which different types of modelling techniques were used, including queuing theory, simulation, as well as time-series analysis.

Chapter 4 introduces the reader to the proposed model, commencing with an overview of the data used for the analysis, followed by a discussion of the assumptions made for the purpose of the model. That is followed by an explanation of the model, in which each phase of the model is described, tested and validated. The chapter concluded with a section on the implementation of the model.

The results generated by the proposed model are illustrated in Chapter 5. The results of the respective phases are presented, followed by results generated from the validity tests.

The purpose of Chapter 6 is to discuss the results illustrated in Chapter 5. An evaluation of the results is performed, followed by a section on the practicality of the implementation of the model. The chapter also touches upon the challenges obtained in congestion analysis.

The final chapter of this thesis provides a summary of the preceding six chapters and recommends propositions for future studies in the field of congestion analysis.

CHAPTER 2

Dry bulk shipping and Brazilian grain trade

Contents

2.1	Dry bulk shipping	7
2.1.1	<i>Terminology and policies</i>	8
2.1.2	<i>Congestion at dry bulk ports</i>	8
2.1.3	<i>Dry bulk grain trade</i>	9
2.2	Brazilian grain industry	10
2.2.1	<i>Trade and seasonality</i>	10
2.2.2	<i>Congestion at Brazilian grain ports</i>	13
2.2.3	<i>Port of Paranagua</i>	15
2.3	Chapter summary	17

Chapter 2 provides background to the environment of the problem stipulated in Chapter 1. §2.1 opens with a brief introduction to dry bulk shipping followed by a discussion of port congestion and the unique characteristics of the grain trade. §2.2 narrows the focus to the Brazilian grain industry by providing insight to trade patterns, local congestion levels and an introduction to The Port of Paranagua. Chapter 2 closes with a brief summary of the chapter in §2.3.

2.1 Dry bulk shipping

According to Stopford [26], dry bulk cargo is defined by the following characteristics: Cargo that is transported in ship- or hold-size parcels; loaded by either gravity or with pumps; discharged by either grabs, suction or pumps; and can be stowed in its natural form. Examples of dry bulk cargoes include iron ore and coal, each capturing about a third of total dry bulk trade, followed by grains, which absorbs about 9% of the trade [4]. Other minor bulks include selected wood products, minerals and fertilisers.

Dry bulk seaborne trade increased by 85% over the past decade, exceeding 3.9 billion tonnes in 2013. The corresponding dry bulk fleet increased by 140% over the same period reaching a total of 9 959 vessels in 2013 [4]. Vessel sizes range between 10 000 dead weight tonnes (dwt) and 400 000 dwt. The four major vessel types are presented in Figure 2.1. Coal and iron ore are predominantly shipped in capesize vessels with carrying capacity of 100 000 dwt and above. Grains and other minor bulks are shipped in smaller vessels such as panamax, supramax and handysize vessels. Panamaxes range between 60 000 dwt and 100 000 dwt and are usually

gearless. Supramaxes range between 40 000 dwt and 67 000 dwt, and handysize vessels range between 10 000 dwt and 40 000 dwt. The majority of supramaxes and handysizes are geared with cranes and grabs to self-load and discharge its cargoes [26].

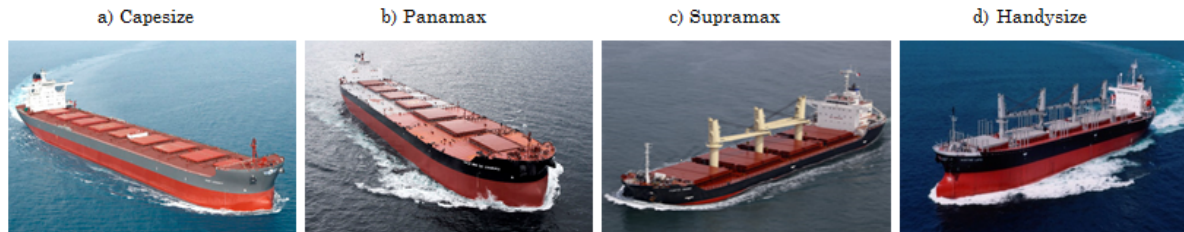


FIGURE 2.1: *The main types of dry bulk vessels [4].*

2.1.1 Terminology and policies

The volume of cargo loaded per shipment, referred to as the stem size, is subject to physical restrictions at both load and discharge ports, typical parcel sizes, and buyer requirements. As these factors evolve, stem sizes evolve accordingly [26].

A port refers to a collection of terminals, and each terminal has one or more berths where vessels are either loaded or discharged. Prior to entering the port, vessels wait in an allocated anchorage upon their scheduled time to berth. Berthing policies at the majority of bulk ports are based on a first-come, first-served (FCFS) basis [1]. In the event of physical or administrative inefficiencies, for example when a vessel's allocated cargo is not ready to be loaded at the storage facility or the required administrative documents could not be rendered in time, the next vessel in line will advance to the allocated berth.

Vessels' expected time of arrival (ETA) at their destined anchorage areas are reported to the harbour master at least three to five days prior to the anticipated arrival date. The notice period varies according to the port's arrival policy [10]. Approaching vessels' expected order of arrival forms the basis of a port's berthing schedule. Berthing schedules are recorded in line-up reports which are distributed to all interested parties, including vessel owners, charterers and brokers. Line-up reports keep interested parties informed of potential changes in shipping schedules.

Maneuvering the vessel from the anchorage area to its allocated berth is either done by the captain of the vessel or if the topography of the port requires piloted steering, by the port's pilot. Upon arrival at a loading berth, inspections are performed to establish whether the vessel adheres to the required levels of seaworthiness and cleanliness. If an inspection is failed, the reason for failure is addressed and corrected, and the inspection is repeated [6]. At a discharge berth, cargo inspections are performed prior to discharge, and seaworthiness and cleanliness inspections are performed prior to departure [16].

2.1.2 Congestion at dry bulk ports

Port congestion occurs when the number of vessels arriving at a port within a given time frame exceeds the number of vessels that can be served during that time frame. The level of congestion is therefore subject to the relationship between the demand for vessels calling at a port and the port's capacity. Regarding the former, the demand for vessels is a function of trade volumes either exported from or imported to the port. For each commodity, trade volumes are determined

by the exporting countries' availability of exportable supplies as well as the importing countries' demand for the commodity.

The capacity of the port, on the other hand, is subject to its physical and operational capacity. The physical capacity is determined by the number of terminals and the dimension restrictions of these terminals, whereas the operational capacity is determined by the efficiency of a series of processes involved in a vessel's port turnaround-time. These processes include the movement from anchorage to berth, the cleaning and inspections of the vessel and the load or discharge of the cargo. A port's load and discharge rates are subject to the quality and quantity of shore equipment, the availability and efficiency of the port's labour force, and the possible impact of external events. Examples of external events include weather related delays, labour strikes, maintenance shut downs, holidays and cargo availability issues. The sporadic nature of these external events contributes to the volatility of congestion levels.

Congestion levels can be eased by either expanding a port's physical capacity or improving its operational capacity. According to Valentin [30], examples of the former include the addition of a new terminal; the expansion of an existing terminal; the expansion of storage facilities; the addition of additional port equipment; or capacity improvement of the access channel to the berths. Operational adjustments include changes to ports' rules and regulations such as extending daily operational hours.

High congestion levels have been reported at the majority of the key dry bulk ports, including Australian coal and iron ore exporting ports, Indian coal importing ports, Chinese iron ore importing ports, and Brazilian iron ore and grain exporting ports. Of these ports, Brazilian grain exporting ports experienced the highest levels of congestion in 2013 [4].

2.1.3 Dry bulk grain trade

Dry bulk grain trade involves the bulk shipment of maize, wheat, soybeans, soybean meal and barley, of which maize accounted for 26%, wheat 33%, soybeans 22%, soybean meal 13% and barley the remaining 6% in 2013 [7].

According to the United States Department of Agriculture (USDA) [28], global grain production increased by 41% between 2003 and 2013 as a result of 13% increase in global planted acreage combined with 22% improvement in yields. Yield growth was enabled by increased fertiliser application, improved seed technology, and more efficient farming techniques. The increase in grain supplies was driven by an acceleration in demand for grains, especially in emerging economies such as Asia, Africa and South America. The high rate of growth in emerging economies are ascribed to the high income elasticity of meat and the corresponding demand for animal feed [26], which encompasses more than 36% of total grain usage [28]. In China, for example, the world's leading consumer of grains captivating 21% of global grain consumption, income per capita increased by 416% between 2002 and 2012. According to data provided by World Bank [34], the increase in income per capita contributed to a 54% increase in grain consumption per capita over the same period. Although China is the second largest grain producer in the world, the country's restricted scope for acreage expansions necessitate more grain imports to meet the growing demand. As a result of the increasing disparity between the areas with excess grain supplies and those with grain supply deficits, seaborne grain trade increased by 46% over the past decade.

Long term projections by the USDA indicate continued strong growth in global agricultural trade, of which more than 95% of the growth in grain imports are expected to come from low to middle income countries [29]. The increasing demand for grains, oilseeds and other crops

encourage further acreage expansions, for example, large scale acreage expansions are expected to occur in the former Soviet Union (FSU) and Sub Saharan African, as well as in Indonesia, Argentina and Brazil.

USA and Brazil are the two major grain exporting countries, captivating 18% and 15% of total grain trade in 2013 [7]. For each producing country, each type of grain has a unique seasonal cycle. The USDA defined these seasonal cycles as local marketing years, referring to the twelve-month period following the onset of the harvest [28]. Exports from the respective supplying countries thus enter the market at different stages of the year. For example, US soybean exports usually start during September and peaks during the fourth quarter of the year, whereas Brazilian soybean exports enter the market towards the end of January, and peak during the second quarter of the year. Harvests' commencement dates vary within a window of time at the beginning of the marketing year as it is subject to weather conditions during the planting and vegetative stages of the crops.

The extent of a country's seasonal fluctuation of exports is subject to its storage capacity. In case of ample capacity, as is the case in the United States, grains can be stored until favourable market conditions encourage trading. However, in developing countries where storage facilities are limited, farmers are pressured to release the harvested crops to the market leading to high export volumes during and immediately after harvesting, followed by weak export volumes during the off-peak season.

Regarding the handling of grains, exposure to moisture is avoided. According to Thomas *et al.* [18], a grain cargo's moisture content may not exceed 14% due to the risk of caking, moulding or germination, which lowers the quality of the cargo. In case the cargo is damaged, receivers of the cargo may refuse to pay for the cargo. In order to avoid moisture exposure, load or discharge operations are suspended and hatches are covered in the event of rain or severe humidity.

2.2 Brazilian grain industry

Having provided a brief overview of the dry bulk shipping industry with particular emphasis on global grain trade, the focus is narrowed to the Brazilian grain industry.

2.2.1 Trade and seasonality

Acreage expansions and efficiency levels in Brazil's agriculture sector accelerated in line with the increase in global grain demand as discussed in §2.1.3. As a result, production of Brazil's two major crops, soybean and maize, reached record levels during the 2012/2013 marketing year. Regarding soybeans, 84.8 million tonnes of soybeans were harvested, of which half were exported and 37.7 million tonnes crushed into soybean meal¹ and oil². Domestic consumption of soybean meal surpassed 15 million tonnes during 2012/2013, and 13.2 million tonnes were exported. Maize production reached 81.5 million tonnes during the 2012/2013 marketing year, of which 52.5 million tonnes were consumed domestically and a record breaking 26 million tonnes were exported, compared to 12.7 million tonnes in the previous year. Brazil is a net wheat and net barley importer, with imports reaching 7.5% million tonnes and 36.9% million tonnes respectively in 2012/2013 [28]. Throughout this thesis, Brazilian grain exports refer to maize, soybeans and soybean meal exports exclusively.

¹Soybean meal is used as high protein animal feed in either pellet or meal form.

²Soybean oil is predominantly used for household purposes.

Brazil has limited storage facilities, which necessitates the immediate distribution of the majority of soybean and maize harvests [23]. Substantial volumes of grains are thus channeled from farms to ports at the peak of the respective seasons, adding condensed pressure to the Brazilian logistical infrastructure. Since the volume of exports is restricted by hinterland infrastructure capacity, growth in exports is subject to the rate of growth in infrastructural improvements and the level of global grain prices.

According to Williams [32], soybean harvesting starts in January and is usually finished by April. The first soybean shipments usually leave the ports by the end of January, followed by a slight pick up in volumes in February, and increase substantially as of March onwards. Soybean exports usually peak in either April or May, from where it tapers down with a long tail.

Soybean and soybean meal exports peak and trough at similar times despite the time discrepancy between bean harvesting and crushing [32]. However, soybean meal exports tend to be more evenly spread throughout the year leading to less variation between peak and off-peak volumes. Contrary to the strong growth projection of soybean exports, soybean meal exports are forecast to grow by less than 3% over the next decade. The limited growth in soybean meal exports is ascribed to increasing domestic demand driven by strong growth in pork and poultry production, as well as slower expansion in crushing capacity on the back of increasing competition from Argentina [29].

Brazil harvests two maize crops per year. The first crop is planted during September and harvested between January and March. The second crop, referred to as the Safrinha crop, is planted as soon as land becomes available from the first maize as well as the soybean harvests. Given the larger area available for Safrinha planting, production volumes are considerably higher than the first maize harvest. Safrinha harvests usually commence in May and are completed during July or August. The maize destined for export purposes usually reach the ports by the end of July, a time when, albeit declining, soybeans are still shipped at a strong pace. Given the overlap in export cycles, competition between maize and soybean volumes adds pressure to the limited infrastructural capacity of the ports.

Given the seasonal nature of grain exports it is expected that the monthly arrivals at any given port follows a similar seasonal pattern. To illustrate, Figure 2.2 presents the monthly arrivals and departures at the Port of Paranaguá between January 2011 and December 2013.

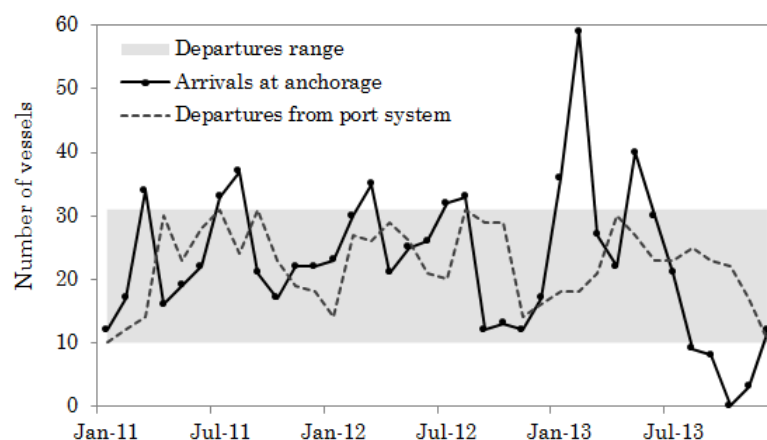


FIGURE 2.2: Monthly vessel arrivals and departures at the Port of Paranaguá.

The aforementioned bi-annual seasonal peaks are evident in Figure 2.2. The shaded area in

Figure 2.2 indicates the limited range of monthly departures over the three year period, ranging between 10 and 31 vessels, whereas the range of monthly arrivals fluctuate between 0 and 60 vessels during the same period. This highlights that monthly departures are restricted to a port's physical and operational capacity whereas monthly arrivals have no ceiling.

From Figure 2.2 it is also evident that the level of fluctuation of arrivals is irregular. The varying spikes and troughs are mainly driven by a combination of the following three factors: 1) the supply and demand balance of global grain supplies, 2) ocean freight market conditions, and 3) short term fluctuation in importing countries' profit margins. What follows is a discussion of each of these factors.

Regarding the first of the listed factors, when global supplies of a commodity are under pressure as a result of weak exports from one or more of the major exporting countries, more focus is placed on other supplying countries. As a result, a surge in arrivals are often observed at the ports of the alternative suppliers. On the contrary, when buoyant supplies are expected from a supplying country on the back of a bumper harvest, vessels tend to be strategically repositioned to that area in order to be available for service once the harvested volumes reach the port. This repositioning usually occurs at the onset of the anticipated bumper harvest, causing a spike in arrivals at the port.

The second external event of influence on arrival patterns is the relative strength or weakness of the ocean freight market. In the case of weak freight rates caused by excess availability of vessels in the market or a global lack of demand for shipping, an urgency is triggered to reposition vessels to areas of high exportable supplies.

A case when both the first and the second of these external factors aligned occurred in January and February 2013. In the previous year, drought in the US diminished soybean harvests causing a global shortage. Given the sub-standard volumes of exports that entered the market since the onset of the US soybean harvests in September 2012, the focus was shifted to Brazil where a record soybean crop was expected. These record volumes, seasonally entering the market from January onwards, were thus expected to fill the gap in demand. At the same time, the freight market experienced the weakest levels since October 2008 due to an oversupply of vessels in the market. As a result, Brazilian grain ports experienced a surge in arrivals from January onwards as vessels were desperate for cargoes and thus willing to wait for the harvested volumes. The spike in arrivals at Paranagua is evident in Figure 2.2, when 39 vessels arrived during January 2013 and 59 vessels arrived during February 2013, which equates to a year-on-year increases of 70% and 97% respectively [32].

The third factor of influence on arrival patterns is the short term fluctuation in importing countries' profit margins. A sudden spike or trough in arrivals may occur in the urgency to optimise an opportunity of profit or to avoid a potential loss. In the case of soybeans, since China imports almost two-thirds of global soybeans, encompassing 75% of Brazilian exports in 2013 [7], soybean crush margins³ are usually indicative of arrival urgency at the load ports.

From the discussion it is evident that all of these factors have an impact on the level of urgency in the market, either encouraging or discouraging owners to send vessels to a specific loading zone. Given the range of influential factors as well as the fluctuating degree of market reaction to these factors, the level of urgency in the market adds substantial volatility to arrival patterns.

Information on all of these factors are either publicly available or can be derived from published figures. However, the market's degree of reaction to these factors vary from case to case. If,

³The crush margin is the differential between the cost price of soybeans and the market price of its products, soybean meal and oil.

for example, an overreaction on a previous occurrence had negative implications, market players would try to avoid repeat, thus lowering the degree of impact of the second reaction. This uncertainty complicates the modelling of vessel arrival patterns.

2.2.2 Congestion at Brazilian grain ports

The major Brazilian grain exporting ports are illustrated in Figure 2.3. The five highlighted ports on the South East coast captivated 87% of market share in 2013. Of the total of 84 million tonnes of grain exported from Brazil in 2013, Santos exported 28.1 million tonnes, followed by 17.7 million tonnes from Paranagua. 12.8 million tonnes of grains were exported from Rio Grande, 7.8 million tonnes from Sao Francisco do Sul and 6.3 million tonnes from Tubarao. The remaining 11 million tonnes were predominantly shipped from the following ports in the north: Sal Luis, Salvador, Manaus and Santarem [7]. For the remainder of this study, these remaining ports are collectively referred to as the sixth port.



FIGURE 2.3: A map of Brazil's major grain exporting ports [4].

Paranagua, Santos, Tubarao, Sao Francisco do Sul and Rio Grande collectively captured 96% of Brazilian grain port congestion in 2012 and 2013 [4]. Recalling from the introductory section of Chapter 1, the increase in Brazilian grain export volumes over the past decade amidst limited expansion in infrastructural capacity caused severe bottlenecks at the major Brazilian grain ports. The subsequent delays were exacerbated by the volatility in arrival patterns and the influence of external events listed in §2.1.2. In what follows, a description of arrival patterns at Brazilian grain ports is provided, followed by a brief discussion of each of the key influential external factors.

1. **Weather related delays:** Brazil has a tropical and summer rainfall climate. Precipitation levels usually peak in January, often raining two to three times a day, followed by a gradual decline towards the relatively dry winter months of June, July and August. These dry

months are followed by scattered showers in September, increasing in frequency towards December when it rains on a daily basis [25]. The seasonal variation in rainfall is higher in the central and northern regions of Brazil than in the south of Brazil [23]. Figure 2.4 illustrates the average monthly rainfall as well as the average number of precipitation days at Paranagua as published by the World Meteorological Organization (WMO) [35]. As mentioned in Section 2.1.3, grains are moisture sensitive. The following articles in Soybean and Corn Advisor establish the negative impact of rain on port efficiency: according to an article published in August 2013, 51 days of loading were reportedly lost due to rain during the first six months of 2013, of which 15 days of loading were lost during March alone [25].

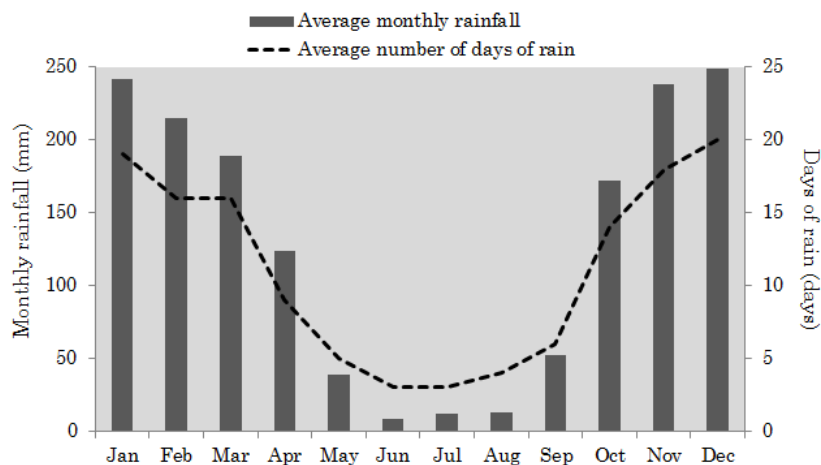


FIGURE 2.4: *The average monthly rainfall in Paranagua.*

- Labour strikes:** Labour strikes occur on a regular basis across various sectors of the shipping industry including dock workers, health inspectors, and pilots. Although strikes occur throughout the year, higher probability of occurrence has been noted during the three months prior to the start of the New Year, informally referred to as strike season. If port operations cannot proceed due to absence of labourers, delays are imminent. However, port operations often proceed despite striking labourers, for example if sufficient skeleton staff is available to perform the duties of the striking labourers, or if the key port sectors such as piloting, inspection and loading procedures are not directly affected by the strike. Furthermore, if the strike is of very short duration on the back of a quick settlement, the level of the strike's impact on overall port efficiency is often negligible.
- Public holidays:** Each port has unique rules and regulations regarding public holidays. Paranagua and Santos, for example, follow reduced operating hours on the major holidays, whereas other ports, including Recife, Suape and Sao Luis continue on normal working hours. From the holiday notices published by Williams [32], it is evident that the ports' respective schedules tend to remain constant over the years, thus the seasonal effect should remain the same for the different years.
- Port development and maintenance closures:** As mentioned in §2.1.2, capacity expansions include the addition of new terminals, the expansion of an existing terminal, expansion of hinterland facilities, addition of new port equipment, and capacity improvement of the access channel. Maintenance includes either periodic or demand-driven maintenance works on port facilities and equipment. In case the scheduled expansion or maintenance

procedures require operations to cease, an interdiction is scheduled which halts all operations for a specified period of time. In order to minimise delays, capacity expansions and maintenance closures are usually scheduled during the off-peak season between November and early February [32].

Recalling from §1.1, capacity expansion of the Brazilian grain logistical supply chain over the past decade has been relatively slow in comparison to the growth in grain volumes dependent on the supply chain. However, a number of expansion projects for both hinterland and port infrastructure improvements have recently been launched. The majority of these projects have been focused to relieve the logistical tension of the southern ports by improving access to and capacity of the northern ports. For example, annual grain exports from Sao Luis, Santarem and Itacoatiara in the north are expected to increase from 8.2 million tonnes in 2013 to 9.5 million tonnes in 2014 due to the near-completion of the BR162 and BR158 road expansion projects. These projects are implemented to improve access from the logistically challenged Matto Grosso region, where almost a third of the national grains are produced, to the northern ports. This improvement in infrastructure will enable Brazil to export up to 8.3 million tonnes of soybeans per month compared to 8.0 million tonnes before [25].

Although the majority of Brazilian grain terminals are government owned, the past decade has experienced a substantial increase in privately owned terminals. Major grain trading houses have made investments to increase the efficiency of the Brazilian grain infrastructure. For example, Bunge developed a terminal at Paranagua for the specific goal of exporting maize cargoes throughout the year, thus eliminating the losses associated with queuing when competing for berth time at the public export terminals [23]. The infrastructural developments in the north of Brazil are also predominantly privately funded.

2.2.3 Port of Paranagua

The Port of Paranagua is situated in Parana State, the major grain producing state in Brazil. Commodities exported from Paranagua include sugar, fertilisers, timber, coffee, steel billets, frozen poultry, vegetable oil, reefer cargo and grains. Three terminals are used for grain loading, of which two are private terminals called Soceppar (Berth 201) and Bunge (Berth 206), and the third consists of three public berths (Berths 212, 213 and 214) collectively referred to as the Export Corridor. The dimensions and characteristics of the three terminals are provided in Table 2.1.

Terminal	Berth(s)	Storage capacity (metric tonnes)	Load rate (tonnes/day)	Ship loaders (no)	Max draft (meters)	Max LOA (meters)
Soceppar	201	210 000	25 000	2	11.3	190
Bunge	206	90 500	10 000	1	10.0	225
Export Corridor	212,213,214	968 000	90 000	2	12	245

TABLE 2.1: *Grain berths at the Port of Paranagua [27].*

Soceppar terminal is predominantly used for sugar loading, however grain is loaded at the terminal during the off-peak months⁴ of the sugar cycle. The terminal has two berthing spaces.

⁴The sugar cycle's off peak season is from March until June.

As mentioned in §2.2.2, Bunge terminal is predominantly allocated for maize, of which the average stem size was 29 000 tonnes in 2013. The number of cargoes per month ranges between zero and seven, of which an average of five during peak months, April until October, and an average of three during off-peak months between November and March. Similar to Soceppar, Bunge terminal has only one berth.

The majority of the Port of Paranagua's grains are exported through the export corridor. The corridor has three berths that share resources such as ship loaders and operating staff. According to an article published by Soybean and Corn [25], vessels loading at the export corridor source their grains from a number of different export sources. The number of sources range between one and seven, and every change incurs extra time spent in port, which results in increased congestion. An estimated 9 000 hours of potential loading operations were lost in 2013 due to excessive switching [25].

From Table 2.1 and the subsequent elaboration thereof, it is evident that the three terminals are not parallel in terms of structure, berth dimensions or service rates. Furthermore, since Bunge and Soceppar are privately owned terminals, the collection of queuing vessels are independent from the vessels queuing at the export corridor.



FIGURE 2.5: An aerial view of the Port of Paranagua [4].

In December 2013, the port authority at the Port of Paranagua announced that port congestion levels were expected to ease in 2014 based on the following alleviating factors:

1. A slight decline in exportable grain volumes were expected for 2014 based on a weaker production outlook than the previous year [28].
2. The port was in the process of installing a new scheduling system called the *Rule 126* that would give berthing priority to vessels contracted to load grains from a smaller number of exporters. An express line would be allocated to vessels loading at least 18 000 tonnes from one exporter, and loading from no more than three different exporters are allowed in this line. This would incentivise vessels to minimise the number of switches between sources [25].
3. Dredging has already started towards the end of 2013 in order to increase the draft capacity of both access channels and berths. The improved draft capacity would ease vessel movement within the port and allow vessels to increase the volume of cargo loaded per shipment as it was previously capacitated by draft restrictions [24].

4. A new ship loader was being installed at the export corridor with expected inauguration to be in June 2014. Loading capacity was projected to improve accordingly from 90 000 tonnes per day to 150 000 tonnes per day [24].
5. Temporary restrictions were put in place to limit maize exports after 15 January 2014 to in order to alleviate congestion during the peak of the soybean export season. Maize shipments will be allowed to resume later in the year [24].
6. A computer based truck scheduling mechanism was put in place in 2012 which continues to improve hinter-land congestion, with a positive knock-on effect on congestion in the port [24].
7. According to the local port officials, an improvement in general operational procedures was projected to result in a 5% improvement in overall port efficiency [24].
8. The port was in the process of testing retractable covers for ship loaders that would allow loading to continue irrespective of the rain. A proposed official installation date has not been secured at the time [24].

According to an article by Black Sea Grain [2], the improvement in efficiency would increase Paranagua's annual export capacity from 17.6 million tonnes in 2013 to 22 million tonnes in 2014.

2.3 Chapter summary

A summary of the main characteristics of relevance to Brazil's bulk grain shipping industry are listed:

1. Multiple dynamic components:
 - (a) Evolving stem sizes as stipulated in §2.1.1;
 - (b) Seasonal arrival and service patterns as highlighted in §2.2.1;
 - (c) Impact of external events as indicated in §2.2.2; and
 - (d) Improvement in service capabilities at the Port of Paranagua as listed in §2.2.3.
2. Vessels' arrival rate often exceed the ports' service capability as indicated in §2.2.2.
3. Difference in both structure and service rates at the Port of Paranagua's three terminals as discussed in §2.2.3.
4. Change in queuing discipline as discussed in §2.2.3.

The information provided in Chapter 2 provides guidance to the areas of focus in the literature survey performed in Chapter 3 and forms a basis for the research assumptions made in Chapter 4.

CHAPTER 3

Literature Review

Contents

3.1	Queuing theory	19
	3.1.1 <i>Brief introduction to queuing theory</i>	19
	3.1.2 <i>Literature review of port queuing models</i>	20
3.2	Simulation	22
	3.2.1 <i>Brief introduction to simulation</i>	22
	3.2.2 <i>Literature review of port simulation studies</i>	23
3.3	Time-series analysis	25
	3.3.1 <i>Brief introduction to multiple regression</i>	25
	3.3.2 <i>Literature review of time-series based port analysis</i>	26
3.4	Chapter summary	26

The purpose of Chapter 3 is to explore previous studies on port congestion analysis. Port operations have been approached by various modelling techniques, including queuing theory, simulation modelling and time series analysis. In what follows a brief introduction to these modelling techniques are provided, followed by an overview of relevant studies performed in the respective fields. The chapter closes with a summary in §3.4.

3.1 Queuing theory

Queuing theory is an analytical approach to port congestion analysis and has been recognised by Shabayek and Yeung [22], amongst other, as one of the favourable tools to conduct port studies. What follows is a brief introduction to queuing theory, followed by a review of a previous studies.

3.1.1 Brief introduction to queuing theory

According to Winston [33], a queuing system is classified according to its input and output processes. In the application of queuing theory to port operations, a port is regarded as a system and the vessels using the system are the customers. The parameters of relevance are the vessels' arrival rate at the port per unit of time and the ports service rate per unit of time. Service in the port refers to either loading or discharging of a cargo. In the case of more than one vessel in the queue, the order of berthing is subject to a predetermined queuing discipline. Once the

service in the port is completed, the system is exited [33]. The type of queuing model applied to any given queuing problem is subject to combination of the aforementioned characteristics. Kendall-Lee standardised the grouping of these characteristics as

$$(A/B/C) : (D/E/F),$$

where

- A = the nature of the arrival process of the customers;
- B = the nature of the system's service process;
- C = indicates the number of parallel service stations in the system;
- D = the queuing discipline;
- E = the maximum number of customers allowed in the system; and
- F = indicates the size of the calling population [33].

Dragovic *et al.* [5] noted that the choice of model is also dependent on whether a deterministic or stochastic approach will be taken. Whilst deterministic approaches are simplistic and easy to implement, the validity of application is limited. Alternatively, stochastic processes are more realistic and dynamic, yet are more complex to implement.

For any queuing system or subset of a queuing system, the following parameters are of relevance: The average number of customers arriving at the system per unit of time, usually denoted as λ , and the average number of customers served per parallel serving station s , usually denoted as μ [33]. The application of queuing theory requires the system to operate in a steady state, which is achieved if the traffic intensity¹ of the system,

$$\rho = \frac{\lambda}{s\mu} < 1. \quad (3.1)$$

From equation 3.1 it is evident that a steady state cannot be achieved if the number of arrivals per time unit exceeds or is equal to the service capacity over that time unit, that is, when $\lambda \geq s\mu$. If this requirement is violated, the system would “blow up”, causing the queue to become infinitely long after a prolonged period of time [33].

Queuing theory can be applied to calculate the two performance indicators of relevance to this study: 1) the number of customers in the queue, usually denoted as L_q , and 2) the average time spent in the queue, usually denoted as W_q . The relation between these two parameters has been established by Little's queuing formula which states the following: for a queuing system in which a steady-state distribution exists,

$$L_q = \lambda W_q. \quad (3.2)$$

3.1.2 Literature review of port queuing models

El-Naggar [15] explored the application of queuing theory at the the Port of Alexandria's container terminal to serve as basis for infrastructural decision-making. The study aimed to calculate

¹The multi server formula is used for demonstrative purposes.

the optimal number of berths at the terminal based on the estimated future volumes to be handled by the terminal. In order to achieve this goal, the trade-off between the marginal cost of the construction and maintenance of an additional berth and the corresponding marginal delay costs of waiting vessels was analysed. An $(M/E_k/s) : (FCFS/\infty/\infty)$ queuing model was used to calculate the waiting times associated with the respective number of berths. The analysis indicated that 33 berths were to be the optimal scenario, and the model proved to be viable and in best interest of both ship operators and the port authority.

Leachman and Jula [12] performed a study on congestion in container terminals on the West Coast of the United States. The study highlighted the limited range of literature available on the analysis of congestion levels of large port networks, as opposed the large number of studies performed on individual terminals or ports. In order to analyse the entire port network under study, simplistic identical queuing models were developed and implemented for the respective ports. One of the simplification techniques was to conglomerate all the terminals per port into single queuing systems. Empirical data were used to establish generalised variances for the arrival and service rates of the respective ports, which were used as input parameters to the proposed queuing model. The model was used as basis to perform elasticity analysis of potential infrastructure developments and employment of additional staff. Despite the relative weakness of the results, the model was able to provide a broad indication of expected port performance given a change in infrastructure or staffing.

In 2011, Oyatoye *et al.* [17] launched a study at Tin Can Island Port in Nigeria to investigate the leading causes of port congestion, and to determine whether the port had an adequate number of berths given the volume of goods handled at the port. An $(M/M/10) : (FCFS/\infty/\infty)$ queuing model was implemented for this purpose, assuming equal service times at the respective berths. Given the seasonal variation in throughput volumes, the model was run for each month. Since the monthly number of vessels arriving at Tin Can Island Port exceeded its service capacity, implying $\rho > 1$, no steady state existed at the port. The conclusion was drawn that an additional berth was indeed required given the volumes traded through the port.

In 2010, Dragovic *et al.* [5] published a review of past studies performed on multiple server queuing models with stationary waiting time probabilities. The reviewed studies were categorised according to their respective methodological approaches, and a classification tool was provided to assist future modelers to pair any given multi server queuing problem's set of characteristics with the most applicable approach. Dragovic *et al.* [5] acknowledged that, although research established that analytical solutions of queuing models can be used to analyse ports, it remains an imperfect tool due to the numerous assumptions required to build the model. It noted that problems do exist for which no suitable models can be applied, irrespective of the degree of decomposition or simplification of the system. The study criticised the large number of theoretical queuing models available in the literature constructed to fit complex systems, yet lack proof of practical applications. The numerous assumptions involved in implementing queuing theory in port operation analysis often weaken the accuracy of results, especially if the problem is of high complexity. Emphasis was also placed on the the increasing application of simulation modelling as an alternative to analyse ports, yet criticized its high dependency on input data.

In order to overcome the restrictive nature of queuing models, Render [19] suggested simulation as alternative approach to realistic modelling of queuing systems.

3.2 Simulation

As mentioned in §3.1, Dragovic *et al.* [5] noted an increasing tendency to use simulation modelling as alternative to analyse ports. An introduction to simulation is provided, followed by examples of simulation studies focused on port operations.

3.2.1 Brief introduction to simulation

According to Render *et al.* [19], the objective of a simulation model is to generate results for strategic decision making by imitating real-world scenarios mathematically. This approach avoids changes or investments to the actual system until the most advantageous solution is determined. Upon embarking a simulation study, Render *et al.* [19] advises following the step-wise approach illustrated in Figure 3.1:

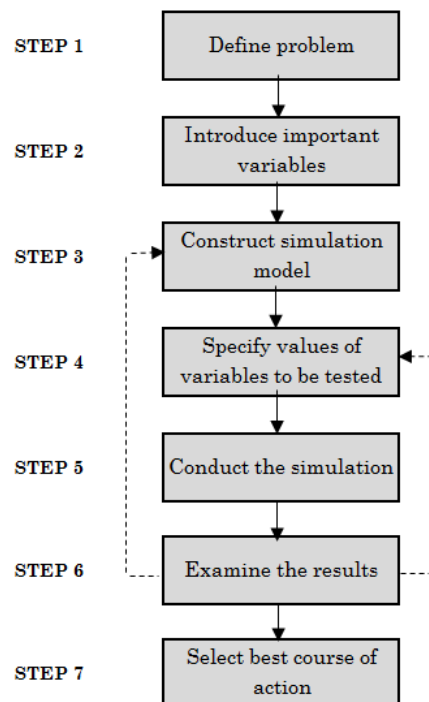


FIGURE 3.1: A step-wise approach to simulation modelling [19].

The first step requires a clear definition of the problem, followed by an introduction to all the variables of relevance in the second step. Thirdly, the simulation model is constructed using the appropriate software. Upon completion of the model construction, the fourth step commences in which a set of values are assigned to the variables as input to the first potential solution. Once assigned, the model is run during the fifth step to produce the first set of results. In step six, the results are examined, upon which the user has the choice of either modifying the model which takes the process back to step 3, or changing the set of input data by revisiting the fourth step. The cycle is repeated to produce several sets of results. During the seventh and final step, these results are compared to determine the best course of action.

When the variables required in the fourth step are of probabilistic nature, Monte Carlo simulation is often implemented to generate values for these variables. In the application of Monte Carlo

simulation, Render *et al.* [19] recommends that the the five steps presented in Figure 3.2 are followed in order to simulate a value for each input variable.

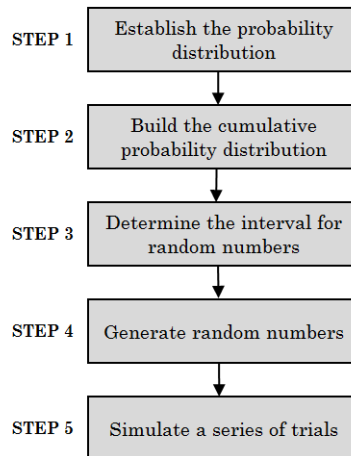


FIGURE 3.2: A step-wise approach to Monte Carlo simulation [19].

The types of simulation languages that have been incorporated for port operation modelling include *MODSIM III*, *AweSim*, *Arena*, *Extend*, *Witness*, and *GPSS/H*. The modeler has the choice of either developing the model with a general purpose programming language (GPPL) or implementing an existing simulation package or language (GPSL/SP) [36].

3.2.2 Literature review of port simulation studies

Fuller *et al.* [6] explored the relationship between grain export volumes and congestion costs at a representative US Gulf port elevator. The purpose of the study was to identify an equilibrium point between capacity expansion and the costs associated with congestion levels. A simulation model was constructed to generate potential congestion scenarios and corresponding costs for various levels of capacity expansions as well as various levels of exports. The simulation model consisted of five sub-models, each representative of a unique yet interrelated subsection of the inter modal grain export system. Sensitivity analysis of the simulated results indicated the critical level of volume input where additional congestion costs exceeded that of the capital investment of capacity expansion.

Mavrakakis and Kontinakis [14] performed a simulation study of the congested waterways in the Bosphorus Straits. A discrete event model was built to estimate future waiting times at the Straits' entrances. In the proposed simulation model, vessels were considered to be moving points, transiting the system at a constant speed within a pre-defined route. To ensure efficient modelling, the system was decomposed into a set of parameters particular to maritime traffic systems. Once established, these parameters were adjusted according to the unique characteristics of the Bosphorus system [14]. Simulated results proved that a linear increase in the arrival rate of vessels lead to an exponential increase in both the number of ships waiting to enter the system and the average waiting time at anchorage. The results also identified the types of vessels that caused the most congestion, as well as the types of vessels that have negligible impact on congestion. Another observation obtained from marginal analysis of the results was the indication of the critical point at which the Bosphorus becomes saturated [14].

A study by Valentin *et al.* [30] evaluates the application of discrete event simulation to model large maritime infrastructure systems. Valentin *et al.* [30] begins the paper by highlighting the characteristics of large infrastructure simulation studies:

- the objective to simulate potential medium to long term scenarios;
- the presence of seasonal or cyclical patterns in system utilisation;
- the impact of external factors on a system's performance levels, such as weather or tides;
- the possibility of changes of internal and/or external factors whilst a simulation study is performed;
- and the involvement of multiple system users.

Multiple potential outcomes of these characteristics broaden the range of simulated results, thus weakening the probability that a specific outcome will occur. Accurate parameters and variables are thus critical to the reliability of simulation models. In order to identify the relevant parameters and variables, the system has to be analysed and tested to determine the types of elements involved in the system, establish the inter-relational structure of the system's elements, and calculate the probability distributions of events. These tests, referred to as experiments by Valentin *et al.* [30], increase in number and complexity as the size and complexity of the system increase.

For maritime studies in particular, reruns of these experiments are often required due to the changing nature of the maritime industry [30]. Examples of changing factors include physical expansions of a port's structural layout; the introduction of new technology; a change in scheduling of port operations; and an increase in ship sizes or change in the types of ships used. These changes usually incur a change in systems' performance, thus necessitating reruns to quantify the impact of the change. In case different results emerge, the simulation model has to be revised to incorporate these changes.

Valentin *et al.* [30] highlighted that domain experts often lack the required skills to rebuild or adjust an existing simulation model, necessitating the input of a simulation expert. In an ever changing environment, the latter may be too expensive leaving the simulation model unchanged amidst changes in the actual system. The growing discrepancy thus weakens the simulation model's results over time. In order to overcome these challenges, a unique simulation tool to model large maritime infrastructure systems was introduced, called *Scenario Navigator*. Although the large infrastructure simulation models are easily created and updated with the *Scenario Navigator*, availability and access to the software is an obvious prerequisite.

According to a study performed by Boland [3], port congestion levels at the Port of Newcastle's three coal terminals in Australia are forecasted with great accuracy. The Port of Newcastle is one of the subsections of the Hunter Valley Coal Chain (HVCC), the world's largest coal export operation consisting of 35 coal mines, coal railings of up to 380 kilometers, and more than 1400 coal shipments per annum [3]. Forecasting is done by the Hunter Valley Coal Chain Coordinator (HVCCC), a centralised system established to coordinate all movement of coal between the Hunter Valley mines and the Port of Newcastle. A range of optimisation and simulation techniques have been implemented by the HVCCC for planning and forecasting purposes, including an optimisation model to compare different expansion strategies, three simulation models focused on the respective subsections of the supply chain, and an additional simulation model specifically implemented to assess the overall movement of coal of the supply chain [3].

The level of detail of all of the models used by the HVCCC is broken down to daily operational levels. Input to these models are provided in the format of shipment loads, referred to as

shipping stems. Prior to 2011, shipping stems were manually generated. In 2011, Boland [3] developed a multi-phase optimisation-based framework to generate reliable input data for the optimisation models used by the HVCCC. The developed framework is able to accommodate the dynamic nature of the HVCCC, including the increase in coal supplies, infrastructure expansions, and both short and long term variation in demand patterns. As result, the generated shipping stems reflected characteristics of historical trends, represented future demand scenarios, and have manually adjustable parameters to test various potential scenarios. Boland [3] highlighted the lack of research focused on data generation for shipping models, as well as the importance to model arrival patterns accurately in order to ensure validity of computational studies involving arrival patterns.

In summary, although simulation studies have proved increasing success in modelling port operations, its high dependency on data and extensive development time are restrictive in the event of limited data and/or development time.

3.3 Time-series analysis

Having discussed the application of both queuing theory in §3.1 and simulation modelling in §3.2, the remainder of Chapter 3 is focussed on the application of time-series analysis in port congestion analysis, with specific focus on multiple regression.

3.3.1 Brief introduction to multiple regression

Regression is a non-parametric statistical approach in which the relationship between a dependent variable and an independent, or explanatory, variable is studied [8]. In multiple regression modelling, more than one explanatory variable is incorporated to study the impact of multiple influences on the dependent variable. The stochastic regression function for the population can be written as

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \dots + \beta_n X_{nt} + u_t, \quad (3.3)$$

where

- Y = the dependent variable;
- X_n = the explanatory variables;
- n = number of explanatory variables;
- β_0 = the intercept term;
- β_t = partial regression coefficients;
- u = the stochastic disturbance term; and
- t = the t_{th} observation.

One of the main objectives of multiple regression analysis as stipulated by Gujarati [8] is to enable the prediction of the dependent variable's mean value, given the values of the explanatory variables.

3.3.2 Literature review of time-series based port analysis

In study performed by Shabayek [22], a combination of regression and queuing theory was implemented to evaluate and forecast port performance at the Kwai Ching container terminals in Hong Kong. The presence of trend and seasonal fluctuation in arrival and service rates differentiate this problem from typical queuing problems, hence prohibiting the application of one of the mainstream queuing models. The distributions of the arrival and service rates were empirically established by conglomerate analysis of previous years' arrival and service rates. It was assumed that the eighteen servers of relevance operated in parallel. In conjunction with the identification of the other queuing model criteria, an $(M/G/18) : (FCFS/\infty/\infty)$ model was established. The trends for both arrivals and services were established by means of regression analysis, and seasonal indices were calculated based on monthly data of the previous four years. Results indicated that the incorporation of trend and seasonality within the queuing model improved the accuracy of the model, and could be applied to estimate future port performance indicators such as the expected average waiting time at anchorage.

In a study performed by Voss [31], it was proved that the time spent waiting in a queue is non-linear to the utilisation of the relevant server or number of servers. Therefore, when the utilisation of a system is approaching one, indicating that the system is operating close to its maximum capacity, a small change in service time may lead to a substantial change in queuing time.

3.4 Chapter summary

The literature review verifies that port congestion analysis has been approached by various methodologies including queuing theory, simulation, regression analysis and a combination of these methods. Given the wide spectrum of potential modelling techniques available within these methodologies, it is critical to identify a modelling approach that matches the expectations, characteristics, and restrictions of the problem under study. Chapter 3 thus forms the basis upon which the methodology presented in Chapter 4 is built.

CHAPTER 4

Multi-Phase Congestion Model

Contents

4.1	Data	27
	4.1.1 <i>Historical Brazilian grain exports</i>	28
	4.1.2 <i>Brazilian grain export forecasts</i>	31
	4.1.3 <i>Brazilian grain port schedules</i>	32
	4.1.4 <i>Congestion at Brazilian grain ports</i>	33
	4.1.5 <i>Data quality assurance and limitations</i>	33
	4.1.6 <i>Summary of datasets</i>	34
4.2	Model assumptions	34
4.3	Modelling approach	35
	4.3.1 <i>Phase 1: Export volume allocation per port</i>	39
	4.3.2 <i>Phase 2: Estimate monthly arrivals at port</i>	40
	4.3.3 <i>Phase 3: Estimate monthly export capacity</i>	41
	4.3.4 <i>Phase 4: Conversion of queue length</i>	43
	4.3.5 <i>Phase 5: Conversion from queue length to waiting time</i>	44
4.4	Validity and reliability of the MPCM	45
4.5	Implementation and revision	46
4.6	Chapter summary	46

Chapter 4 provides a detailed description of the proposed model. The chapter opens with a discussion of the data available for the study in §4.1, followed by a list of assumptions in §4.2. The multi-phase congestion model is introduced in §4.3 by discussing the reasons for deciding upon the identified technique, followed by a description of each of the five phases of the model in §4.3.1 to §4.3.5. The tests performed to ensure the validity and reliability of the model are presented in §4.4, and the implementation and revision of the model are explained in §4.5. The chapter is closed with a summary §4.6.

4.1 Data

The data used in this study has been sourced through Brokerage A [4]. This includes access to historical Brazilian grain export volumes; forecasts of Brazilian grain export volumes; summaries of shipping schedules provided in port line-up reports; and historical congestion levels

at Brazilian grain ports. What follows is an introduction to the respective datasets as well as acknowledgement of primary sources.

4.1.1 Historical Brazilian grain exports

Recalling from Chapter 1, Brazilian grain exports collectively refer to maize, soybean and soybean meal exports. For historical trade data on these commodities, both country and port specific volumes are retrieved by Brokerage A [4] from Global Trade Information Systems (GTIS) [7]. GTIS is an online trade information database covering more than 77 countries. The trade data is released on a monthly basis, with dates of releases varying according to GTIS's agreement with the respective countries' custom offices. In the case of Brazil, trade data of any given month are usually published between the seventh and the eleventh of the following month. Both annual and monthly historical export volumes are of relevance to this study.

An extract of GTIS's annual port level data is illustrated in Figure 4.1. The bar chart provides a breakdown of Brazil's annual grain export volumes between 2004 and 2013 according to the six ports defined in Chapter 2. The increase in grain exports discussed in Chapter 2 is evident in Figure 4.1, increasing from 38.4 million tonnes in 2004 to a total of 82.6 million tonnes in 2013.

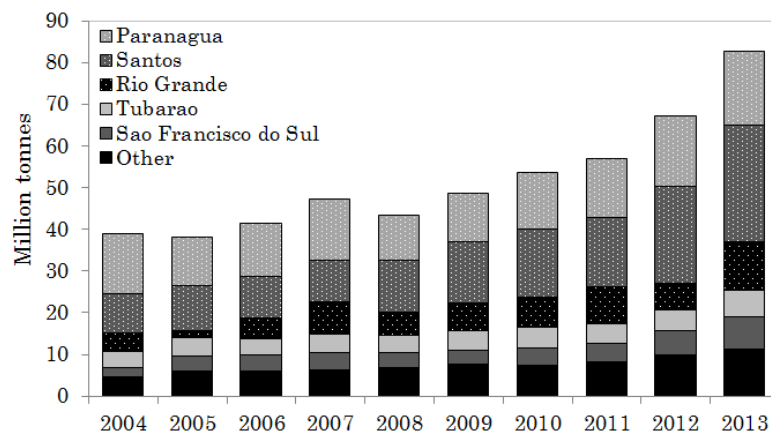


FIGURE 4.1: Annual Brazilian grain exports from the major ports [7].

The historical maximum exported from each port is derived from these historical figures. Table 4.1 provides a summary of the six ports' maximum values, as well as the corresponding year in which these values were exported.

Nr	Port	Historical maximum	Year
1	Paranagua	17.7m	2013
2	Santos	28.1m	2013
3	Tubarao	11.7m	2013
4	Rio Grande	6.3m	2013
5	Sao Francisco do Sul	7.8m	2013
6	Other	11.0m	2013

TABLE 4.1: Historical maximum volumes exported per port [7].

The market share of the respective ports between 2010 and 2013 is presented in Figure 4.2.

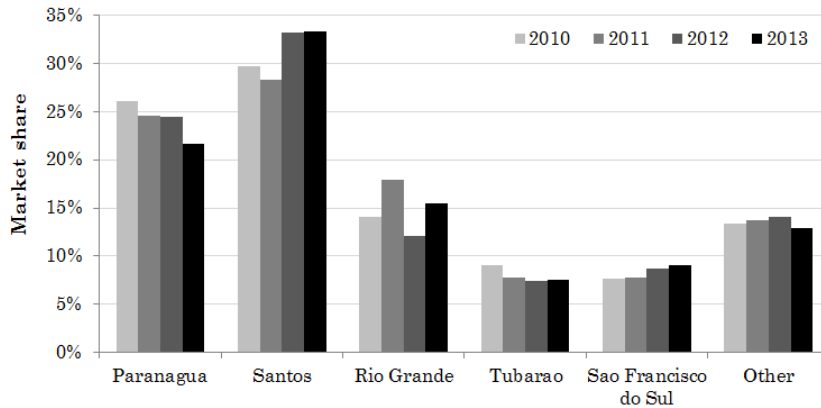


FIGURE 4.2: *Distribution of grain export market share per Brazilian grain port [7].*

An extract of GTIS's port level monthly export data is illustrated in Figure 4.3. Monthly exports of maize, soybeans and soybean meals from the Port of Paranagua between January 2010 and December 2013 are presented.

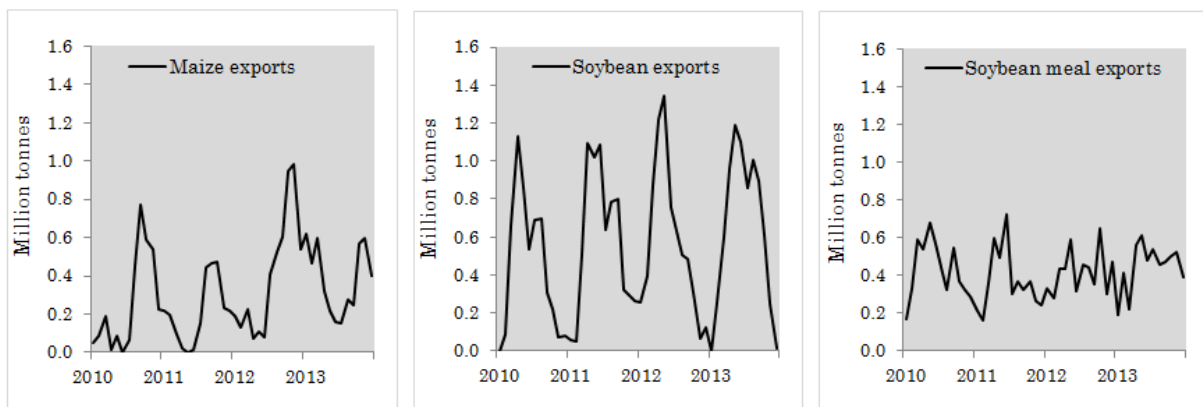


FIGURE 4.3: *Monthly maize, soybean and soybean meal exports from the Port of Paranagua [7].*

From Figure 4.3, seasonality in both maize and soybean exports is detected, whereas seasonality in soybean meal seems insignificant. In order to confirm the visual analysis, autocorrelation functions are calculated in SPSS (Statistical Package for the Social Sciences) [9]. If significant autocorrelation is identified at regular periodic intervals, the presence of seasonality can be confirmed. The output for maize, soybeans and soybean meals from SPSS is presented in Figures 4.4, 4.5 and 4.6 respectively.

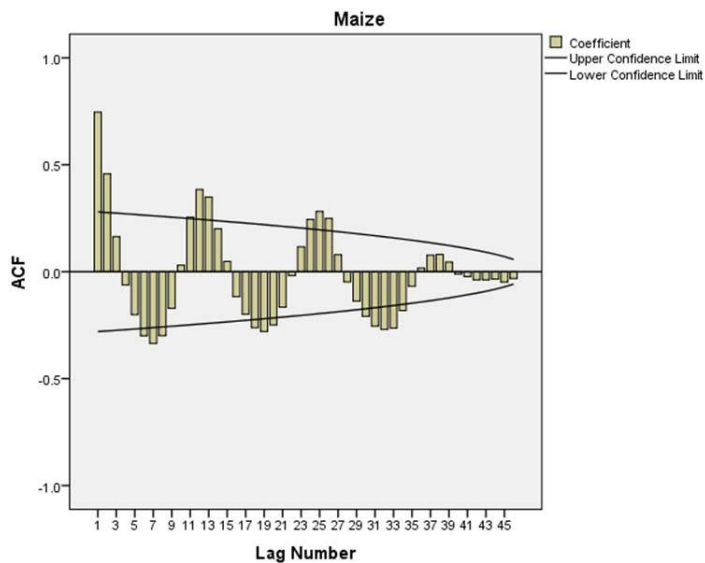


FIGURE 4.4: *The autocorrelation function of maize exports from the Port of Paranagua.*

From the autocorrelation function presented in Figure 4.4, it is evident that an oscillation is present and significant autocorrelations are detected at lag 6, 12, 18, 24 and 30. The presence of seasonality in maize exports is thus confirmed.

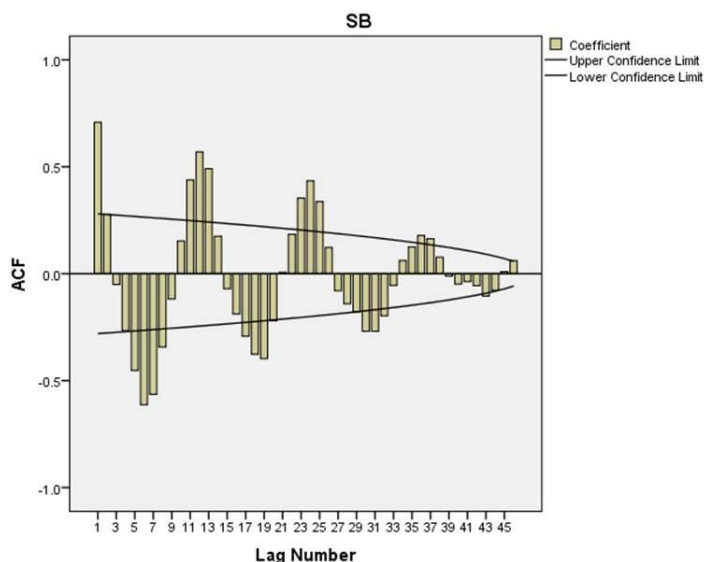


FIGURE 4.5: *The autocorrelation function of soybean exports from the Port of Paranagua.*

Similar to the illustration of the autocorrelation function for maize exports in Figure 4.4, oscillation and autocorrelations at lag 6, 12, 18, 24, 30 and 36 are evident in soybean exports presented in Figure 4.5. This observation confirms the presence of seasonality in soybean exports.

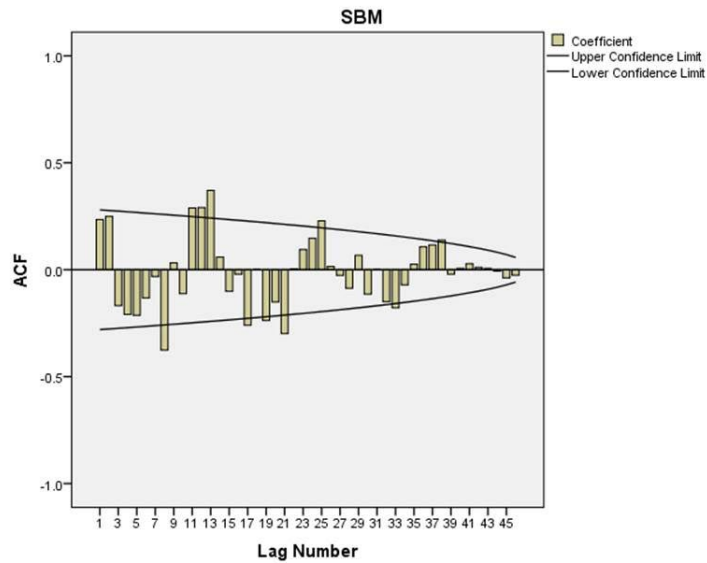


FIGURE 4.6: *The autocorrelation function of soybean meal exports from the Port of Paranaguá.*

In the case of soybean meals, of which the autocorrelation function is presented in Figure 4.6, oscillation is present, but to a lesser degree compared to maize and soybeans. In summary, the illustrations of the autocorrelation functions confirm that seasonality is present in maize, soybean and soybean meal exports from the Port of Paranaguá. However, whereas strong seasonality is detected in both maize and soybean exports, seasonality in soybean meal exports tends to be weaker.

Given the confirmation of seasonality of relevance in the Brazilian grain trade, it is critical to take this aspect into consideration when an applicable modelling approach is identified.

4.1.2 Brazilian grain export forecasts

Brazilian maize, soybean and soybean meal export forecasts are provided by the Brokerage A's analytics division [4]. Both monthly and corresponding calendar year forecasts are mathematically derived¹ from annual marketing year export forecasts published by the United States Department of Agriculture (USDA) [28]. The USDA's short term annual forecasts are revised on a monthly basis and the long term annual forecasts are revised on an annual basis. With every release of revised data, Brokerage A's forecasts are updated accordingly.

The annual export forecasts of the three commodities are summed to determine total annual grain export demand from Brazil. Brokerage A's forecasts as on 1 April 2014 are used as input to the model during Phase 1, which is to be discussed in §4.3.1. The forecasts for 2014 to 2017 are illustrated in Figure 4.7 along with the preceding actual values.

The anticipated decrease in 2014's export volumes on the back of weaker grain crops as mentioned in Chapter 2 is evident in the Figure 4.7, with total export volumes expected to fall by 2.7 million tonnes year-on-year.

¹Calculations are based on historical seasonal variation.

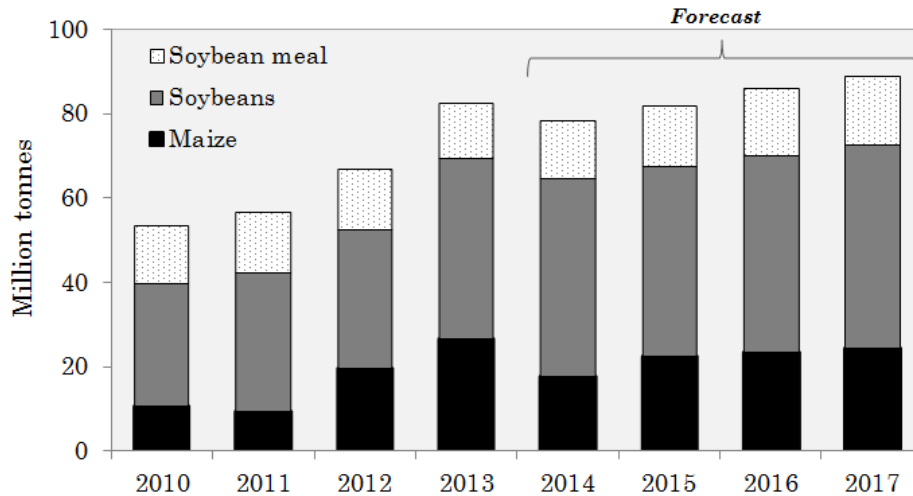


FIGURE 4.7: Brazilian grain export forecasts as provided by Brokerage A [4].

4.1.3 Brazilian grain port schedules

Recalling from the background on dry bulk shipping provided in Chapter 2, port line-up reports are distributed on a regular basis to keep all interested parties updated on changes in shipping schedules. Some agencies distribute a retrospective summary at the end of each month to provide the final list of shipments that occurred during that month. The monthly summaries retrieved by Brokerage A [4] from Williams Brazil [32] are used in this study. To illustrate, a snapshot of a line-up of grain vessels at The Port of Paranaguá in January 2011 is provided in Table 4.2. The following information is provided for each listed vessel in Table 4.2 (column headings provided in brackets): the scheduled vessel’s name (VESSEL), its estimated time of arrival at the port’s anchorage area (ETA), its estimated time of berth (ETB), its estimated time of sailing (ETS), the volume of cargo loaded (LOADED), and the type of cargo loaded (CARGO). The rest of the columns in Table 4.2 are not of relevance for this study.

PARANAGUA PORT - PR									
VESSEL	ETA	ETB	ETS	LOADED	CARGO	SHIPPERS	DESTINATION	TERMINAL	BUYERS
VESSEL TO LOAD GRAINS AT SOCEPPAR TERMINAL									
IOANNIS K	25.12.10	28.12.10	03.01.11	43 900 000	MAIZE	-	ALGERIA	SHED 201	BUNGE
GENCO EXPLORER	15.01.11	15.01.11	17.01.11	25 000 000	MAIZE	-	MOROCCO	SOCEPPAR	BUNGE
GENCO EXPLORER	17.01.11	17.01.11	20.01.11	28 875 000	MAIZE	-	MOROCCO	SOCEPPAR	BUNGE
IMPERIAL SPIRIT	18.01.11	27.01.11	28.01.11	8 000 000	MAIZE	-	ARGELIA	SOCEPPAR	BUNGE
VESSEL TO LOAD GRAINS AT BUNGE TERMINAL									
NILL	NILL	NILL	NILL	NILL	NILL	NILL	NILL	NILL	NILL
VESSEL TO LOAD GRAINS AT SHED 212 TERMINAL - EXPORT CORRIDOR									
MIMOSA	23.12.10	02.01.11	06.01.11	33 585 000	PELLETS	-	C/P	SHED 212	CARGILL
AVOCET	26.12.10	06.01.11	09.01.11	43 573 000	PELLETS	-	C/P	SHED 212	COAMO
DORO	02.01.11	07.01.11	09.01.11	57 000 000	MAIZE	-	C/P	SHED 212	TRANSGRAIN
HEROIC STRIKER	10.01.11	15.01.11	18.01.11	50 275 000	PELLETS	-	C/P	SHED 212	COAMO
VESSEL TO LOAD GRAINS AT SHED 213 TERMINAL - EXPORT CORRIDOR									
UBC SAGUNTO	07.01.11	16.01.11	18.01.11	28 872 000	SOYABEAN	-	C/P	SHED 212	CARGILL
POS ETERNITY	07.01.11	18.01.11	22.01.11	60 000 000	MAIZE	-	C/P	SHED 212	CHS
OCEAN BREEZE	19.01.11	22.01.11	25.01.11	55 100 000	PELLETS	-	C/P	SHED 213	L. DREYFUS
JIN SHUN	23.01.11	26.01.11	30.01.11	44 000 000	PELLETS	-	C/P	SHED 213	BUNGE
VESSEL TO LOAD GRAINS AT SHED 214 TERMINAL - EXPORT CORRIDOR									
JIN YUAN	22.12.11	31.12.10	05.01.11	49 553 000	MAIZE	-	C/P	SHED 214	TOYOTA
CLIPPER MORNING	23.12.11	05.01.11	07.01.11	24 623 000	SOYABEAN	-	C/P	SHED 214	CARGILL
DORO	02.01.11	10.01.11	13.01.11	50 299 000	MAIZE	-	C/P	SHED 214	TRANSGRAIN
SANTA ANNA	27.01.11	28.01.11	31.01.11	32 806 000	PELLETS	-	C/P	SHED 214	COAMO
				TOTAL	636 461 000				

TABLE 4.2: January 2011 vessel line-up at the Port of Paranaguá.

The difference between a vessel’s ETA and ETB, provided in Columns 2 and 3 of Table 4.2, signifies the time spent waiting at anchorage, referred to as waiting time. The difference between a vessel’s ETB and ETS, provided in columns 3 and 4 of Table 4.2, signifies a vessel’s total time

spent in port, referred to as service time. Service time includes the time spent maneuvering from anchorage to berth, performing inspections, administration procedures, cleaning the holds, loading the cargo, and any delays during port operations.

The volume of cargo loaded per shipment provided in column 4 of Table 4.2 is measured in metric tonnes. The total volume of cargo loaded during the given month is summed in the last row of Table 4.2. Regarding the types of cargoes specified in column 5 of Table 4.2, it is important to note that these names often vary from the three cargoes stipulated in §1.4: maize, soybeans, and soybean meals. Discrepancies are mainly due to either sub-type or spelling variants of these cargoes. With reference to the provided example: 'Pellets' is a format in which soybean meals are shipped, and 'soyabean' is an alternative spelling of 'soybean'.

4.1.4 Congestion at Brazilian grain ports

Brokerage A's analytics division tracks congestion at Brazilian grain ports on a weekly basis [4]. The queue lengths at the relevant ports as well as the corresponding average waiting times are calculated from the line-up reports discussed in the preceding section, §4.1.4. The dataset contains both weekly and monthly records of which the first recording was made in April 2013.

The following method is used to determine the queue lengths at any given port: from the pool of vessels that arrived at the port prior to or on the date of analysis, count the number of vessels that are scheduled to berth after the date of analysis. The average waiting time of the identified vessels is calculated accordingly. To illustrate, the snapshot provided in Figure 4.2 in the preceding section is used as example. On the first of January 2011, vessels *Mimosa*, *Avocet* and *Clipper Morning* had arrived (ETA) prior to 1 January 2011 and were scheduled to berth (ETB) after 1 January 2011 as listed in Table 4.3 below.

Nr	Vessel name	ETA	ETB	Waiting time
1	Mimosa	23.12.10	02.01.11	10 days
2	Avocet	26.12.10	06.01.11	11 days
3	Clipper Morning	23.12.10	05.01.11	13 days

TABLE 4.3: A snapshot of a vessel line-up to illustrate the calculation of waiting time.

From Table 4.3 it is evident that congestion levels at the Port of Paranaguá on 1 January 2011 is calculated at 3 vessels waiting at anchorage for $(10 + 11 + 13)/3 = 11.3$ days on average.

4.1.5 Data quality assurance and limitations

Line-up reports are known to contain inaccuracies. The majority of the inaccuracies are typing errors, for example, dates will include entries where 31 days are indicated for a 30-day month, or on a line-up published in 2013 would have a 2003-dated entry. Manipulation is done by revising the obvious mistakes and comparing the dubious entries with line ups from alternative sources in case of availability. For this study, line-up reports from LBH [11] are used if comparative analysis is required.

It should be noted that discrepancies exist between export volumes computed from port line-up reports and the volumes published by GTIS. The two major reasons for these discrepancies are the following: firstly, time lags often exist between the actual sailing dates and the official export dates reported to customs. Secondly, given the inaccuracies often pertained by port line-up

reports, including double entries, basic typos, and unrevised data after changes in the schedule occurred, discrepancies are inevitable.

Williams Brazil [32] line-up reports are restricted to a limited level of detail. The unit of measurement for the estimated time of arrival, time of berth, and time of departure of the respective vessels are presented in days. A second limitation with regard to the Williams Brazil line-up reports is the lack of recording of the number of suppliers per shipment. A third limitation is the availability of both historical and recent line-up reports. The earliest copy available for this study is the report distributed at the end of March 2010, and the latest line-up available is the report distributed at the end of June 2014.

4.1.6 Summary of datasets

Having discussed the data of relevance to this study, a summary thereof is provided in Table 4.4. Table 4.4 is used as a reference point in the remainder of the thesis.

Primary source	Dataset	Basis	Detail	Section discussed
GTIS	Historical exports	Annual	Per port	§4.1.1
GTIS	Historical maximum	Annual	Per port	§4.1.1
GTIS	Historical exports	Monthly	Per port	§4.1.1
Brokerage A	Forecast volumes	Annual	Brazil	§4.1.2
Brokerage A	Historical congestion	Monthly	Per port	§4.1.4
Williams Brazil	Line-up reports	Monthly	Per port	§4.1.3

TABLE 4.4: A summary of the available input data.

These datasets will be used as basis upon which the required model is build.

4.2 Model assumptions

A model will be created to translate the anticipated annual grain exports from Brazil into monthly congestion levels at a specified port. Certain assumptions are necessary to fulfill this goal.

1. *Closed system.* It is assumed that all Brazil's exportable grain supplies are channeled via the six ports listed in 4.1.1.
2. *Seasonal down-time.* Recalling from Chapter 2, maintenance and capacity expansions are usually scheduled during the off-peak season between November and early February in order to minimise delays. It is assumed that future maintenance and expansion related delays will be restricted to this seasonal pattern.
3. *Berth utilisation.* The monthly number of departures from any given port is assumed to be equal to the monthly number of departures from the corresponding queue. This is based on the assumption that the berthing space will be filled by the next vessel in line as soon as the latest vessel departs from the berth. Extended berth vacancy will therefore only occur when the queue is empty.
4. *Linear capacity expansion.* Detailed analysis of historical capacity expansions and operational improvements are beyond the scope of this study. Therefore, in order to incorporate

the increase in efficiency, a broad assumption is made that, unless stated otherwise, port capacity increases linearly per annum.

5. *Shipping market information.* The model is developed for users within the shipping industry. It is thus assumed that the user has access to line-up reports and port expansion plans distributed by port agents.
6. *Arrival patterns.* Arrival patterns of the respective commodities are subject to the seasonal trade patterns of the respective commodities. It is assumed that minor variation in arrival patterns occur between consecutive years.
7. *Switching between ports.* It is assumed that vessels have allocated assignments at the respective ports which prohibits switching between ports.

4.3 Modelling approach

Before proceeding to the description of the proposed modelling approach, the research question stipulated in Chapter 1 is recalled:

Given the anticipated annual grain export volumes from Brazil, is it possible to estimate both trend and level of fluctuation of future monthly congestion levels at a port in the Brazilian port network within reasonable deviation of actual congestion levels?

In order to answer the research question, an applicable modelling technique with the ability to be able to translate annual Brazilian grain export forecasts into monthly congestion levels at a nominated port needs to be identified, with congestion levels referring to the number of queuing vessels as well as the waiting time of the queuing vessels.

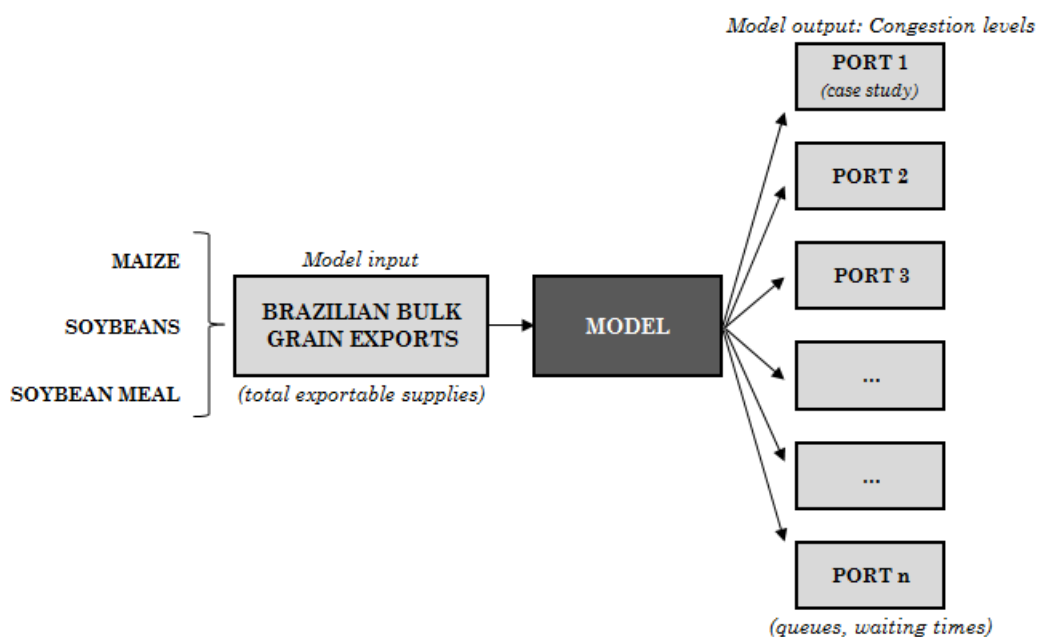


FIGURE 4.8: An illustration of the required model.

In order to identify an applicable modelling technique, the characteristics of the problem at hand are recalled from Chapter 2 to form the basis of the identification process:

1. Multiple dynamic components:
 - (a) Evolving stem sizes;
 - (b) Seasonal arrival and service patterns;
 - (c) Impact of external events; and
 - (d) Improvement in service capabilities;
2. Vessels' arrival rate often exceed the ports' service capability;
3. Difference in both structure and service rates at the relevant terminals; and
4. Change in queuing discipline.

Matching the problem's characteristics to the requirements of the modelling techniques usually applied in queuing problems as discussed in Chapter 3, it is found that neither queuing theory nor discrete event simulation modelling are feasible approaches to the problem at hand. In the case of queuing theory, the following reasons prohibit the feasible application thereof:

1. With reference to characteristic number 1, in order to accommodate all the dynamic components listed, extensive analytical manipulation to standard queuing models would be required;
2. With reference to characteristic number 2, since the vessels' arrival rates exceeding the ports' service capabilities, the steady-state assumption as stipulated by Little's theorem in Chapter 3 is violated;
3. With reference to characteristic number 3, the assumption of parallel service times at the different terminals are violated;
4. With reference to characteristic number 4, the change in queuing discipline would require the basis of the model to change and thus impede on the continuity required for model development.

Regarding discrete event simulation modelling, the evolving nature of the model components would require regular structural adjustments. Recalling from Chapter 3, Valentin [30] highlighted that the regular employment of a simulation expert are often too expensive which leaves the simulation model un-changed amidst changes in the actual system. However, in order to explore the possibility of a simulation model for the purpose of this study, the assumption was initially made that a simulation expert is available for periodic updates. A potential model was subsequently constructed in *AnyLogic*.

The approach, however, deemed infeasible. The limited level of detail of the data available for the study called for numerous assumptions to be made, which weakened the accuracy of the results to great extent. For example, as mentioned in §4.1.5, the historical arrivals and departures that form the basis of the study are only available on a daily basis, whereas shipping movements analysed for simulation studies are sensitive to the hour and predominantly measured accordingly. Furthermore, the number of suppliers used per shipment is unknown which has a significant impact on total loading time as discussed in Chapter 2.

Since both queuing theory and discrete event simulation are deemed not applicable solutions to the problem at hand, a macro approach is proposed where the port of relevance is assessed as a unit at which vessels arrive and get serviced. Recalling from Chapter 2, since port congestion is formed when the number of vessels arriving at a port within a given time frame exceeds the number of vessels that can be served by the port during that time frame, the research question is answered by analysing the trade-off between the anticipated future monthly arrivals at the port and the monthly export capacity of the port.

This trade-off is quantified by means of a proposed congestion equation (CE). The CE is based on the birth-death principle where the state of any given system at time t represents a queuing scenario at that moment in time, and transition from state t to state $t + 1$ occurs on monthly intervals. Births are representative of the arrivals of vessels at anchorage, and deaths are representative of the departures of vessels from the anchorage area which is subject to the export capacity of the port. The collective impact of the number of arrivals at a system and the departures from the system during any given time interval determine the level of change in queue length. Therefore, for any given port, the length of the queue at the end of interval t , is subject to the

1. length of the queue at the beginning of interval t ;
2. the volume of tonnage that arrived at anchorage during interval t ; and
3. the export capacity of the port during interval t .

Let Q_{jt} denote the length of the queue in metric tonnes at port j , $J = \{j/j = 1, 2, 3, 4, 5, 6\}$, at the beginning of interval t , for which $T = \{t/t = 1, \dots, n\}$. Let Y_{jt} denote the volume of arrivals in metric tonnes at the system during interval t , and Z_{jt} the export capacity in metric tonnes during time t at port j . In order to calculate the queue length at the end of interval t , which is equal to the length of the queue at the beginning of interval $t + 1$, thus $Q_{j(t+1)}$ for port j , the aforementioned CE is implemented as

$$Q_{j(t+1)} = Q_{jt} + Y_{jt} - Z_{jt}, \quad t \in T. \quad (4.1)$$

Months are used as time intervals t and the equation is repeated for n consecutive months, with n depending on the length of the projection period. In order to determine the required input variables to equation (4.1), and to translate the output from equation (4.1) into the required format, several iterations are necessary. A multi-phase congestion model (MPCM) is proposed for this purpose. As illustrated in Figure 4.9, the MPCM consists of five separate yet integrating phases comprising of optimisation techniques as well as time series analysis.

The five phases of the MPCM are stipulated as follows:

1. During the first phase, linear programming is used to allocate the total Brazilian annual export forecasts for maize, soybeans and soybean meals to the six ports listed in §4.1.1. From the output, the anticipated annual exports from the port is retrieved to be used as input to the second phase.
2. During the second phase, historical arrival patterns at the port's grain terminals are analysed to establish the monthly seasonal indices of the three commodities under study. The expected monthly volume equivalent of arrivals in metric tonnes are determined by distributing the annual volumes calculated in Phase 1 according to these seasonal indices.

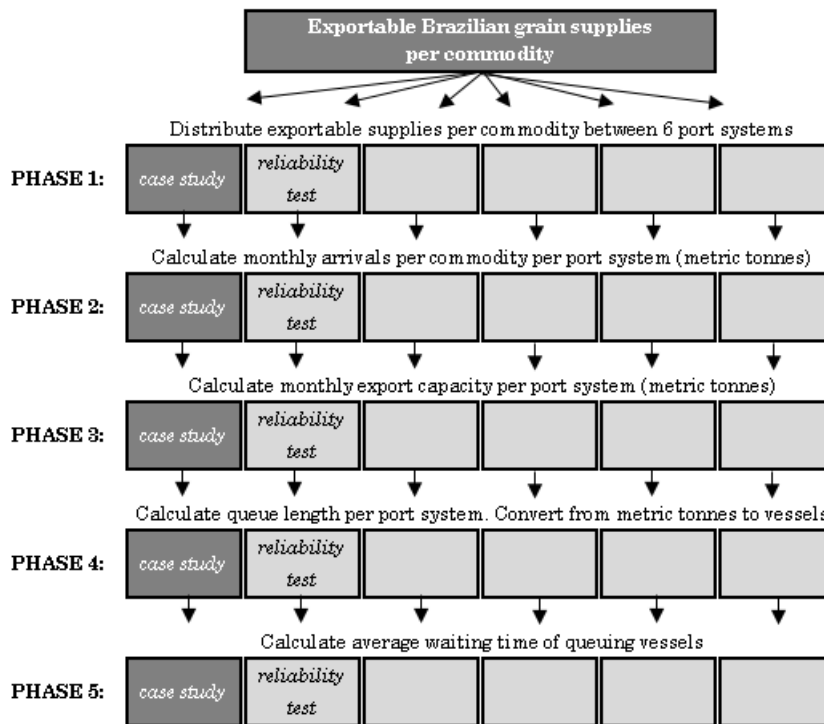


FIGURE 4.9: An illustration of the Multi-Phase Congestion Model.

3. Once the expected monthly cluster of arrivals in metric tonnes at the port is determined, the monthly export capacity in metric tonnes is calculated in the third phase. Multiple regression analysis is used for this purpose.
4. Given an initial queue length, the results obtained from the second and third phases are implemented in equation (4.1) introduced in §4.3 to determine the length of the queue at different time intervals in the future. During the fourth phase, the calculated queue in metric tonnes is converted into an estimated queue in number of vessels.
5. Once the number of vessels in the queue is established, a conversion factor is used to determine the corresponding average waiting time during the fifth and final phase.

The results generated in phases four and five are finally categorised into quintiles as presented in Table 4.5.

Quintiles	Level	Queue (vessels)	Waiting time (days)
1	Low	0-3	0-8
2	Low/Medium	4-7	9-16
3	Medium	8-13	17-24
4	Medium/High	14-33	25-33
5	High	34+	34+

TABLE 4.5: The categorisation of queues and waiting times into quintiles.

This categorisation provides insight to the relative severity of the predicted congestion levels in relation to historical levels experienced at Brazilian grain ports. The quintiles are derived from

monthly queues and waiting times at all Brazilian grain ports between May 2012 and December 2013.

Data input

The following input data is required before the MPCM can be run:

1. The initial queue length at port j at time $t = 1$ in metric tonnes, Q_{j1} , to serve as input to equation (4.1) at the start of the evaluation period. The initial queue length is derived from an evaluation of the line-up data at time $t = 1$ as described in §4.1.3.
2. Updated forecasts of annual trade volumes upon release of actual figures by GTIS as described in §4.1.2.
3. Projected percentage increase in capacity at the respective ports, which is retrieved from market research.

The rest of the chapter is divided into five main parts, each of which presents a description of the MPCM's respective phases.

4.3.1 Phase 1: Export volume allocation per port

The objective of the first phase of the MPCM is to allocate Brazil's annual grain export forecasts described in §4.1.2 to the six ports listed in §4.1.1. The allocation of volumes is subject to the maximum possible throughput per port, and tend to fluctuate in the event of port expansions, operational efficiency improvements or strategic shifts in trade volumes. However, in the absence of these changing factors, historical observations indicate minimal year-on-year variation in port volume distribution.

Given this dynamic nature of both volume and distribution of exports, linear programming (LP) is implemented to ensure optimal yet realistic distribution of exports. For the LP designed for this purpose, referred to as the Export Allocation LP, there are three pools of commodities, V_i , $I = \{i/i = 1, 2, 3\}$, supplying export volumes to six ports, A_j . Let V_1 denote maize exports, V_2 soybean exports and V_3 soybean meal exports, and let A_1 represent Paranagua, A_2 Santos, A_3 Tubarao, A_4 Rio Grande, A_5 Sao Francisco do Sul, and let A_6 represent the remainder of the ports, collectively referred to as Other. Let x_{ij} denote the volume of cargo i shipped via port j . An illustration of the Export Allocation LP follows.

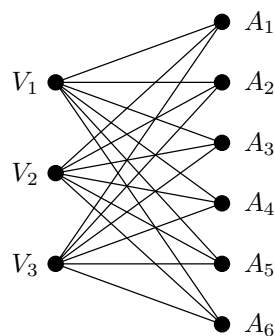


FIGURE 4.10: An illustration of the Export Allocation Linear Program.

The objective of the Export Allocation LP is to minimise the annual variation in volumes of the three commodities at the six ports, d_{ij} , subject to the following three constraints: 1) the availability of exportable supplies; 2) throughput capacity constraints and 3) limited variance in historical trends. The objective function of the LP can thus be formulated as

$$\text{Minimise } \sum_{i=1}^3 \sum_{j=1}^6 d_{ij}. \quad (4.2)$$

The first constraint in the Export Allocation LP, 4.3, addresses the expected availability of exportable supplies per year from the three pools of commodities, V_1, V_2, V_3 . The constraint ensures that the sum of the volumes expected to be shipped via the six ports do not exceed the total volumes available for export from Brazil for the specified year, thus

$$\sum_{j=1}^6 x_{ij} \leq V_i, \quad i \in I. \quad (4.3)$$

Constraint 4.4 addresses the ports' throughput capacity, ensuring that the exports fall within the permissible range which ranges between zero and the maximum capacity of the port [3]. Let b_j represent the historical maximum throughput and δ_j the anticipated year-on-year increase in capacity. The permissible range of each port A_j is thus denoted as $[0, b_j + \delta_j]$. The historical maximum throughput b_j is retrieved from GTIS [7] as described in §4.1.1, whereas the anticipated increase is inserted during the initialisation phase as discussed in §4.3. The permissible range thus stipulates the second constraint of the LP as

$$\sum_{i=1}^3 x_{ij} \leq b_j + \delta_j, \quad j \in J. \quad (4.4)$$

Constraints (4.5) - (4.8) are included to ensure non-negativity of volume, capacity, improvement and deviation variables:

$$d_{ij} \geq 0, \quad i \in I; j \in J; \quad (4.5)$$

$$b_j \geq 0, \quad j \in J; \quad (4.6)$$

$$\delta_{ij} \geq 0, \quad i \in I; j \in J; \text{ and} \quad (4.7)$$

$$x_{ij} \geq 0, \quad i \in I; j \in J. \quad (4.8)$$

In summary, an Export Allocation LP is used to determine the optimal allocation of the available exportable supplies of the three relevant commodities to the six nominated ports in the Brazilian grain port network. *Excel Solver* is used to solve the LP for each calendar year.

4.3.2 Phase 2: Estimate monthly arrivals at port

The second input factor of equation (4.1) is the tonnage in metric tonnes expected to arrive at port j during interval t denoted as Y_{jt} . From the discussion of arrival patterns in §2.2, it is evident that the modelling thereof needs to accommodate year-on-year changes in annual export volumes as well as seasonal patterns. Since months are used as base time unit for the equation, the expected monthly arrivals at the port need to be calculated. This is achieved by

proportionally dividing the annual export forecasts of the three commodities calculated in §4.3.1 across the year according to their unique seasonal cycles. Three sets of seasonal indices are calculated for this purpose by applying a multiplicative decomposition forecasting method. The multiplicative model is chosen as opposed to the additive model because the variation in arrivals increases over time. Line-up data between January 2011 and December 2013 are used as basis for the analysis [32].

As proposed by Makridakis [13], the first step to calculating seasonal indices by means of a multiple decomposition forecasting method is to calculate the trend using a centered 12-month moving average. After the trend is established, the ratio of the independent variable Y_{jt} to the trend variable P_{jt} is determined for each month t , $t = 1, \dots, 12$, in order to isolate the seasonal S_{jt} term as well as the error term E_{jt} ,

$$R_{jt} = \frac{Y_{jt}}{P_{jt}} = \frac{S_{jt}P_{jt}E_{jt}}{P_{jt}} = S_{jt}E_{jt}, \quad j \in J; t \in T. \quad (4.9)$$

Once the changing trend is eliminated, the seasonal indices are calculated. This is done by gathering the detrended values for a given month and calculating the average across years. The indices are converted to percentages in order to establish the monthly proportional division, thus $0 \leq S_t \leq 100$. The sum of the normalised indices per calendar year should equate to one. The indices are assumed to be identical for the respective years, implying $S_t = S_{t+12} = S_{t+24}$ for all $t = 1, \dots, T$. The seasonal indices represent the estimated arrival pattern, and are used to calculate the volume distribution per commodity V_i for all $i = 1, 2, 3$ per month t . Finally, for any given year, the total monthly arrivals at port j are calculated as

$$Y_{jt} = \sum_{i=1}^3 (S_{jti} \times V_i), \quad j \in J; t \in T. \quad (4.10)$$

The results obtained from Phase 2 is presented in Chapter 5. Recalling from §4.1.5, actual arrival volumes are not available beyond June 2014. The hold-out period for Phase 2 is therefore shortened from 12 to 6 months.

4.3.3 Phase 3: Estimate monthly export capacity

Once the initial queue length in metric tonnes, Q_{jt} , and the monthly cluster of arrivals in metric tonnes, Y_{jt} , at port j over time $t = 1, \dots, T$ are established, the third input to equation (4.1) is calculated, which is the monthly export capacity in metric tonnes at port j denoted as Z_{jt} .

As mentioned in Chapter 2, exports are capacitated by the physical and operational capacity of the port. In order to establish the impact of capacity expansions and operational inefficiencies, multiple regression is used. Eleven dummy variables, M_{jkt} , are introduced to account for monthly seasonality. December is chosen as base month due to the limited volume of cargo usually exported at that stage of the off-peak season. The seasonal dummy variables incorporate the seasonal fluctuation of the external factors discussed in Chapter 2: maintenance related down time, weather related delays and labour inefficiencies such as public holidays. Therefore, for all the months $t = 1, \dots, n$ at port j ,

$$M_{jkt} = \begin{cases} 1, & \text{if } k = 1, \dots, 11; \\ 0, & \text{otherwise.} \end{cases} \quad j \in J; t \in T. \quad (4.11)$$

A twelfth variable, referred to as the capacity variable C_{jt} , is added to capture the impact of port developments on monthly export capacity at port j . Based on the *Linear capacity expansion* assumption, it is assumed that historical values of C_{jt} increased linearly per annum. For the first twelve months of the dataset starting January 2011, C_{jt} is set to 1, and for each succeeding year until January 2013, variable C_{jt} is increased by 1. Since capacity expansions are usually performed during the off-peak months at the end of the year, the linear increase occurs every January. Taking all of these variables into account, the export capacity at port j during month t is formulated as

$$Z_{jt} = \beta_{j0} + \sum_{k=1}^{11} \beta_{jk} M_{jkt} + \beta_{j12} C_{jt} + u_{jt}, \quad j \in J; t \in T, \quad (4.12)$$

where Z_{jt} represents the export capacity of port j during month t . The coefficients β_{jk} , $t = 1, \dots, 12$ determine the variance in Z_{jt} according to the respective values of k , and u_{jt} is the residual term. In order to establish the input for equation (4.12), as well as the validity thereof, the following iterative process is pursued:

1. Use export volumes for the 36-month period starting January 2011 to produce the regression coefficients stipulated in equation (4.12);
2. Review the regression results to evaluate the goodness-of-fit of the model;
3. Test the required assumptions of relevance to multiple regression modelling;
4. Upon confirmation of the goodness-of-fit and proof of validity, apply the coefficients calculated in Step 1 to forecast the monthly export capacity during the hold-out period and beyond. In what follows, the method to calculate future values of the capacity variable C_{jt} is discussed.

For future values of the capacity variable, C_{jt} , the anticipated expansion in the port j 's capacity is taken into consideration. The anticipated year-on-year percentage increase in a port's export capacity is adjustable. Since the historical maximum of port j in any given year is denoted as b_j , and the year-on-year increase in capacity at port j expected that year is denoted as δ_j , the total anticipated export capacity for the year is $b_j + \delta_j$. In order to find C_{jt} for the upcoming year, the anticipated export capacity $b_j + \delta_j$ of port j is set equal to the sum of port j 's expected monthly export capacity of that year as stipulated in equation (4.12),

$$b_j + \delta_j = \sum_{t=1}^{12} Z_{jt} \quad t = 1, \dots, 12. \quad (4.13)$$

By incorporating equations (4.11) and (4.12) it is derived that

$$b_j + \delta_j = 12\beta_{j0} + \sum_{k=1}^{11} \beta_{jk} + 12\beta_{j12} C_{jt}, \quad t = 1, \dots, 12, \quad (4.14)$$

from which C_{jt} is calculated as

$$C_{jt} = \frac{b_j + \delta_j - 12\beta_{j0} - \sum_{k=1}^{11} \beta_{jk}}{12\beta_{j12}}, \quad t = 1, \dots, 12. \quad (4.15)$$

4.3.4 Phase 4: Conversion of queue length

Once the three inputs to equation (4.1) are established, that is, 1) the initial queue length in metric tonnes, Q_{jt} , at port j ; 2) the monthly arrivals in metric tonnes, Y_{jt} , at port j ; and 3) the monthly export capacity, Z_{jt} , of the port j , the respective inputs are incorporated to establish the output of equation (4.1). The output of equation (4.1), the estimated queue length at port j at time intervals $t = 1, \dots, T$, is in metric tonnes. The objective of the study, however, stipulates that the output of the model should be in *number of vessels* and *average waiting time* of the queuing vessels. The former part of the objective is addressed in this phase: given the estimated volume of cargo to be loaded by the queuing vessels $Q_{j(t+1)}$, determine the number of vessels that will carry the sum of that volume, $L_{j(t+1)}$. In order to achieve this goal, an analysis of the typical volume of cargo per grain shipment from port j is pursued.

Given the evolving and probabilistic nature of stem sizes, Monte Carlo simulation is implemented to generate values for these variables. Recalling from Chapter 3, Render *et al.* [19] recommends five steps to be followed when Monte Carlo simulation is applied. In what follows, the application of each step will be explained with respect to the problem at hand. The line-up data received from Williams Brazil [32] discussed in 4.1.3 is used as basis for the stem size analysis.

Step 1: Establish the probability distributions of the input variables: Stem sizes from historical line-up reports of port j are grouped into 1 000 dwt segments for 2011, 2012 and 2013 respectively. Stem sizes below 10 000 dwt are grouped into a single segment referred to as '5-10' and stem sizes that exceed 70 000 dwt are grouped into a segment referred to as '70+'. The number of vessels per segment per year is calculated accordingly of which a selected extract ranging between 40 000 dwt and 70 000+ dwt is visualised in Figure 4.11. From the information provided in Figure 4.11 it is evident that the grain vessels calling at the Port of Paranagua range predominantly between 55 000 dwt and 65 000 dwt, of which the 60 000 dwt to 61 000 dwt segment is most prominent.

Step 2: Build cumulative probability distributions for the selected variables: The empirical probability distributions for 2011, 2012 and 2013 established in Step 1 are used to construct the cumulative probability distributions for the respective years as displayed in Figure 4.12 on the following page. The evolution of stem sizes is evident from Figure 4.12 as the proportion of vessels in larger segments increase over time in favour of the smaller vessels. In order to estimate future stem sizes, a growth factor between 1% and 5% is applied to the larger vessels in favour of the smaller vessels.

Step 3: Establish intervals for random numbers: The cumulative distribution for each year is used as basis for the required intervals stipulated for 2013, 2014, 2015 and 2016. Each interval corresponds to an 1 000 dwt segment.

Step 4: Generate random numbers: Random numbers R_i , ($0 \leq R_i \leq 1$), are generated with the Linear Congruential Generator (LCG). Variables a , c , m are assigned as follows: $a = 10$, $c = 7^5$ and $m = 2^3 - 1$.

Step 5: Simulate a series of trials: A series of stem sizes is generated using the inverse of the cumulative probability distribution to find the corresponding stem sizes. In order to

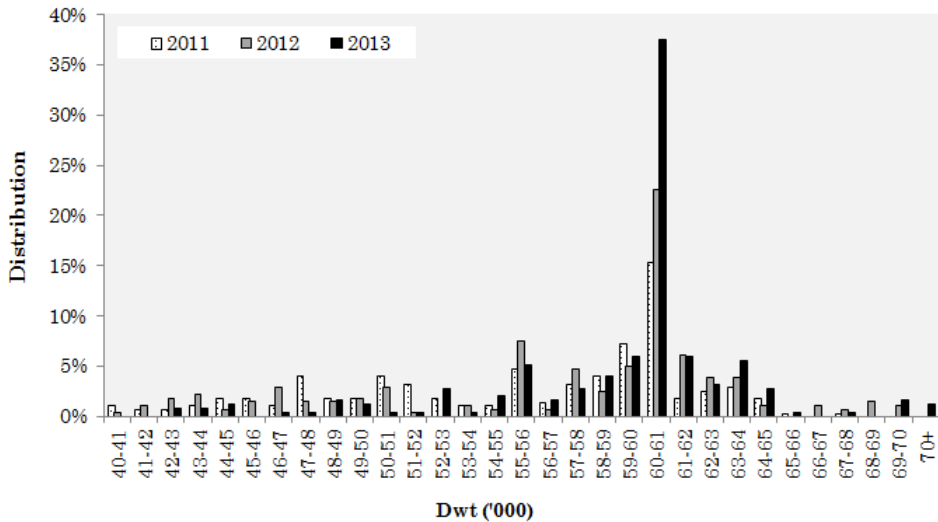


FIGURE 4.11: *The historical distribution of stem sizes at Paranagua.*

reach the halfwidth of a 95% confidence interval, the required number of iterations $n^* = 1530$ is determined. The simulation is thus repeated 1530 times for each of the 12 months in 2013, 2014, 2015 and 2016.

For order of clarity, Step 5 is illustrated by means of the following example: Suppose a random number of 0.2 is generated, the cumulative distribution for vessels arriving at the Port of Paranagua as provided in Figure 4.13 is used to determine the corresponding stem size interval. From Figure 4.13 it is evident that the '55-56' interval corresponds to the generated random number 0.2, which implies that the midpoint of the interval, 55 500 dwt, is subsequently extracted.

From the series of simulated stem sizes, the first m number of vessels whose cumulative loads reach the estimated queue length in metric tonnes, $Q_{j(t+1)}$, is the corresponding number of vessels $L_{j(t+1)}$ in the queue.

4.3.5 Phase 5: Conversion from queue length to waiting time

Once the length of the queue L_{t+1} is determined, the corresponding waiting time W_{t+1} is derived. Although the application of Little's Theorem discussed in §3.1 may seem the obvious solution, the violation of the steady state assumption as highlighted in §4.3 prohibits the application thereof.

Based on the observation made in Chapter 1, the lag-relationship between queues and waiting times are explored. A linear multiple regression model is constructed in which waiting time W_{t+1} is regressed against the queue length L_t of the previous month. This regression function can be written as

$$W_{t+1} = \beta_0 + \beta_1 L_t + e_t, \quad t \in T. \quad (4.1)$$

By implementing this function, the direction of the queue drives the direction of the waiting time. For every additional ship in the queue, the waiting time for the next period is on average β_1 days per ship. In order to determine the waiting time for each time interval over the analysed period, the equation is repeated for t consecutive months.

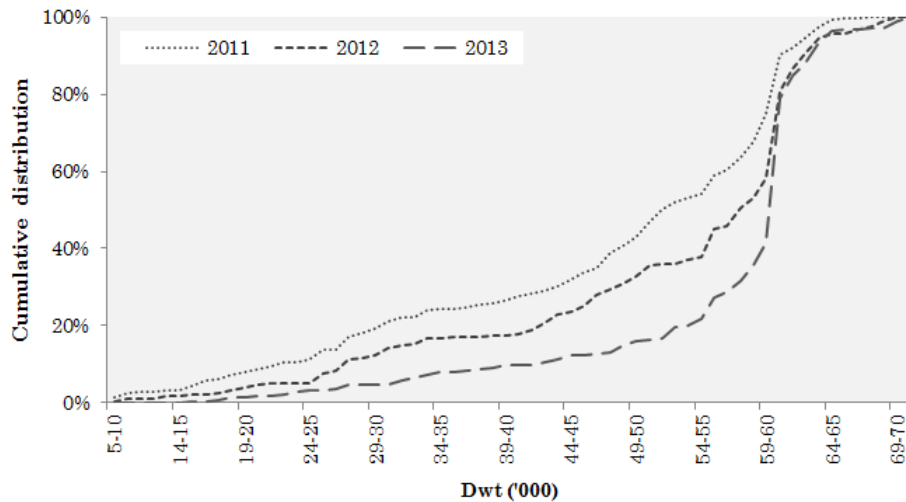


FIGURE 4.12: *The actual cumulative distribution of stem sizes at the Port of Paranagua.*

The method is validated by comparing actual waiting times to the calculated waiting times for the fitted period between January 2013 and December 2013, as well as the hold out period between January 2014 and December 2014. The converted results, that is, the estimated average waiting time per month at Paranagua fulfills the latter part of the objective of the study. These results are also displayed in Chapter 5.

4.4 Validity and reliability of the MPCM

Having discussed the data used for the study in §4.1, the assumptions made in §4.2, the modelling approach §4.3 as well as the five phases of the methodology in sections 4.3.1 to 4.3.5, the validity and reliability of the MPCM are explored in §4.4.

For any given model, the measure of its validity is the extent to which it fulfills the purpose for which it was developed. For a forecasting model, the validity is thus based on the accuracy of the results generated by the model. In order to measure the validity of the MPCM, cross validation is applied by using 2013 as base year to predict monthly congestion levels in 2014. The generated results are subsequently compared to the actual congestion levels in 2014 as reported by Brokerage A [4]. The validity of the MPCM is demonstrated in §5.7 in Chapter 5.

The reliability of any given model is established by repeating its implementation on different scenarios and retrieving sufficient results. The reliability of the MPCM is therefore tested by applying the proposed methodology on another port in the Brazilian grain network. The Port of Sao Francisco Do Sul is identified as an applicable port. At both ports, soybeans take prevalence followed by maize and soybean meal at a lesser scale. Furthermore, at geographical level, Sao Francisco Do Sul is within close vicinity to the Port of Paranagua which implies similar weather patterns. Although the scale of volume differs between the two ports, the volume of cargo exported is of no significance to the application of the model. The reliability of the MPCM is also demonstrated in §5.7 in Chapter 5.

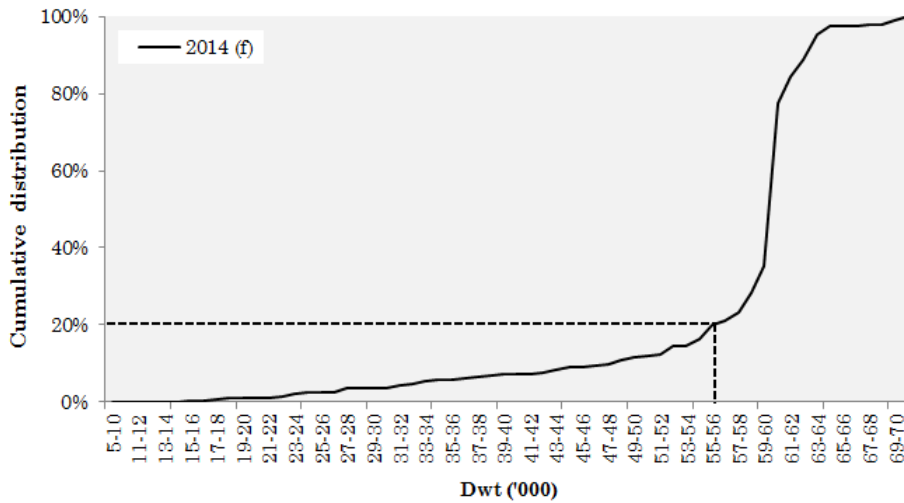


FIGURE 4.13: An example of the application of the inverse cumulative probability distribution.

4.5 Implementation and revision

Each of the respective phases are implemented in *Microsoft Excel*. As discussed in §4.3.2, since the output of the CE for any given month is used as input to its successive month, the accuracy of the forecast for any time $t + 1$ is subject to the accuracy of the forecast of time t . Regular updates of the MPCM are advised as it will improve the accuracy of the forecasts and reduce the risk of convergence. The ideal scenario would require the model to be updated as soon as every month-end congestion levels are published by Brokerage A [4]. However, if the ideal scenario cannot be materialised, it is advisable that the MPCM is revised at least once every four months at the following critical stages of the Brazilian grain export cycle:

1. First review: At the onset of the soybean export season at the end of January;
2. Second review: At the onset of the maize export season at the end of May;
3. Third review: At the onset of the off-season for grain exports at the end of September.

This review schedule ensures that the user is informed of the expected rate of increase as well as the expected peak of congestion at the onset of the soybean and maize seasons, as well as the expected rate of decline at the end of the season.

4.6 Chapter summary

The proposed methodology to forecast port congestion at the Port of Paranaguá is presented in Chapter 4. A detailed overview of the data used as basis to the study is provided in §4.1, followed by an introduction to the multi-phase congestion model in §4.3. In sections 4.3.1 to 4.3.5, the respective phases of the MPCM are described. The tests performed to ensure the validity and reliability of the MPCM are provided in §4.4, and a brief description of the implementation and revision of the MPCM is given in §4.5. The results generated in Chapter 4 are presented in Chapter 5.

CHAPTER 5

Results

Contents

5.1	Brief review of MPCM methodology	47
5.2	Phase 1: Results	48
5.3	Phase 2: Results	51
5.4	Phase 3: Results	53
	5.4.1 <i>Regression coefficients</i>	54
	5.4.2 <i>Evaluation of regression results</i>	54
	5.4.3 <i>Tested assumptions</i>	55
	5.4.4 <i>Predicted monthly export capacity</i>	57
5.5	Phase 4: Results	58
5.6	Phase 5: Results	60
	5.6.1 <i>Long term outlook generated by the MPCM</i>	63
5.7	Validity of the MPCM	65
5.8	Chapter summary	66

The results obtained by the MPCM are presented in Chapter 5. The chapter opens with a brief review of the proposed methodology in §5.1, followed by the results obtained during each of the five phases in sections 5.2 to 5.6. The long term outlook generated by the model is presented in §5.6.1, and the the validity of the model is established in §5.7, The chapter is concluded with a brief summary in §5.8.

5.1 Brief review of MPCM methodology

To recall from Chapter 4, the MPCM consists of five individual yet integrative phases which translate the anticipated annual grain export volumes from Brazil into monthly congestion levels at a specified port in the Brazilian port network. What follows is a brief review of the application of these five phases with respect to the Port of Paranagua.

1. **Phase 1:** Annual maize, soybean and soybean meal export forecasts from Brazil were allocated to six mutually exclusive ports in the Brazilian grain port network, of which the Port of Paranagua is a part. Linear programming was implemented for this purpose.

2. **Phase 2:** Future monthly arrivals at the Port of Paranagua were calculated by seasonally distributing the port's anticipated annual grain exports calculated in Phase 1. Monthly seasonal indices were used for this purpose.
3. **Phase 3:** The monthly export capacity at the Port of Paranagus was calculated by applying multiple regression. Monthly dummy variables were used to address seasonal variation in export capacity and a capacity variable was included to incorporate expansions in port capacity.
4. **Phase 4:** In Phase 4, the initial length of the queue at the Port of Paranagua as well as the monthly output from Phases 2 and 3 were used to estimate the monthly queues over the analysed period. Since the output of Phases 2 and 3 were in metric tonnes, the calculated monthly queues were also in metric tonnes. In order to convert the queues from metric tonnes to the corresponding number of vessels in the queue, the inverse of the cumulative distribution function of stem sizes was used.
5. **Phase 5:** The results generated in the fourth phase, that is, the monthly number of vessels queuing at the Port of Paranagua, were converted into the average monthly waiting time of these queuing vessels. Linear regression was applied for this purpose.

From the output of Phases 4 and 5 of the MPCM, the future levels of congestion at the Port of Paranagua, that is, the estimated queues and waiting times, were established. The anticipated extent of congestion was categorised according to the quantiles presented in Table 4.5 in Chapter 4.

In what follows the results generated during the five respective phases are presented. The MPCM was run to produce results for the 48-month period between January 2013 and December 2016. The 12-month period from January to December 2013 was regarded as the model fit period and the 12-month period from January to December 2014 was regarded as the hold-out period. The remaining 24 month period ranging between January 2015 and December 2016 was referred to as the long term forecast period.

5.2 Phase 1: Results

In Phase 1, the Export Allocation LP was run to allocate total exportable maize, soybean and soybean meal supplies from Brazil to the six ports stipulated in §4.1.1. Input to the LP for the 2013 model fit period is presented in Table 5.1.

Constraint	Variable	Symbol	2013
Exportable supplies	Maize	V_1	26 611 555
	Soybeans	V_2	42 789 897
	Soybean meals	V_3	13 324 077
Maximum capacity	Paranagua	$b_1 + \delta_1$	17 704 758
	Santos	$b_2 + \delta_2$	28 136 278
	Tubarao	$b_3 + \delta_3$	11 675 864
	Rio Grande	$b_4 + \delta_4$	6 342 642
	Sao Francisco do Sul	$b_5 + \delta_5$	7 835 121
	Other	$b_6 + \delta_6$	11 059 874

TABLE 5.1: *Input to the Export Allocation Linear Program for 2013.*

Given the input for the 2013 period presented in Table 5.1, the Export Allocation LP was run in Excel Solver to determine the allocation of maize, soybean and soybean meal exports per port. The results obtained from the LP as well as the corresponding actual values reported in GTIS [7] are presented in Figure 5.1.

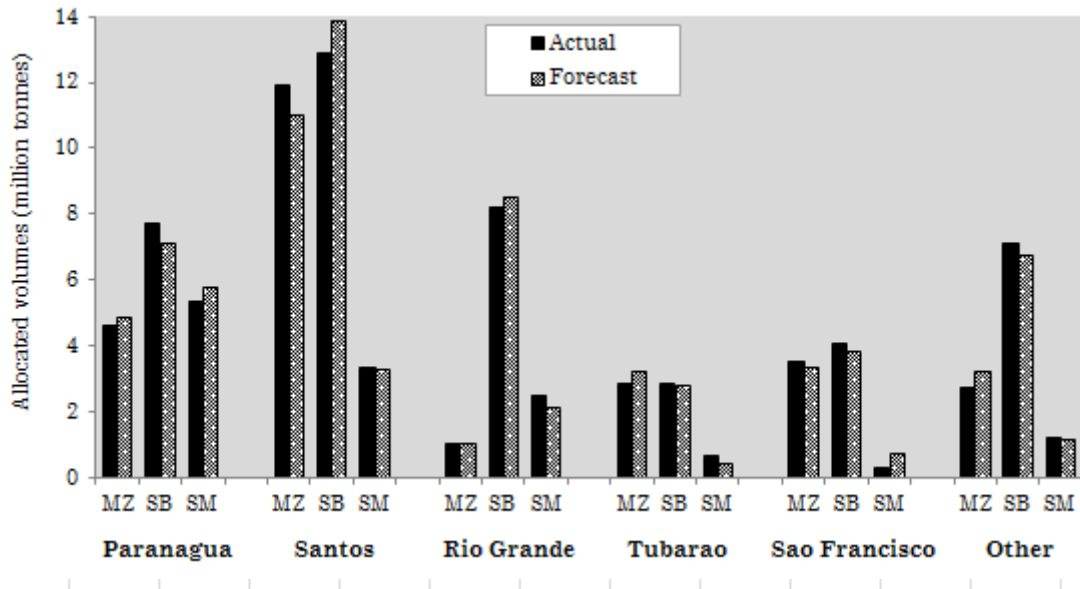


FIGURE 5.1: Actual vs estimated exports per port in 2013.

As is evident from Figure 5.1, the generated values were within close vicinity of the actual values. In order to confirm the potential insignificance in disparity, a Wilcoxon Signed Rank test, a Sign test, and a pairwise Student's t test were performed. The hypothesis tested was

H_0 : there is no significant difference between the actual values and the generated results

H_1 : there is a significant difference between the actual values and the generated results

SAS (Statistics Analysis System) [21] was used to perform the three tests. The results obtained were evaluated based on the tests' respective p-values. If the p-values proved to be less than 0.05, the H_0 hypothesis was to be rejected in favour of the H_1 hypothesis, indicating that a significant difference exist between the two sets of values. However, if the p-values proved to be larger than 0.05, the H_0 hypothesis was not to be rejected, and an insignificance in disparity between the two sets of values would be confirmed. The output produced by the three tests are presented in Table 5.2.

Test (n=18)	Statistic	p-value
Wilcoxon Signed Rank	S = -16.5	0.3527
Signed	M = 0	1.000
Student's pairwise t	t = -0.9556	0.4951

TABLE 5.2: Output of the Wilcoxon Signed Rank test, the Sign test, and the Student's t test.

As indicated in Table 5.2, the p-values produced by the Wilcoxon Signed Rank test, the Sign test, and the Student's pairwise t test exceeded 0.05, which indicated that the H_0 hypothesis should not be rejected. It was thus confirmed that no significant difference existed between the actual values and the values calculated by the Export Allocation LP.

The insignificance of disparity proved that it was feasible to implement the Export Allocation LP during the first phase of the MPCM. Upon proof of its feasibility, the LP was run for 2014, 2015 and 2016. The results obtained are presented in Table 5.3.

Port	Commodity	Symbol	2014	2015	2016
Paranagua	Maize	x_{11}	2 769 891	3 025 475	2 269 106
	Soybeans	x_{21}	6 472 915	8 580 703	10 725 879
	Soybean meals	x_{31}	7 494 400	6 470 005	5 081 198
Santos	Maize	x_{12}	7 146 009	10 531 308	10 082 625
	Soybeans	x_{22}	14 532 196	10 407 718	10 027 323
	Soybean meals	x_{32}	3 227 694	4 464 991	5 294 069
Rio Grande	Maize	x_{13}	599 661	1 460 798	1 825 997
	Soybeans	x_{23}	9 898 098	8 769 424	8 901 555
	Soybean meals	x_{33}	1 482 185	1 989 322	1 491 991
Tubarao	Maize	x_{14}	1 714 865	1 990 127	2 487 658
	Soybeans	x_{24}	3 658 939	3 935 581	3 563 030
	Soybean meals	x_{34}	925 833	499 921	374 941
Sao Francisco du Sol	Maize	x_{15}	2 093 636	2 341 849	2 927 311
	Soybeans	x_{25}	4 848 393	4 856 872	4 289 907
	Soybean meals	x_{35}	188 080	73 991	55 493
Other	Maize	x_{16}	3 527 252	3 027 293	3 784 116
	Soybeans	x_{26}	7 289 184	8 554 458	9 111 001
	Soybean meals	x_{36}	721 300	1 020 749	765 562

TABLE 5.3: *Projected exports per commodity per port as generated by the Export Allocation Linear Program*

A summary of the generated results is illustrated in Figure 5.2. The bar chart presents both historical and projected grain exports per port per annum.

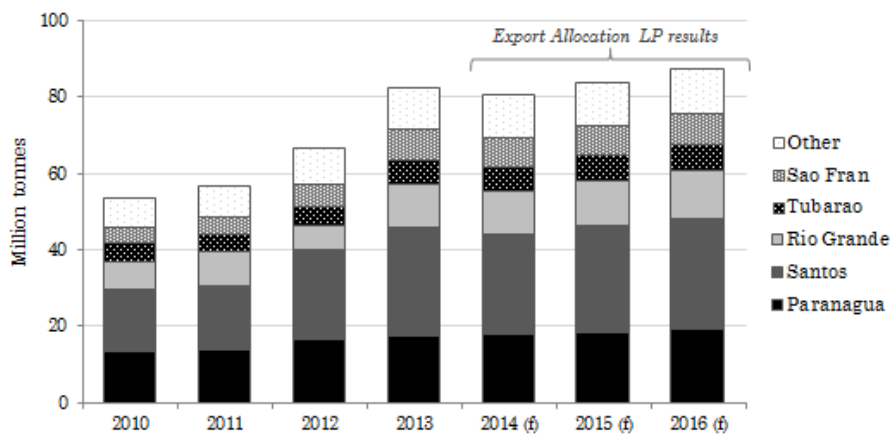


FIGURE 5.2: *Export allocation per port as calculated by the Export Allocation Linear Program.*

From the output of Phase 1, the annual maize, soybean and soybean meal exports allocated to the Port of Paranagua were retrieved to be used as input to Phases 2 and 3 of the MPCM. What follows is a discussion on the incorporation of Phase 1's outputs in Phase 2 as well as an illustration of the results produced.

5.3 Phase 2: Results

In Phase 2, the focus of the study was narrowed to the Port of Paranagua exclusively. The objective of this phase was to estimate the anticipated monthly arrivals at the port's anchorage area. In order to achieve this, the annual volumes of maize, soybeans and soybean meals allocated to the Port of Paranagua during Phase 1 were proportionally distributed across the year according to the three commodities' unique sets of seasonal indices. The seasonal indices were calculated by applying multiplicative decomposition to historical monthly arrival data over the three year period between January 2011 and December 2013. The seasonal indices were normalised to ensure that the sum of the seasonal indices for any given year equated to one. The calculated seasonal indices for maize, soybean and soybean meal arrivals are presented in Table 5.4, and are complimented with an illustration thereof in Figure 5.3.

Month	Maize	Soybeans	Soybean meals
January	0.106	0.028	0.089
February	0.023	0.174	0.123
March	0.027	0.159	0.070
April	0.026	0.122	0.064
May	0.036	0.146	0.106
June	0.088	0.105	0.107
July	0.162	0.113	0.084
August	0.161	0.064	0.130
September	0.120	0.026	0.031
October	0.070	0.014	0.055
November	0.096	0.017	0.063
December	0.085	0.031	0.079

TABLE 5.4: Seasonal indices of maize, soybean and soybean meal arrivals at the Port of Paranagua.

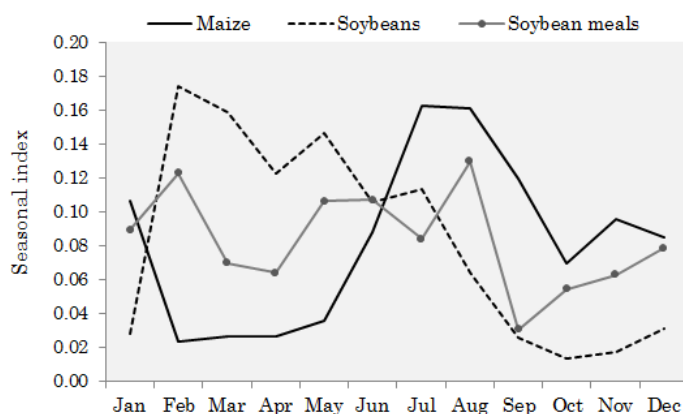


FIGURE 5.3: Illustration of seasonal indices of maize, soybean and soybean meal arrivals at the Port of Paranagua.

Reviewing Figure 5.3, a an increase in maize arrivals is observed in June and July, and an increase in soybean arrivals is observed in February. These observations are to be expected at the beginning of the respective maize and soybean seasons. Regarding soybean meal exports, it is observed that the seasonal fluctuation in arrivals is less severe compared to the seasonal

fluctuation in soybean and maize arrivals. This observation aligns with the conclusion drawn from the analysis of the autocorrelation function graphs presented in §4.1.2.

These seasonal indices were used to distribute the annual volumes of maize, soybeans and soybean meals proportionally across 12 months. The estimated monthly arrivals of maize are presented in Figure 5.4, soybeans are presented in Figure 5.5 and estimated soybean meal arrivals are presented in Figure 5.6. As was noted in §4.1.5, actual data on monthly arrivals were not available beyond June 2014, which shortened the hold-out period from 12 to 6 months. The black lines represent the actual values, whereas the dotted grey lines represent the calculated values. What follows is a brief description of each set of results, of which maize arrivals are presented first.

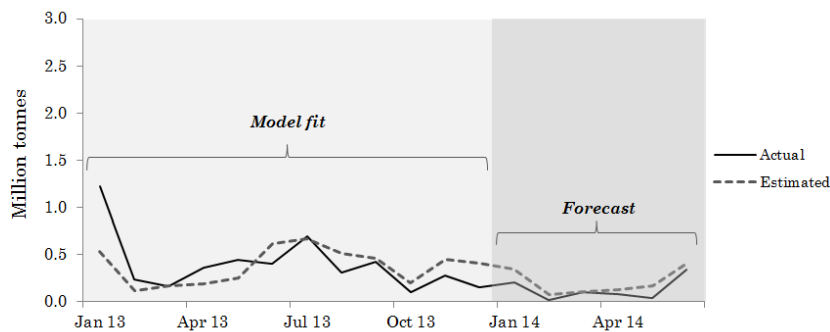


FIGURE 5.4: *Actual vs estimated maize arrivals at the Port of Paranagua.*

From the maize arrivals presented in Figure 5.4, it is observed that both model fit and hold-out periods are estimated with reasonable accuracy. For the hold-out period, the mean absolute deviation was calculated at 73,527 tonnes, which is the equivalent of one and a half vessel per month. The Mean Absolute Percentage Error for the hold-out period was calculated at 58%. Given the low level of exports during the first six months, the MAPE may be inflated due to the low base.

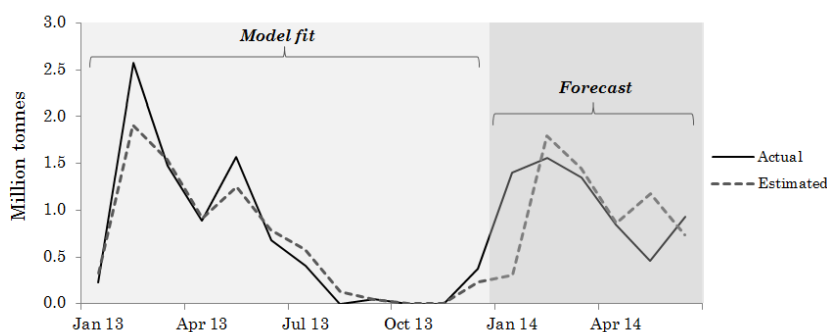


FIGURE 5.5: *Actual vs estimated soybean arrivals at the Port of Paranagua.*

In the case of soybean arrivals presented in Figure 5.5, it is noted that the oscillation in the fitted period do not reach the same extent as the actual values, and the forecasted increase in arrivals at the beginning of the 2014 forecast period lags that of the actual arrivals. The reasons behind the discrepancy is that the seasonal indices are empirically calculated based on historical observations and therefore do not take unforeseen changes in arrival patterns into account. The spikes in arrivals were caused by the reasons stipulated in the discussion on arrival patterns in Chapter 2: 1) A weak US season lead to an increased urgency to get soybean volumes from Brazil, and 2) limited alternative trade caused an influx of vessels to the east coast of South

America in anticipation of the buoyant grain volumes to come. Regarding the lag observed at the beginning of the forecast period, the harvest in Brazil was earlier than usual and therefore not taken into account by the seasonal indices. Despite the aforementioned discrepancies, the MAPE for the fitted period was calculated at 22% and the MAPE for the hold-out period was calculated at 37%.

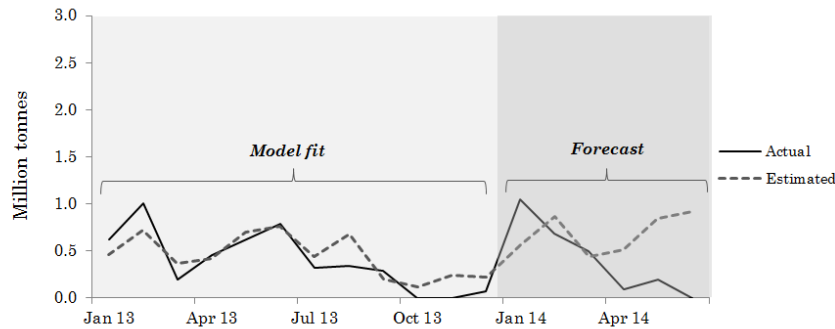


FIGURE 5.6: *Actual vs estimated soybean meal arrivals at the Port of Paranagua.*

From Figure 5.6 it is observed that the estimated soybean meal arrivals deviates substantially from the actual arrivals. The deviation is confirmed with the MAPE for the hold-out period calculated at 64%. The high percentage error is due to soybean meal exports being less seasonal than maize and soybeans as highlighted in the discussion in §4.1.2, and therefore not forecasted with great accuracy using seasonal indices. However, since soybean meal volumes are merely 16% of total grain exports from Brazil, the deviation is negligible.

Once the monthly maize, soybean and soybean meal arrivals were calculated, the arrivals of the three commodities were added to form the conglomerate volume of arrivals expected at the Port of Paranagua.

5.4 Phase 3: Results

In Phase 3, multiple regression was used to estimate monthly export capacity at the port. Monthly seasonal dummy variables were used to address seasonal variation in weather patterns, maintenance closures and holidays, and a capacity variable was added to incorporate capacity expansions. The following process was implemented to generate the required results:

1. Monthly data for the 36-month period starting January 2011 were used to produce the required regression coefficients;
2. The regression results were reviewed to evaluate the model's goodness-of-fit;
3. The required assumptions of relevance to multiple regression modelling were tested;
4. Upon confirmation of goodness-of-fit and proof of validity, the coefficients calculated in Step 1 were applied to forecast monthly export capacity for the hold-out period of 2014 and beyond.

In what follows, the results obtained from respective these steps are presented in the stipulated order. A summaries of the regression results are provided in Tables 5.5 and 5.6, and the full regression results are included in Appendix 8.2. All output figures less than zero were rounded

to three decimal figures, whereas output figures larger than zero were rounded to the closest integer. All p-values smaller than 0.05 were highlighted in bold.

5.4.1 Regression coefficients

Description	Coefficient	p-value
Intercept	570 378	0.001
JAN	-192 058	0.295
FEB	-108 254	0.552
MAR	418 013	0.029
APR	873 360	< 0.0001
MAY	971 018	< 0.0001
JUN	682 125	< 0.0001
JUL	490 597	0.012
AUG	712 541	0.001
SEP	661 473	0.001
OCT	690 759	0.001
NOV	280 583	0.131
C	159 008	0.002

TABLE 5.5: *Coefficients and statistics of the monthly export capacity at the Port of Paranagua.*

From Table 5.5 it is observed that the p-values between March and October were less than 0.05, whereas the p-values of November, January and February exceeded 0.05. With December used as base month for the dummy variables, it proved that export capacity during the 8-month period starting in March differs substantially from export capacity during the 4-month period starting in November. Recalling from the discussion on rain related delays and the impact of the holiday season in Chapter 2, it was evident that the peak-rain season between November and February combined with the public holidays in December had a substantial impact on export capacity.

Regarding the capacity variable C_{jt} , since the corresponding p-value was less than 0.05, the increasing trend in export capacity was confirmed. This was to be expected on the back of continuous improvements and expansions in port operational capacity. These results were interpreted as follows: for every 1 basis point increase in C_{jt} , the average export capacity was expected to increase by the value of the corresponding coefficient. At Paranagua, for example, if C_{jt} was increased by 1, the average export capacity would increase by 159,008 tonnes for the specified month, which equated to the equivalent of about 3 ship loads.

5.4.2 Evaluation of regression results

	Statistic
Significance F	< 0.0001
R^2	0.832
Adjusted R^2	0.745
Durbin-Watson	2.314

TABLE 5.6: *Regression results of monthly export capacity at the Port of Paranagua.*

Table 5.6 indicates that the p-value of the F-statistic was less than 0.05, which suggested that the regression is significant at a 95% confidence level. Table 5.6 also provides the R^2 and the

Adjusted R^2 , which indicate how much of the variation in export capacity could be explained by the variation of the independent variables. With an R^2 of 83.2% it was confirmed that 83% of departure volumes at Paranagua can be explained by the independent variables. However, since the R^2 can be artificially inflated due to the inclusion of unnecessary independent variables, the Adjusted R^2 was also evaluated. An Adjusted R^2 of 74.3% however confirmed that the chosen regression model was a good fit.

5.4.3 Tested assumptions

The validity of the multiple regression model is subject to the following assumptions [8]:

1. The error term u_t has a mean value of zero, that is, $E(u_i) = 0$;
2. Homoscedasticity, that is, the variance of u is constant, that is, $var(u_i) = \sigma^2$
3. No autocorrelation exists between error terms u_i and u_j , that is, $cov(u_i, u_j) i \neq j$.

The first assumption was tested by calculating the mean of the error terms for the $t = 36$ observations. Since $E(u_{36}) = 0$, it was concluded that the first assumption does hold.

In order to test the second assumption which requires the error terms to be homoscedastic, a scatter plot of the dependent variables Y_t and the residuals u_t presented in Figure 5.7 was observed.

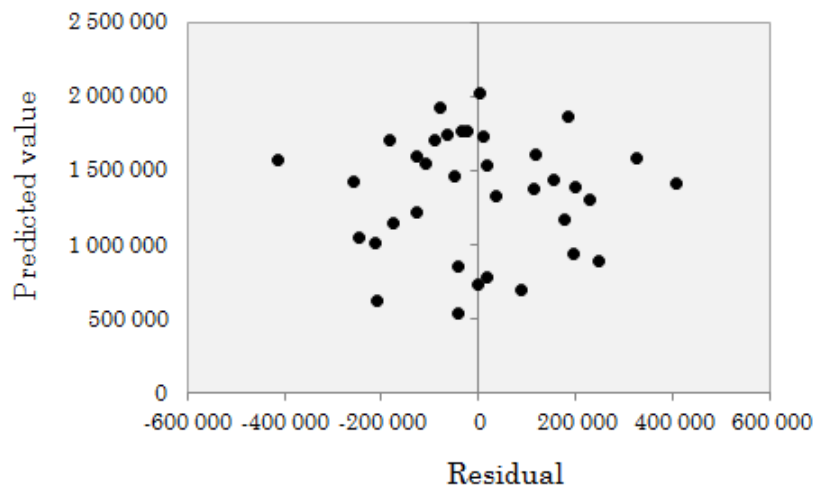


FIGURE 5.7: Predicted value vs residual scatter plot to test for homoscedasticity.

From Figure 5.7 it was evident that the error terms remain within a constant range. In order to confirm the conclusion drawn from the visual analysis, White's general test for heteroscedasticity was used for this purpose. The hypothesis tested was

H_0 : there is no heteroscedasticity

H_1 : there is heteroscedasticity

In regressing the independent variables, the squares of the independent variables, and the cross-products of the independent variables to the square of the error terms from the original regression

analysis, a p-value of 0.1098 was produced. Since the p-value was larger than 0.05, the H_0 was not rejected and the absence of heteroscedasticity is confirmed.

The third of the listed assumptions stipulates that no autocorrelation may exist between two adjacent error terms. In order to test for autocorrelation, the following two scatter plots were constructed: 1) a residual scatter plot with the lagged residuals u_t on the Y-axis and the residuals u_{t-1} on the X-axis as presented in Figure 5.8, and 2) a residual scatter plot with the residuals u_t on the Y-axis and time t on the X-axis as presented in Figure 5.8.

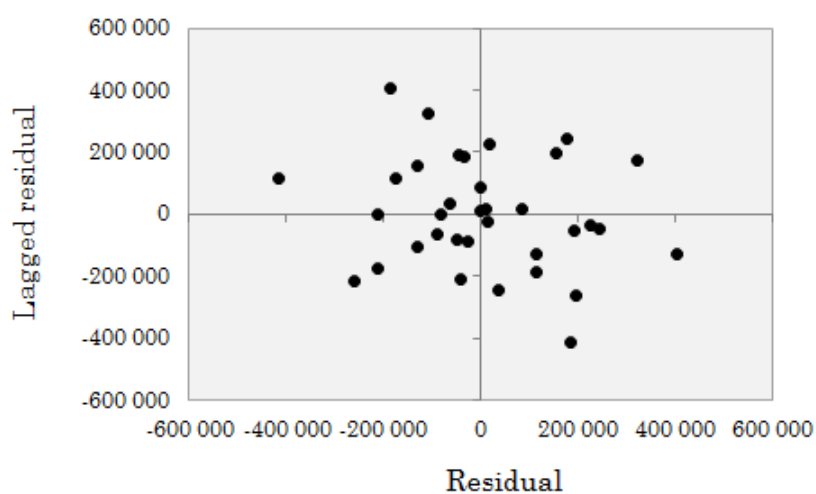


FIGURE 5.8: *Lagged residual vs residual scatterplot to test for autocorrelation.*

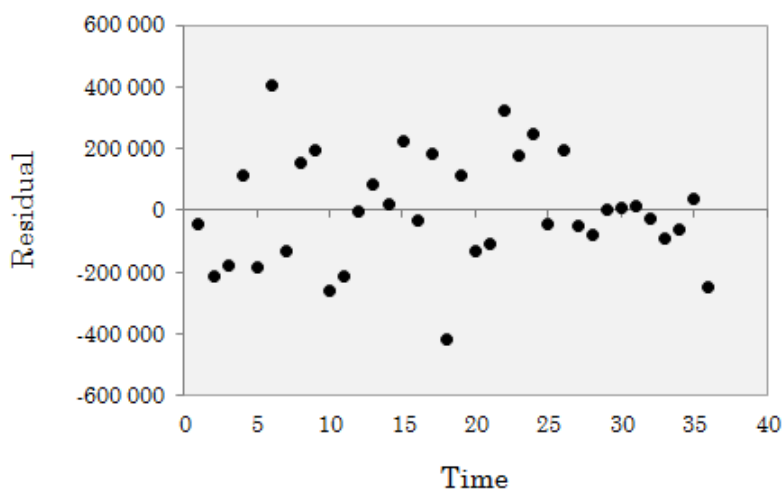


FIGURE 5.9: *Residual vs time scatterplot to test for autocorrelation.*

From Figures 5.8 and 5.9 it is evident that no patterns were formed as the observations appear to be random in both cases. From the visual analysis, it was assumed that the data is not autocorrelated. In order to establish the observation, a Durbin-Watson test was performed. A critical value of $dw = 2.314$ is calculated¹. Since the lower and upper bounds for a $n = 36$, $k = 12$ regression model were found to be $d_L = 0.748$ and $d_U = 2.398$ respectively according to the 0.05 significance Durbin Watson table [8], the absence of autocorrelation was confirmed.

5.4.4 Predicted monthly export capacity

Upon confirmation of the total goodness-of-fit, the coefficients calculated in Step 1 were applied to forecast monthly export capacity for the hold-out period in 2014 and beyond. The results for the model-fit and hold-out period are displayed in Figure 5.10.

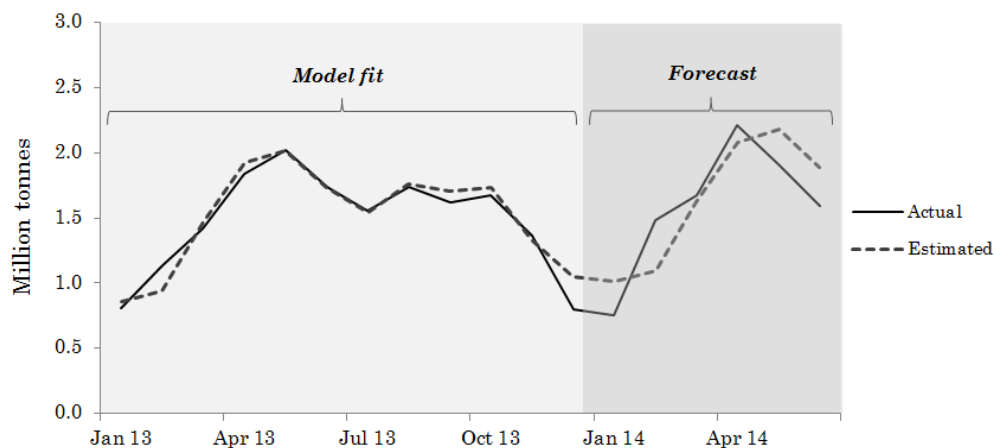


FIGURE 5.10: Actual vs estimated monthly departures from the Port of Paranagua.

The future values of the capacity variables were calculated by implementing Equation 4.15. Table 5.7 provides a breakdown of the total export capacity for the respective years, as well as the corresponding capacity variables as calculated by Equation 4.15.

Year	Percentage expansion	Export capacity	Capacity variable
2013	n.a.	17,704,758	3.00
2014	22%	21,599,805	4.86
2015	23%	26,567,760	7.46
2016	10%	29,224,536	8.86

TABLE 5.7: Incorporation of capacity expansions at the Port of Paranagua.

¹The input data to the Durbin-Watson test calculation is provided in Table 8.3 in Appendix 8

From Table 5.7 it is evident that the substantial expansion projected for 2014 and 2015 are reflected in the capacity variables. The 22% increase estimated in 2014 correspond to a capacity variable of 4.86, and the 23% increase estimated for 2015 correspond to a capacity variable of 7.46.

With the MAPE for the hold-out period calculated at 17%, it was confirmed that the multiple regression model is a good fit.

5.5 Phase 4: Results

During the fourth phase of the MPCM, the output retrieved from the second and third phases were incorporated in the congestion equation. The results obtained were in metric tonnes, and were converted to the corresponding number of vessels by applying the inverse cumulative distribution function.

As recommended in §4.5 the model was revised every four months, of which the first revision took place at the onset of the soybean season at the end of January in 2013. A revision of data refers to resetting the queue at the beginning of a period to the actual queue calculated from the line-ups distributed at that time. These periodic reviews ensure that degeneration is minimised.

The results for both model fit and hold-out periods are presented in Figure 5.11, and the accompanying goodness-of-fit measures are presented in Table 5.8.

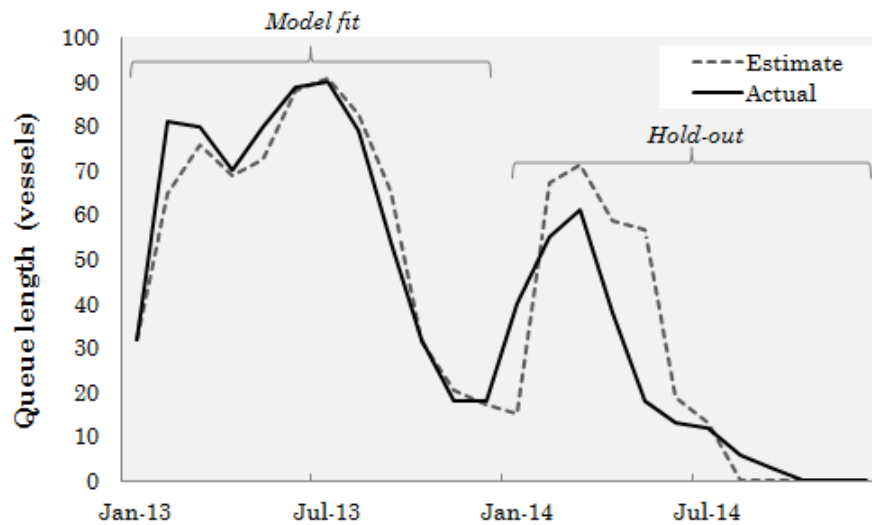


FIGURE 5.11: Actual vs estimated output of Phase 4.

Period	Fit (1a)	Fit (1b)	Fit (1c)	Hold-out (2a)	Hold-out (2b)	Hold-out (2c)
Date of review	31-01-2013	30-04-2013	30-09-2013	31-01-2014	30-04-2014	30-09-2014
MAD (vessels)	7.2	3.3	3.7	17.1	12.9	0.8
MAPE (%)	8.9%	4.1%	10.0%	39%	63.7%	25%

TABLE 5.8: Goodness-of-fit measurements of the periodic reviews for queues.

From Figure 5.11 and Table 5.8 it is evident that reasonable goodness-of-fit was achieved over the short term, especially with regard to the anticipated direction of the trend. An exception

was observed during hold-out period 2b, where the estimated values was 63.7% from the actual value, which is an overestimation of 13 vessels on average. The observation regarding the good projection of the direction of the trend was confirmed with the information provided in Table 5.12 in which the direction of the trend for both the actual and estimated values are provided.

A comparison of trend directions over the model fit and forecast period as illustrated in Table 5.12 indicates that the anticipated direction of the trend as projected by the MPCM deviated from the actual values only three times. A good anticipation of direction is therefore confirmed.

	Month	Actual	Estimate	Direction
Fit	Base: Jan-13	n/a	n/a	n/a
	Feb-13	↑	↑	Similar
	Mar-13	↓	↑	Opposite
	Apr-13	↓	↓	Similar
	May-13	↑	↑	Similar
	Jun-13	↑	↓	Opposite
	Jul-13	↑	↑	Similar
	Aug-13	↓	↓	Similar
	Sep-13	↓	↓	Similar
	Oct-13	↓	↓	Similar
	Nov-13	↓	↓	Similar
	Dec-13	↓	↓	Similar
Forecast	Jan-14	↑	↑	Similar
	Feb-14	↑	↑	Similar
	Mar-14	↑	↓	Opposite
	Apr-14	↓	↓	Similar
	May-14	↓	↓	Similar
	Jun-14	↓	↓	Similar
	Jul-14	↓	↓	Similar
	Aug-14	↓	↓	Similar
	Sep-14	↓	↓	Similar
	Oct-14	↓	↓	Similar
	Nov-14	↓	↓	Similar
	Dec-14	↓	↓	Similar

FIGURE 5.12: A comparison of trend directions in queues at the Port of Paranagua.

5.6 Phase 5: Results

During the fifth and final phase of the model, the estimated number of vessels in the queue over the period of analysis were converted into the estimated average waiting time per month. This was achieved by incorporating linear regression model of which the coefficients and statistics are listed in Table 5.9 and the goodness-of-fit measurement are listed in Table 5.10.

Variable	Coefficient	Statistic
Intercept	14.010	0.012
L_t	0.753	<0.0001

TABLE 5.9: *Coefficients and statistics of the regression model used to convert queue lengths to waiting time.*

From Table 5.9 it is observed that the p-values for both the intercept and the lagged queue parameter are less than 0.05. This observation confirmed that the length of the queue at the preceding time interval has a significant impact on the waiting time of the vessels in the current time interval.

	Statistic
Significance F	<0.0001
R^2	0.618
Adjusted R^2	0.605

TABLE 5.10: *Goodness-of-fit measurements of the regression model used to convert queue lengths to waiting time.*

From Table 5.10 it is evident that a reasonable goodness-of-fit was obtained with the proposed linear regression model. With the p-value of the F-statistic being less than 0.05, it suggested that the regression is significant at a 95% confidence level. An assessment of the R^2 indicated that 61.8% of the variation in waiting times could be explained by the length of the queue at the preceding time interval.

The results of both the model fit and hold-out periods are presented in Figure 5.13, and complemented with a summary of goodness-of-fit measurements in Table 5.11.

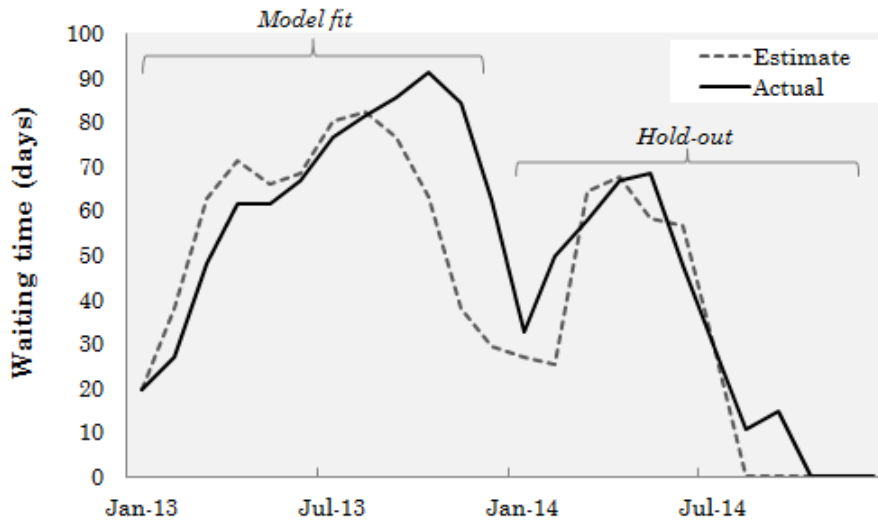


FIGURE 5.13: Actual and estimated values for the output produced during Phase 5 for the model fit and the hold-out period.

Period	Fit (1a)	Fit (1b)	Fit (1c)	Hold-out (2a)	Hold-out (2b)	Hold-out (2c)
Date of review	31-01-2013	30-04-2013	30-09-2013	31-01-2014	30-04-2014	30-09-2014
MAD (days)	11.8	2.7	29.3	9.4	8.1	3.7
MAPE (%)	29.3%	4.0%	37.5%	19.9%	39.2%	25%

TABLE 5.11: Goodness-of-fit measurements of the periodic reviews for waiting times.

From Figure 5.13 and Table 5.11 it is evident that a good direction in trend is provided, whereas a deviation from the actual values do occur. In the hold-out period, the deviation ranges between 3.7 and 9.4 days. A mean absolute deviation was estimated at 6.4 days for the fitted period and 8.3 days for the hold-out period, which equated to a mean absolute percentage error of 10.7% and 29.3% respectively.

Similar to the analysis performed at the end of Phase 4, the direction of the waiting time trend as projected by the MPCM was compared to the actual direction of the trend. An illustration of the comparison is presented in Table 5.14.

From Table 5.14 it is evident that, although the direction of the trend is less accurately estimated than the direction of the queue, an accurate projection was made for the majority of time periods under analysis. During the hold-out period, the direction of the trend was projected correctly for 9 times out of the 12 months.

Upon establishing reasonable goodness-of-fit, the coefficient determined by the regression model was applied to estimate the waiting times for vessels for the long term forecast period ranging between January 2015 and December 2016. The long term projections are presented in §5.6.1.

	Month	Actual	Estimate	Direction
Fit	Base: Jan-13	n/a	n/a	n/a
	Feb-13	↑	↑	Similar
	Mar-13	↑	↑	Similar
	Apr-13	↑	↑	Similar
	May-13	↑	↓	Opposite
	Jun-13	↑	↓	Opposite
	Jul-13	↑	↑	Similar
	Aug-13	↑	↑	Similar
	Sep-13	↑	↓	Opposite
	Oct-13	↑	↓	Opposite
	Nov-13	↓	↓	Similar
	Dec-13	↓	↓	Similar
Forecast	Jan-14	↓	↓	Similar
	Feb-14	↑	↓	Opposite
	Mar-14	↑	↑	Similar
	Apr-14	↑	↑	Similar
	May-14	↑	↓	Opposite
	Jun-14	↓	↓	Similar
	Jul-14	↓	↓	Similar
	Aug-14	↓	↓	Similar
	Sep-14	↑	↓	Opposite
	Oct-14	↓	↓	Similar
	Nov-14	↓	↓	Similar
	Dec-14	↓	↓	Similar

FIGURE 5.14: A comparison of trend directions in waiting times at the Port of Paranagua.

5.6.1 Long term outlook generated by the MPCM

The long term outlook generated by the MPCM is presented in this section, in conjunction with an overview of the sensitivity analysis that can be performed with the model. Figure 5.15 presents long term outlook given the base scenario used as input. Recalling from §2.2.3, an increase in export capacity for 2015 was projected at 22%, and an increase in export capacity for 2016 was projected at 10%. As presented in Figure 5.15, an overall decrease in both queues and corresponding waiting times are observed over the peak periods, whereas no congestion is observed during the off-peak periods. A detailed breakdown of Figure 5.15 is provided in Table 5.12.

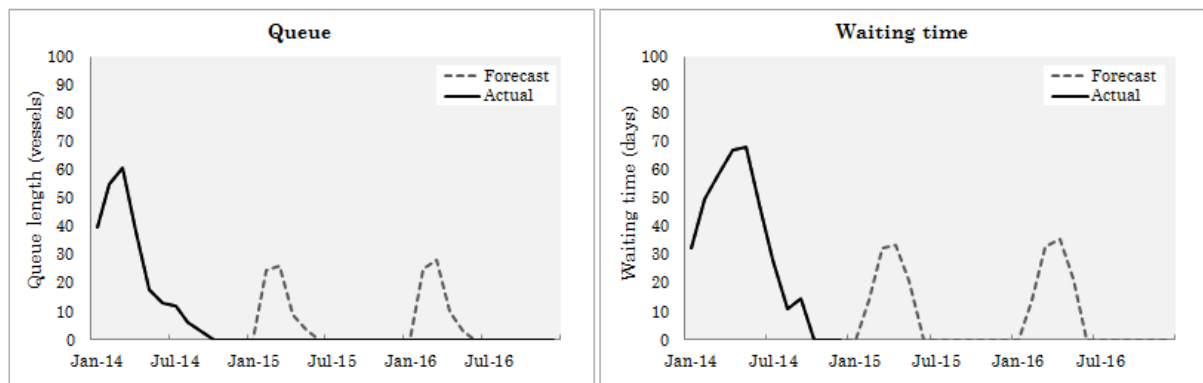


FIGURE 5.15: Base scenario: Long term outlook of congestion levels at the Port of Paranagua.

Month	Queue (Vessels)	Level	Waiting time (days)	Level
Jan 2015	0	Low	0	Low
Feb 2015	24	Medium/High	14.0	Low/Medium
Mar 2015	26	Medium/High	32.4	Medium/High
Apr 2015	9	Medium	33.7	High
May 2015	3	Low	20.8	Medium
Jun 2015	0	Low	0	Low
Jul 2015	0	Low	0	Low
Aug 2015	0	Low	0	Low
Sep 2015	0	Low	0	Low
Oct 2015	0	Low	0	Low
Nov 2015	0	Low	0	Low
Dec 2015	0	Low	0	Low
Jan 2016	0	Low	0	Low
Feb 2016	25	Medium/High	14.0	Low/Medium
Mar 2016	28	Medium/High	33.1	Medium/High
Apr 2016	10	Medium	35.4	High
May 2016	3	Low	21.6	Medium
Jun 2016	0	Low	0	Low
Jul 2016	0	Low	0	Low
Aug 2016	0	Low	0	Low
Sep 2016	0	Low	0	Low
Oct 2016	0	Low	0	Low
Nov 2016	0	Low	0	Low
Dec 2016	0	Low	0	Low

TABLE 5.12: Categorisation of congestion outlook for the Port of Paranagua in 2015 and 2016.

From Table 5.12 it is evident that congestion levels are still expected to be in the medium to high range during peak periods, but not to the extent seen in previous years. With the exception of April 2015 and 2016, where waiting times are expected to reach “high” levels, the remainder of the peak periods are expected to range between low/medium and medium/high. It is also noted that the duration of the peak period is expected to be shorter, with congestion levels falling back to “low” levels as early as May in both 2015 and 2016.

In order to assess what the congestion outlook would be if the export capacity do not materialise to the extent that was projected, the following scenario is constructed: the year-on-year increase for both 2015 and 2016 are adjusted to 5%. The output presented in Figure 5.16 indicate the higher levels of congestion in the case of less expansions.

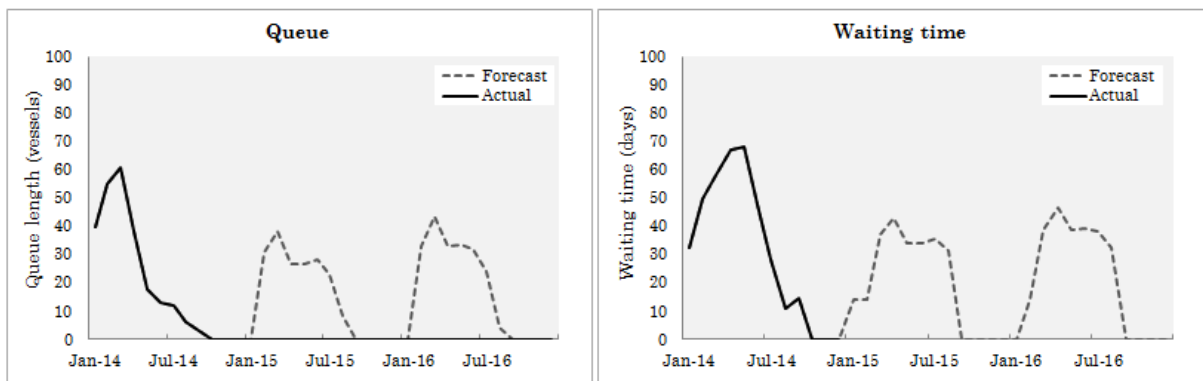


FIGURE 5.16: Scenario of limited expansions: Long term outlook of congestion levels at the Port of Paranagua.

The final case presented is a scenario in which the projected congestion levels given in the event of no capacity improvements made. From Figure 5.17 it is evident that congestion levels are projected to be substantially higher in the case of no capacity expansions.

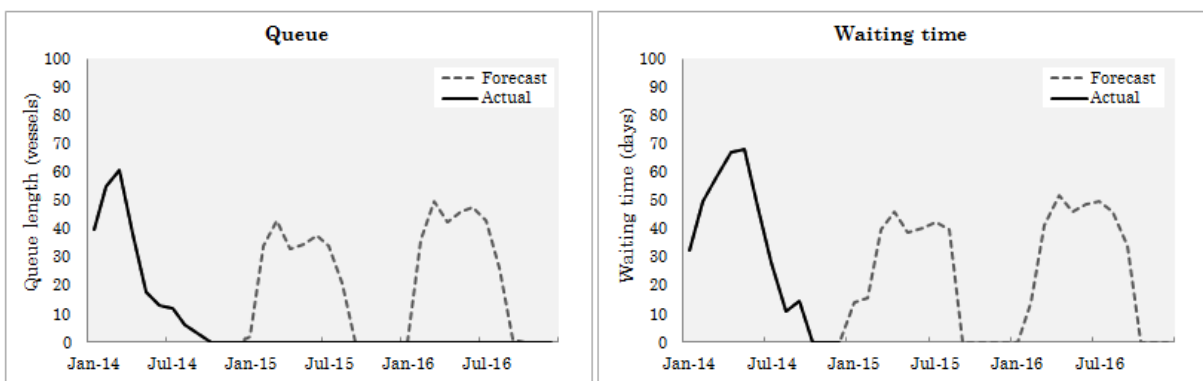


FIGURE 5.17: Scenario of no expansions: Long term outlook of congestion levels at the Port of Paranagua.

5.7 Validity of the MPCM

The validity of the MPCM was tested by comparing the generated output with actual congestion levels. Input data from January 2011 to December 2013 were used as input to the model in order to forecast monthly congestion levels for the 12 month hold-out period starting January 2014. Since actual data was available until the end of December 2014, the results generated for 2014 are subsequently compared to actual data as published by Brokerage A [4]. These comparisons and subsequent discussions of goodness-of-fit have been presented at each of the respective phases' results in Sections 5.6 to 5.6.

The reliability of any given model is established by repeating the implementation of the MPCM on an alternative yet parallel scenario. The model was applied to the Port of Sao Francisco Do Sul, of which the results for the queue projections are presented in Figure 5.18, and the results for the corresponding waiting time projections are presented in Figure 5.19.

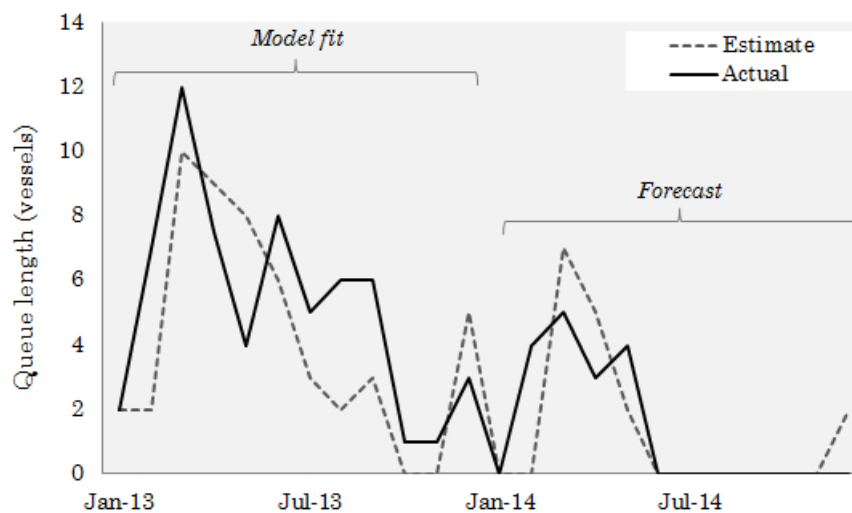


FIGURE 5.18: Model output of queues at Sao Francisco do Sul.

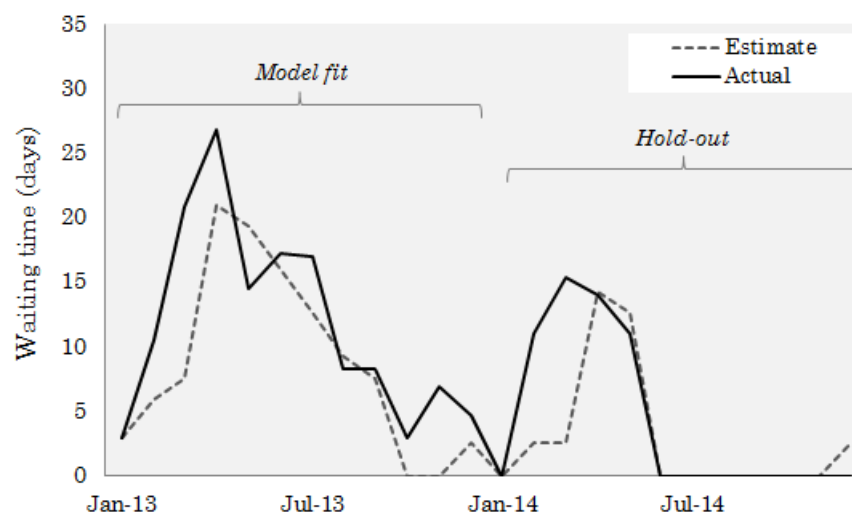


FIGURE 5.19: Model output of waiting times at Sao Francisco do Sul.

From Figure 5.18 it is evident that the general trend of the congestion forecasts are aligned with the trend of the actual values published by Brokerage A.

5.8 Chapter summary

The results generated by the MPCM are presented in Chapter 5. A brief review of the proposed methodology is provided in §5.1, followed by the results generated in each of the five respective phases of the model in sections 5.2 to 5.6. A long term outlook is provided in §5.6.1 and the validity of the model is presented and discussed in §5.7. The results presented in Chapter 5 are succeeded by a discussion thereof in Chapter 6.

CHAPTER 6

Discussion

Contents

6.1	Discussion and evaluation of the MPCM	67
6.1.1	<i>Model strengths</i>	68
6.1.2	<i>Model weaknesses</i>	68
6.2	Comparison to previous studies	69
6.3	Contributions of the study	71
6.4	Chapter summary	71

In Chapter 6, the results generated in Chapter 4 and presented in Chapter 5 are discussed and evaluated. The main objective of the study is revisited in §6.1, which forms the basis upon which the model is assessed. In §6.2, the outcome of the study is compared to the outcomes achieved by other studies with similar objectives and characteristics, and in §6.3 the contributions made by this study is revisited. The chapter is concluded with a brief summary in §6.4.

6.1 Discussion and evaluation of the MPCM

In order to evaluate the results obtained by the MPCM, the main objective of the study as stipulated in §1.3 is revisited:

The main objective of this study is to identify and develop a forecasting model to predict both trend and fluctuation in congestion at a port in the Brazilian grain port network given the annual tonnage of grains to be exported from Brazil.

The Port of Paranagua was chosen as case study. In order to derive the monthly congestion levels at the Port of Paranagua from Brazil's total exportable grain supplies, a macro approach was taken in which the trade-off between aggregate monthly arrivals and the corresponding monthly export capacity was analysed. The foundations of the model were based on a combination of methodologies discussed in Chapter 3.

Firstly, similar to the model used to predict congestion levels at the Port of Newcastle in Australia [3], the model required multiple phases to translate the volume of exportable supplies into congestion levels. Secondly, similar to the study by Shabayek [22], time series analysis was applied to quantify the seasonal variation in vessels' arrival patterns and ports' export capacity. Thirdly, similar to the study performed by Leachman [12], a single methodology was proposed

for the respective ports in the port network in order to provide a broad indication of anticipated congestion levels given a change in trade volumes or infrastructure. The proposed methodology was tested on both the Port of Paranagua and the Port of Sao Francisco do Sul.

A review of the results presented in Chapter 5 indicated that the trend in congestion levels was predicted with great accuracy and the level of fluctuation was predicted within reasonable deviation of the actual figures. By categorising the results obtained by the MPCM according to the five quantiles introduced in Chapter 4, the relative level of congestion was quantified. The relativity speaks to all historical congestion levels reported at the respective ports in the port network. It can therefore be concluded that the main objective of the study has been reached.

6.1.1 Model strengths

A critical evaluation of the modelling approach identified the following model strengths:

1. *Practical*: Input to the model is easily updated upon publication of new information in the market.
 - When the monthly publication of the USDA's grain export forecasts is released as discussed in 4.1.1, the model is easily updated with the revised annual maize, soybean and soybean meal forecasts and the new model output is generated. This provides insight to how different volumes of grain exports affect congestion levels.
 - When information on port expansions is published via news articles or port agency reports, the anticipated increase in capacity is adjustable which also triggers the revision of the model output.
2. *Flexible*: Given the macro approach, the structure of the model is not sensitive to alterations in operational policies or procedures. For example, when the Port of Paranagua's berthing policy changed, the adjustment did not necessitate a structural change to the model itself. The adjustment was addressed by updating the anticipated improvement in efficiency levels.
3. *Sensitivity analysis*: Potential future scenario's could be tested to analyse the impact of potential capacity expansions on future congestion levels.

Having listed the strengths of the model, a discussion of the identified weaknesses follow.

6.1.2 Model weaknesses

A comparison between the actual and predicted values indicated that the margin of error tend to be more significant during periods of high congestion. The increase in disparity could be explained by the conclusion drawn from a study performed by Mavrakakis [14]: a linear increase in the arrival rate of vessels lead to an exponential increase in both the number of ships waiting to enter the system and the average waiting time at anchorage. Given the linear approach taken with the MPCM, the exponential increase in congestion levels amidst a linear increase in arrivals was not taken into account. Another reason for the increasing disparity in times of high congestion could be ascribed to the non-linear relationship between utilisation and waiting times as established by Voss [31] in §3.3. Voss noted that, when a port is operating a maximum capacity, a slight disruption may have a substantial effect on port efficiency, with has an aggregated impact on port congestion.

A second weakness is the risk of degeneration. On the long term, results tend to weaken due to the consequential nature of the model, that is, that the output estimated in the next month is used as input to calculate the output of the month after next. For example, if one of the early monthly forecasts is significantly wrong, the remainder of the forecasting period will also be wrong. On the short term, however, if the current state of congestion is known, it is expected that the MPCM will provide reasonable to good results for the upcoming one to four months.

Further to the risk of consequentiality in terms of time, the consequentiality with respect to the different phases of the model also proposes a risk to the model. The example illustrated in Figure 6.1 is taken from the results presented in Chapter 5. When the arrival patterns for January 2014 were estimated incorrectly due to the reasons listed in §5.3, the impact of these errors were evident in the results presented in §5.6.1.

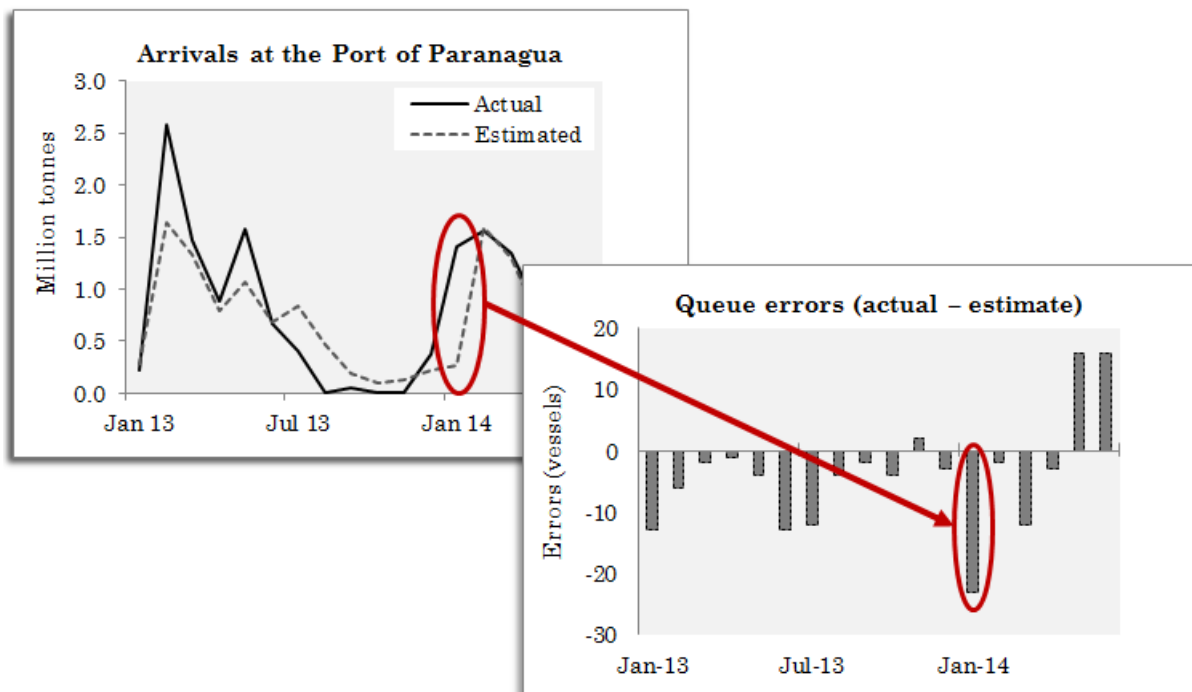


FIGURE 6.1: A demonstration of consequentiality in the model.

Having provided an evaluation of the applied methodology, a comparison is drawn to other methodologies applied to problems with similar characteristics.

6.2 Comparison to previous studies

The three major challenges faced during the course of the study were 1) the seasonal variation in arrivals and export capacity, 2) the ever-changing environment of the shipping industry, and 3) the limited level of detail of the data available for this study. In what follows the MPCM is compared to models built for similar environments. The examples are taken from the literature review presented in Chapter 3.

Seasonality in shipping trade flows was addressed by Oyatoye *et al.* [17], and Shabayek [22]. Oyatoye *et al.* applied queuing theory to analyse the leading causes of congestion at Tin Can

Island port in Nigeria. Seasonality was addressed by running the proposed queuing model for each consecutive month. However, upon applying the model to a specific month, the backlog created by the previous month was not incorporated. The application of this model was therefore not a feasible solution to the problem at hand since the backlog formed at the beginning of the Brazilian maize or soybean season usually determines the level of congestion for the remainder of the season. The study by Shabayek [22] on congestion analysis at Kwai Ching container terminals in Hong Kong also used queueing theory. Seasonality in arrival and service rates was addressed by using regression analysis to estimate future trends in arrival and service patterns. The 18 terminals of relevance were assumed to operate in parallel. However, as explained in §4.3, the assumption of parallel service times could not be applied to the problem at hand which discarded the possibility of applying the named approach.

In order to address the ever changing environment of the maritime industry, the flexibility of the MPCM was of high importance and has been achieved as highlighted in 6.1. With respect to other studies, Dragovic commented that the intricate range of model requirements in a mathematical approaches may compromise the models' flexibility by becoming too theoretical and subsequently inflexible to change [5]. In simulation modelling, on the other hand, Valentin [30] noted that domain experts often lack the required skills to rebuild or adjust an existing simulation model to address the evolving nature of the industry. Since the regular hiring of a simulation expert may be too expensive, the simulation model may be left unchanged amidst changes in the actual system, and the growing discrepancy would weaken the simulation model's results over time. Although Valentin proposed a unique simulation tool to model large maritime infrastructure systems called called *Scenario Navigator*, availability and access to the software was an obvious prerequisite.

Regarding the last of the three challenges faced during the course of this study, macro approach was taken to overcome the limited level of detail of the data available for the study. In order to portray what can be achieved in circumstances of detailed information, a comparison is drawn between the MPCM and the model developed for the Hunter Valley Coal Chain Coordinator (HVCCC). Recalling from Chapter 3, forecasting of congestion levels at the Port of Newcastle is done with great accuracy. Further to the mere brilliance of the model developed for this system, the detailed level of data used as input to the model enables accurate forecasting. The level of detail is obtainable due to the fact that the whole supply chain is a consolidated system from the point of production until the point of export. The absence of external players and the common goal of efficiency encourage transparency in information flows. Input to the model is thus available at molecular level, including daily updates on vessel arrivals, types of cargoes to be loaded, stem sizes of cargoes to be loaded, efficiency throughout the coal chain, and port operational efficiency. Similarities and differences between the HVCCC and MPCM are listed in Table 6.1.

HVCCC	MPCM
Input from a consolidated system	Input from detached sources
Real time input data	Combination of real time input data and empirical analysis.
Input data available on daily basis	Input data available on a monthly basis
Model revised on a daily basis	Model revised on a periodic four-month basis

TABLE 6.1: *The key differences between the HVCCC model and the MPCM model.*

6.3 Contributions of the study

Recalling the relevance of the study discussed in Chapter 1, the following contributions are confirmed:

1. The information portrayed in this thesis provides insight to the complexity of port congestion modelling, especially in the event of seasonality in both trade patterns and export capacity; a dynamic modelling environment; and limited level of detail of data.
2. The application of sensitivity analysis was demonstrated by analysing the varying impact of different levels of export capacity on congestion levels.
3. The proposed methodology can serve as basis for future development to perform a conglomerate view of congestion levels in the Brazilian port network. The results obtained would enable Brokerage A to provide strategic information to its clients. This information includes the anticipated availability of vessels in the market as well as guidance to the extent of waiting times to be expected, both of which being of critical importance in negotiating freight rates of future shipments.

6.4 Chapter summary

Chapter 6 provided an evaluation of the results generated by the MPCM. The metrics for the evaluation were based on the requirements proposed by the main objective of the study. On the short term, the model proved to provide sufficient direction of the anticipated congestion levels, whereas long term results do present the risk of degeneration. From a review of the results generated by studies with similar characteristics, it was found that extensive structural and operational data are required at a very detailed level in order to generate forecasts within close vicinity of the actual values.

CHAPTER 7

Conclusion

Contents

7.1 Thesis summary	73
7.2 Potential future work	74
7.2.1 <i>Financial analysis of the migration to the northern ports</i>	74
7.2.2 <i>Sensitivity analysis of a change in queuing discipline</i>	74
7.2.3 <i>Impact of market conditions on arrival rates</i>	74

In Chapter 7, the study on forecasting congestion levels at the Port of Paranagua is drawn to a close. The chapter consists of two sections, the first of which providing a brief summary of the work presented in this thesis, and the second section provides recommendations to potential future work in this field.

7.1 Thesis summary

In this thesis, a multi-phase congestion model was proposed with the objective to forecast both trend and level of fluctuation at the Port of Paranagua, given the estimated annual grain volumes to be exported from Brazil as a whole. In what follows, a brief overview of the thesis's six preceding chapters are provided.

In Chapter 1, a brief description of the problem was provided which included the main objectives pursued as well as the scope and relevance of the study. Chapter 1 was closed with a preview of the content of the remainder of the thesis.

In fulfillment of Study Objective 1, background to the environment for which the model was to be built was provided in Chapter 2. The chapter opened with a brief introduction to dry bulk shipping, which was followed by an overview of dry bulk grain trade. The background study was subsequently narrowed to Brazilian grain trade in particular, with specific focus on the characteristics and trade flows at the Port of Paranagua.

In order to create a basis from which the modelling technique was identified, a literature review of previous studies with similar characteristics was performed in Chapter 3. Since port congestion analysis has been approached by various methodologies including queuing theory, simulation and time-series analysis, it was critical to identify a modelling approach that matched the expectations, characteristics, and restrictions of the problem under study. Chapter 3 thus served as basis upon which the choice of modelling technique was made as stipulated by Study Objective 2.

In fulfillment of Study Objective 3, the development of the multi-phase congestion model was introduced in Chapter 4. A detailed description of each of the five phases were provided, as well as an explanation of the application and revision of the model. This was followed by insight to the tests performed to establish the validity and reliability of the model.

In order to illustrate the application of the multi-phase congestion model as stipulated in Study Objective 4, the generated results were presented in the following step-wise manner in Chapter 5: 1) Presentation of the results from the hold-out period, 2) Presentation of results from the medium term forecast period, 3) Presentation of results from the long term forecast period, and 4) Validation of results.

Upon the fulfillment of the final Study Objective, the results were discussed and evaluated in Chapter 6. The discussion included insight to both strengths and weaknesses of the model, and comparisons were drawn to the studies reviewed in Chapter 2.

7.2 Potential future work

During the course of the study, three areas of research were identified for potential future studies. Section §7.2 provides a brief introduction to these areas.

7.2.1 Financial analysis of the migration to the northern ports

In Chapter 2 it is mentioned that infrastructural improvements at the northern ports are creating a shift in export allocation to the northern ports. Although the northern ports are geographically at a disadvantage to the southern ports regarding the major areas of production, the following two aspects encourage the migration: Firstly, the cost of delayed shipments caused by congestion at the southern ports, and secondly, the shorter voyage across the Atlantic Ocean to Europe as well as via the Panama Canal to the eastern markets. The topic suggested for future research would identify the point of equilibrium between the additional hinterland transport costs and the joint saving in costs attributed to congestion and lower freight.

7.2.2 Sensitivity analysis of a change in queuing discipline

In the background study in Chapter 2 it was identified that the queuing discipline at the Port of Paranagua changed from a First-Come-First-Serve (FCFS) basis at all three berths to having two FCFS berths and one express berth for priority vessels who load from a limited number of suppliers. It is recommended that a study is embarked in which this principle is tested on other congestion facing ports.

7.2.3 Impact of market conditions on arrival rates

The commodity specific seasonality in arrivals is addressed in this thesis. However, as identified in the discussion on arrivals in Chapter 2, vessels' arrival patterns are sensitive to market conditions. These conditions include the level of availability of alternative supplies, the strength of the shipping freight market, as well as the economic conditions of the major importing regions. The proposed study would measure the impact of these market conditions on arrival pattern in order to anticipate future arrival patterns.

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CHAPTER 8

Appendix A

#	Actual	Predict	d_i	$ d_i $	Rank	Signed Rank
1	4 616 485	6 001 999	1 385 514	1 385 514	1	1
2	7 735 132	7 897 716	162 584	162 584	2	2
3	5 353 143	3 805 043	(1 548 100)	1 548 100	3	-3
4	11 910 015	11 452 636	(457 379)	457 379	4	-4
5	12 893 109	12 995 406	102 297	102 297	5	5
6	3 333 151	3 688 236	355 085	355 085	6	6
7	999 435	91 321	(908 114)	908 114	7	-7
8	8 206 122	4 425 875	(3 780 247)	3 780 247	8	-8
9	2 470 309	3 234 031	763 722	763 722	9	9
10	2 858 108	2 340 384	(517 724)	517 724	10	-10
11	2 823 224	2 990 183	166 959	166 959	11	11
12	661 309	1 012 076	350 767	350 767	12	12
13	3 489 393	3 019 190	(470 203)	470 203	13	-13
14	4 032 264	3 600 648	(431 617)	431 617	14	-14
15	313 467	526 307	212 840	212 840	15	15
16	2 751 452	1 846 893	(904 560)	904 560	16	-16
17	7 106 255	8 154 597	1 048 342	1 048 342	17	17
18	1 202 167	1 058 384	(143 783)	143 783	18	-18

$T =$	78
$H_0:$	$u_1 = u_2$
$n(n+1) / 2 =$	171
$W(0.025) =$	41
$W(0.975) =$	130
Outcome:	<i>Do not reject H_0</i>

TABLE 8.1: Input data to the Wilcoxon signed rank test.

SUMMARY OUTPUT										
<i>Regression Statistics</i>										
Multiple R	0.912									
R Square	0.832									
Adjusted R Square	0.745									
Standard Error	219514.46									
Observations	36									
ANOVA										
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>					
Regression	12	5.50704E+12	4.5892E+11	9.523808524	2.70327E-06					
Residual	23	1.10829E+12	48186599648							
Total	35	6.61533E+12								
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>		
Intercept	570 378	155 220	3.675	0.001	249 281	891 475	249 281	891 475		
JAN	- 192 058	179 233	- 1.072	0.295	- 562 829	178 713	- 562 829	178 713		
FEB	- 108 254	179 233	- 0.604	0.552	- 479 025	262 518	- 479 025	262 518		
MAR	418 013	179 233	2.332	0.029	47 241	788 784	47 241	788 784		
APR	873 360	179 233	4.873	0.000	502 588	1 244 131	502 588	1 244 131		
MAY	971 018	179 233	5.418	0.000	600 246	1 341 789	600 246	1 341 789		
JUN	682 125	179 233	3.806	0.001	311 354	1 052 897	311 354	1 052 897		
JUL	490 597	179 233	2.737	0.012	119 826	861 368	119 826	861 368		
AUG	712 541	179 233	3.976	0.001	341 769	1 083 312	341 769	1 083 312		
SEP	661 473	179 233	3.691	0.001	290 701	1 032 244	290 701	1 032 244		
OCT	690 759	179 233	3.854	0.001	319 988	1 061 531	319 988	1 061 531		
NOV	280 583	179 233	1.565	0.131	- 90 188	651 354	- 90 188	651 354		
C	159 008	44 808	3.549	0.002	66 315	251 701	66 315	251 701		

TABLE 8.2: *The regression results calculated during Phase 3.*

t	Y_t	e_t	$(e_t - e_{t-1})$	$(e_t - e_{t-1})^2$	e_t^2
1	537 328	- 42 151			
2	621 132	- 211 544	169 393	28 694 101 378	44 750 952 079
3	1 147 399	- 176 356	- 35 189	1 238 242 262	31 101 277 077
4	1 602 746	115 579	- 291 935	85 226 044 225	13 358 611 189
5	1 700 404	- 184 888	300 467	90 280 418 089	34 183 403 064
6	1 411 511	404 559	- 589 446	347 446 979 880	163 667 815 915
7	1 219 983	- 128 975	533 534	284 658 173 467	16 634 518 381
8	1 441 927	155 549	- 284 524	80 954 096 259	24 195 633 988
9	1 390 859	197 351	- 41 802	1 747 407 204	38 947 598 106
10	1 420 145	- 259 512	456 864	208 724 409 920	67 346 586 274
11	1 009 969	- 212 859	- 46 653	2 176 533 511	45 308 900 666
12	729 386	971	- 211 888	44 896 524 544	942 598
13	696 336	86 585	- 87 556	7 666 089 618	7 497 019 948
14	780 140	17 782	68 803	4 733 898 678	316 199 524
15	1 306 406	226 684	- 208 902	43 639 906 336	51 385 484 733
16	1 761 753	- 33 920	260 604	67 914 444 816	1 150 589 013
17	1 859 411	183 614	- 217 534	47 321 041 156	33 713 978 587
18	1 570 519	- 414 763	598 377	358 054 635 211	172 028 346 169
19	1 378 991	114 073	- 528 836	279 667 867 453	13 012 725 378
20	1 600 934	- 129 875	243 949	59 510 951 968	16 867 602 208
21	1 549 866	- 107 855	- 22 020	484 880 400	11 632 772 928
22	1 579 153	323 158	- 431 013	185 772 493 511	104 431 092 964
23	1 168 977	176 863	146 295	21 402 129 495	31 280 638 678
24	888 394	246 086	- 69 223	4 791 823 729	60 558 483 453
25	855 343	- 44 434	290 521	84 402 330 391	1 974 421 087
26	939 148	193 762	- 238 197	56 737 652 011	37 543 793 378
27	1 465 414	- 50 328	244 090	59 580 090 827	2 532 920 166
28	1 920 761	- 81 659	31 331	981 631 561	6 668 212 696
29	2 018 419	1 274	- 82 933	6 877 882 489	1 622 758
30	1 729 527	10 204	- 8 930	79 750 853	104 125 868
31	1 537 998	14 902	- 4 697	22 064 940	222 055 944
32	1 759 942	- 25 674	40 576	1 646 384 725	659 180 695
33	1 708 874	- 89 496	63 822	4 073 247 684	8 009 556 390
34	1 738 161	- 63 646	- 25 850	668 239 733	4 050 786 797
35	1 327 984	35 996	- 99 641	9 928 395 308	1 295 679 020
36	1 047 401	- 245 115	281 111	79 023 394 321	60 081 587 914
Mean =		<u>0.000</u>	Sum =	<u>2 561 024 157 955</u>	<u>1 106 515 095 634</u>

TABLE 8.3: *Input data to the Durbin Watson test.*