Maritime logistics with berth and pipeline allocation

A case study

Paulo Jorge dos Santos Calaia

Dissertation to obtain the Master of Science degree in

Industrial Engineering and Management

Supervisors: Prof. Tânia Rute Xavier de Matos Pinto Varela

Prof. Maria Isabel Azevedo Rodrigues Gomes

Examination Commitee

Chairperson: Prof. Ana Isabel Cerqueira de Sousa Gouveia Carvalho

Supervisor: Prof. Tânia Rute Xavier de Matos Pinto Varela

Members of the commitee: Prof. Nelson Fernando Chibeles Pereira Martins

January 2021

Declaration

I declare that this document is an original work of my own authorship and that it fulfils all requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

Declaração

Declaro que o presente documento é um trabalho original da minha autoria e que cumpre os requisitos do Código de Conduta e Boas Práticas da Universidade de Lisboa.

Agradecimentos

Ao fim de cinco anos de percurso académico, que culminaram na elaboração desta dissertação, gostaria de deixar uma palavra de agradecimento às pessoas que estiveram comigo.

Gostaria de agradecer à professora Tânia Varela e à professora Isabel Gomes pelo incansável trabalho de orientação desta dissertação. Agradeço pelo apoio, pela enorme disponibilidade, assim como pelos ensinamentos, que vou levar para o meu futuro.

Agradecer à minha namorada Rita, pela importância que tem na minha vida e pelo apoio emocional que me deu nesta fase importante.

A todos os meus amigos que me acompanharam neste percurso e o tornaram mais simples.

Por fim, à minha família, em particular aos meus pais e ao meu irmão, por tudo o que representam para mim.

E a todas as pessoas que de alguma forma me ajudaram na realização desta dissertação.

Abstract

This dissertation aims at applying an operational research methodology, with the objective of evaluating policies for allocating vessels to berths and pipelines at the Sines' Liquid Bulk Terminal. This problem is part of what is known in the literature as the Berth Allocation Problem (BAP). The aim is to optimise the operations and costs of the terminal, particularly by minimising Port Operation Time (POT) and Demurrage.

Analysing the terminal data in January 2017, it was noted the inadequate allocation of vessels to berths and pipelines. These are mainly due to the disregard of the variability of the POT and the Demurrages, influencing the evaluation of the terminal's performance. The literature review then addressed the BAP for bulk and container terminals, concluding the lack of exploration of this problem in bulk terminals, of simulation for its resolution and consideration and mitigation of the stochastic nature of the terminal parameters.

Hence, a simulation model was developed, implemented in SIMUL8 software. Once this model was validated, fifteen alternative scenarios were presented, divided according to five characteristics: berth allocation, pipelines allocation, time horizon, uncertainty, and queue policy.

The analysis of results was divided by time horizon. Both in terminating simulations and in long-term simulation, the scenarios that make allocation to pipelines flexible were selected as the best. Also, the optimization-simulation scenarios allow a realistic assessment of the terminal's operational conditions, allowing for more reliable results.

Key words: Liquid Bulk Terminal; Berth Allocation Problem; Port Operational Time; Demurrages; Variability, Stochastic Simulation

Resumo

Esta dissertação pretende aplicar uma metodologia de investigação operacional, com o objetivo de avaliar políticas de afetação de navios a postos de acostagem e oleodutos no terminal de graneis líquidos de Sines. Este problema insere-se no que na literatura é conhecido como *Berth Allocation Problem* (BAP). Pretende-se, pois, otimizar as operações e os custos do terminal, nomeadamente através da minimização do *Port Operational Time* (POT) e de Sobrestadias.

Analisando os dados do terminal em janeiro de 2017, notou-se a desadequada alocação de navios a postos de acostagem e oleodutos. Estas devem-se, sobretudo, à desconsideração da variabilidade do POT e das Sobrestadias, influenciando a avaliação da performance do terminal. De seguida, a revisão de literatura abordou o BAP para terminais de graneis e de contentores, concluindo-se a falta de exploração deste problema em termineis de graneis, de simulação para a sua resolução e da consideração e mitigação da natureza estocástica dos parâmetros do terminal.

Desta forma, foi desenvolvido um modelo de simulação, implementado no software SIMUL8. Validado este modelo, apresentou-se quinze cenários alternativos, divididos de acordo com cinco características: alocação a postos, alocação a pipelines, horizonte temporal, incerteza e política de fila de espera.

A análise de resultados foi dividida por horizonte temporal. Quer nas *Terminating Simulations* quer na simulação a longo prazo, os cenários que flexibilizam a alocação a pipelines foram selecionados como os melhores. Realçar ainda que os cenários de otimização-simulação permitem uma avaliação realística das condições operacionais do terminal, permitindo obter resultados mais fiáveis.

Palavras-chave: Terminal de graneis líquidos; *Berth Allocation Problem*; *Port Operational Time;* Sobrestadias*;* Variabilidade, Simulação estocástica

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List of acronyms

ACD	Activity Cycle Diagram
AEI	Advanced Engineering Informatics
AEJ	Alexandria Engineering Journal
AJSL	Asian Journal of Shipping and Logistics
ALNS	Adaptative Neighbourhood Search
AMM	Applied Mathematical Modelling
ASCJ	Applied Soft Computing Journal
BACAP	Berth Allocation and Crane Assignment Problem
BAP	Berth Allocation Problem
BRKGA	Biased Random Key Genetic Algorithm
CIE	Computers and Industrial Engineering
CL	Contracted Laytime
COR	Computers and Operations Research
CTATS	Container Terminals and Automated Transport Systems
CV	Coefficient of Variation
DSS	Decision Support Systems
EAAA	Engineering Applications of Artificial Intelligence
EJOR	European Journal of Operational Research
ESA	Expert Systems with Applications
FIFO	First In First Out
GA	Genetic Algorithm
GMTS	Generic Multiprocessor Task Scheduling
GRASP	Greedy Randomized Adaptative Search Procedure
GSPP	Generalized Set Partitioning Problem
HPGA	Hybrid Parallel Genetic Algorithm
IFAC	IFAC-Papers Online
KPI	Key Performance Indicator
LCD	Life Cycle Diagram
LPG	Liquid Petroleum Gas
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
MIP	Mixed Integer Programming
MIQP	Mixed Integer Quadratic Programming
ORL	Operations Research Letters
OS	Optimization-Simulation
OT	Operational Time
POT	Port Operational Time
PSO	Particle Swarm Optimization

QCAP Quay Crane Assignment Problem

QCSP Quay Crane Scheduling Problem

ROH Rolling Horizon Heuristic

SA Simulated Annealing

SBAP Strategic Berth Allocation Problem

SEC Swarm and Evolutionary Computation

SMPT Simulation Modelling Practice and Theory

SOCP Second-Order Cone Programming

ST Setup Time

TBAP Tactical Berth Allocation Problem

TD Time for Docking

TRPB Transportation Research Part B

TRPD Transportation Research Part D

TRPE Transportation Research Part E

VRP Vehicle Routing Problem

1. Introduction

1.1 Problem contextualization

The global energy sector directly influences the competitiveness of modern economies. This sector covers all types of energy, such as electric, mechanical, thermal, among others. However, excluding the electricity share, energy production has increased dramatically in the last two decades, as result of developing countries' industrial and economic growth. If, on the one hand, the industrial expansion led to an ever-increasing supply of energy, the exponential growth in the world's population (especially in these countries) has drastically boosted the individual's energy consumption. Living habits, such as private cars, also lead to an increase. A great example of these characteristics is China, where the need for production reached 19.2% in 2013 (Dias et al., 2016). On the other side of the coin is the European Union, which goes against all the trends. If, on one hand, the population is decreasing, on the other hand, awareness of intelligent use of energy is becoming increasingly rooted in people.

Table 1: Forecast of energy source and relative weight, from 2010 to 2040

Fuel	**Quantity (Million barrels of oil equivalent per day)**				**Growth rate (%)**	**Fuel weight (%)**			
	2010	2020	2035	2040	2010-40	2010	2020	2035	2040
Oil	81.8	88.8	95.4	99.6	21.8	31.9	29.6	27.2	24.2
Coal	72.4	87.4	100.0	111.2	38.1	28.2	29.1	28.4	27.1
Gas	55.2	69.4	87.6	110.9	100.9	21.5	23.1	25.0	27.1
Nuclear	14.4	13.9	17.4	23.2	61.1	5.6	4.6	5.0	5.7
Renewable	32.6	40.8	51.0	65.2	100.0	12.8	13.6	14.4	15.9
Total	**256.4**	**300.3**	**351.4**	**410.1**	**59.95**	**100**	**100**	**100**	**100**

Table 1 stratified the energy consumption by source, as well as its forecast until 2040. It is noteworthy the idea already presented: the increase in energy production worldwide, with a forecast of 410.1 million barrels of oil equivalent per day for the year 2040. Several additional factors will influence the value of demand and, consequently, production, such as the increase life expectation and the fact that 68% of the population lives in urban areas (United Nations, 2018).

Moreover, it is relevant the increase in oil production, with a growth rate of 21.8%, even though its comparative share decreases by 7.7 percentage points. It would be expected, considering all the existent environmental agreements, that this, one of the main polluters, would have a total quantity decrease. This value is justified by the referred population growth, by the increasing use of this form of energy in the petrochemical industry in India and China, and also because automobile sector is mainly dominated by cars powered by gasoil and gasoline derivatives, even if it is foreseeable that the consumption per car would decrease in the next few years. In addition, it is forecasted that there will be a decrease in maritime supply due to the rules and regulations issued by the International Maritime Organization (IMO) (Lichtblau, 2014).

Changing the spotlight to the oil weight in the economy, it is important to analyse the European case. It is verified an opposite trend when compared to the rest of the world: there are several primary energy sources, but nuclear energy production stands out in the main one, with 28.7% of the total, as crude oil only represents 9.1% (Dias et al., 2016). In total, however, there is quite low primary energy production for needs' satisfaction, indicating an European case peculiarity: there is a gap between production and consumption, leading to high dependence on importations, for example, of crude oil which has about 88.4% of dependence (Dias et al., 2016). This fact is justified by the scarcity of oil pits in the European continent, which are concentrated in other geographical areas, such as the Middle East and Africa. This indicator shows necessity of European seaports where the oil arrives from the exporting countries, be well organized and operationally efficient.

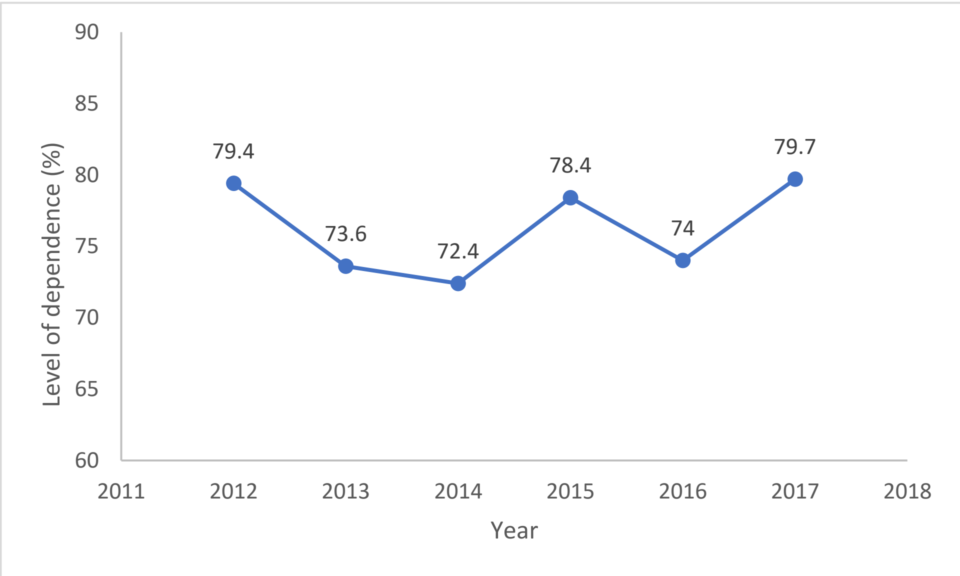

Figure 1: Portuguese level of energy dependence from 2012 to 2017 (DGEG, 2020)

Deepening the analyses of oil in the economy, the Portuguese case follows the European trend. It is observed in Figure 1 that from 2012 to 2017 the energy dependency level remained stable between 2012 and 2017. It was verified a minimum value of 72.4% in 2014 and a maximum of 79.7% in 2017. Nevertheless, such a high value on this parameter indicates that importations are a crucial factor for the country's energy sector, reaching the same end previously mentioned for the European case: seaports, particularly Liquid Bulk Terminals (which, in Portugal, are located in Sines and Matosinhos), must be operationally efficient.

Therefore, logistics efficiency is a central aspect on daily port's operation since it leads to economization of resources, money, and time. For that, a proper policy for managing the vessels and an efficient allocation of them to terminals' berth and pipelines should be oriented to an overall process optimization, to facilitate subsequent activities (such as oil and derivatives distribution). The problem of managing vessels' allocations is called, in the literature, as Berth Allocation Problem (BAP).

In Portugal, Galp Energia group has a fundamental role in this area, holding the two largest Liquid Bulk Terminals in the country: Matosinhos and Sines. The latter, the largest one in Portugal, will have a major importance on energy sector's development, requiring a deeper study on its operations and policies.

1.2 Objectives

The ultimate objective of this dissertation is the application of an operational research methodology to Sines' Liquid Bulk Terminal operations, to provide recommendations of improvements on its operational policies and financial issues.

To achieve the above, the minimization of terminal's performance indicators such as Port Operational Time and Demurrages, which will be defined in this dissertation, are crucial. Given the complexity of all the variables and parameters related to the terminal's activity, intermediate objectives are proposed:

- Search in the literature related to the topic if a gap exists and how it should be fulfilled
- Evaluate the variability of systems' parameters, identifying whether it exists and how should be mitigated
- Proposing alternative scenarios for the operations of the terminal
- Evaluate and produce recommendations about terminal's policies of allocation of vessels to berths and pipelines

1.3 Research methodology

To achieve the objectives above, a research methodology is proposed in Figure 2:

Figure 2: Research methodology

Each step in this research methodology is now explained:

- **Introduction and case study:** An introduction focused on the oil industry at global, European, and national level was developed. Subsequently, the case study sought to explore the Sines' Liquid Bulk Terminal case, emphasizing the problem of the allocation of vessels to berths and pipelines

  Literature review: In a literature review, it will be explored and understand the methods used to solve the Berth Allocation Problem, passing through several operational research approaches. A gap in the state of art will be identified to propose a proper methodology for the problem at hand
- **Model Building, verification, and validation:** To start implementing a simulation model it is crucial that the problem is structured effectively. The idea will be to understand real system's

logic and simplify it through diagrams for a better comprehension of the problem so that, afterwards, it can be implemented in a computer software. In this dissertation, SIMUL8 will be used. Verification allows comparing the conceptual model produced with the representation in the software and recognize anomaly in the structural logic of the implementation. It is important to test the model for completely different scenarios, forcing it to produce results in hypothetical situations with distinct efforts to the system. On the other hand, validation consists in comparing the model behaviour with the real system. It is a very important step in the simulation process, as it allows the model be accepted by decision makers to explore alternative scenarios (Carson & Nicol, 2014). Real data from Sines' Liquid Bulk Terminal will be used as an input in this validation phase

- **Data collection and analysis:** collect and analyse data on vessels' arrival, operating and setup times from Sines' Liquid Bulk Terminal, eliminating outliers that distort information to implement reliable data. Afterwards, identify known or empirical probability distributions to model the data to input in the simulation model.
- **Model application and results:** The evaluation is made in 2 steps: estimate of scenarios' performance and comparison of scenarios. The first allows to test each scenario for one or more Key Performance Indicators (KPI) and compare it with the real system. The second, in turn, allows comparing the outputs' quality of two or more scenarios under the same KPI, using methods, such as Bonferroni method (Carson & Nicol, 2014)
- **Recommendations:** Recommendations are made based on scenarios evaluation. Limitations while performing the dissertation and future work are also highlighted.

1.4 Dissertation structure

This dissertation is structured in 7 chapters, which will allow the problem to be framed in the current context, as well as giving a common thread linking the objectives, the problem and methodology followed:

- **Chapter 1** - Introduction: In this first chapter the contextualization of the energy sector is made, particularizing for the European and Portuguese case. Then, the objectives of the dissertation are presented, as well as the structure followed.
- **Chapter 2** - Case Study: this chapter starts with an overview of a maritime terminal's operation. Afterwards, Port of Sines is introduced, particularly the Liquid Bulk Terminal. Characteristics such as vessels' arrival and products handled are defined, as well as the limitations and the problem itself.
- **Chapter 3** – Literature review: Studies on how to address the Berth Allocation Problem are described. It is divided in containers and Liquid Bulk Terminals and, within each, a division is made based on mathematical optimization, heuristics and meta-heuristics and simulation and simulation-optimizations approaches. Afterwards, gaps in the literature are highlighted through a literature review characterization.

- **Chapter 4** – Simulation model: the simulation model is described through as a conceptual model with the objective of simplifying the Liquid Bulk Terminal operations. The Key Performance Indicators and variables of the system are also defined. Afterwards, implementation of the conceptual model in performed on SIMUL8 software.
- **Chapter 5** – Data analysis: the real data of the terminal are evaluated, and statistical distributions are inferred from them to implement data in the simulation model. The model is validated by comparing the real outputs of the Key Performance Indicators with the outputs of the simulation model under the same conditions.
- **Chapter 6** – Results: alternative scenarios to the real situation of the Sines' Liquid Bulk Terminal are proposed. The results of each scenario are evaluated, divided by their time horizon. The best scenarios are selected for the terminal operations
- **Chapter 7** – Conclusions: Conclusions on the work done are presented, as well as its limitations and future development.

2. Case Study

This chapter aims to provide information about Liquid Bulk Terminals in a general way and particularly define the operations performed at the Liquid Bulk Terminal of Sines. It is divided into two sections: definition of maritime terminal activity and characterization of Sines' Liquid Bulk Terminal. In the first, the terminal operation will be defined, emphasizing the importance of the Port Operational Time (POT), Demurrages and the Berth Allocation Problem (BAP). In the latter, the Liquid Bulk Terminal is detailed, highlighting the existing limitation.

2.1 Liquid Bulk Terminal

2.1.1 Liquid Bulk Terminal characteristics

A maritime terminal is an organization that provides a complete logistics service (handling, storage, control, and transport of cargo), which simultaneously, intends to minimize the associated costs. However, the logistical value associated with is obtained by the combination of transport and storage (primary functions) and by the value creation in the logistics service (secondary function) (Umang et al., 2011).

There are several types of maritime terminals from which stand out, by the quantities handled, containers and liquid bulk ones. Each terminal requires specific handling mechanisms: for containers, cranes are necessary, while in Liquid Bulk Terminals a pipeline system is required (Robenek et al., 2014). The present dissertation will focus on Liquid Bulk Terminals, particularly on the Sines' one, which is illustrated in Figure 3.

Figure 3: Liquid Bulk Terminal of Sines

In general, a Liquid Bulk Terminal has some operations and aspects that characterise it. When a **vessel arrives** at a terminal it is allocated to a **queue to dock**, where it waits its **allocation to berths**. This will depends on characteristics such as vessel's length, quantity transported, among others. Within each berth, the **vessel is allocated to a pipeline**, considering the product type or quantity. Therefore, operationally, an efficient allocation of vessels to berths is as important as allocation of vessels to pipelines.

These vessels' allocation to berths and pipeline are crucial to terminal efficiency. In fact, this is a problem addressed in the literature as Berth Allocation Problem (BAP). This is an approach used to solve problems where allocation policies are a main concern. Then, in the scope of this dissertation, it is necessary to understand deeply what the BAP is about and what are its characteristics.

Given a maritime terminal's layout, the BAP models the allocation of each vessel to a berth, within a specified time horizon. Two specific assumptions must be established:

- Vessels must dock within the quay limits.
- Two vessels cannot occupy the same quay space at the same time.

There are other characteristics that deserve to be analysed, as Bierwirth & Meisel, (2015) suggests. Three attributes are considered for the problem classification, as demonstrates Figure 4:

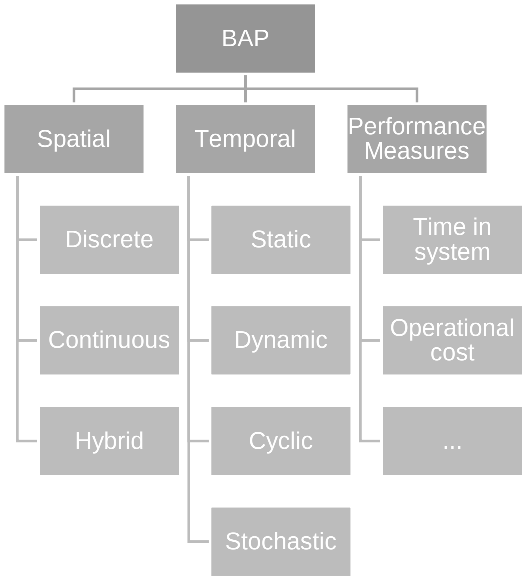

Figure 4: Features of Berth Allocation Problem (Adapted from: Bierwirth & Meisel, (2015))

The spatial attribute refers to the terminal layout, which is classified as **discrete, continuous** or **hybrid**. On one hand, a **discrete** quay is divided into point positions, called berths, which should be allocated to one and only one vessel. On the other hand, **continuous** considers that vessels can occupy any position at the quay. Merging the above two concepts lead to the **hybrid**, which consists of a partition of the quay in berths, with a possibility of each vessel to occupy more than one at the same time.

The temporal attribute concerns with vessels' arrival and is divided into **static, dynamic, cyclic,** and **stochastic**. In **static** classification, it is assumed that all vessels have arrived at the terminal and are waiting for being served. In the **dynamic**, each vessel arrives as an individual and with deterministic arrival time. In **cyclic**, vessels arrive at fixed time intervals. **Stochastic** classification assumes that every vessel arrives randomly according to a probability distribution.

Finally, the BAP is also categorized according to Performance Measures often associated with the **objective function**, such as minimizing total time in system, or even maximizing customers satisfaction.

2.1.2 Liquid Bulk Terminal performance

For management purposes, as well as to obtain performance indicators that allow the study of terminal's operations, it is relevant the definition of two Key Performance Indicators (KPI): Port Operational Time (POT) and Demurrages.

Firstly, POT defines the vessel's total time at the terminal since its arrival to its departure. Within this time interval, POT is divided in waiting Time for Docking (TD), Setup Time (ST) and Operational Time (OT), as mathematically translates Equation (1):

$$POT = TD + ST + OT \tag{1}$$

The first term, TD, represents how long a vessel waits to dock at a berth. It concerns the time interval between the vessel's arrival at the terminal (sea area) and its berthing. This time will change according to rate of vessels' arrival, time in system of the vessel ahead of it in queue and usage of the pipeline line. Since, in real operations, these are stochastic variables, there is considerable variability associated with TD and, consequently, POT.

The second, ST, refers to the time interval since the vessel docked at the berth and the start of reception/shipment operations, comprising all the inherent preparations. This will depend on the time that port workers need to start operations, and berth operational characteristics, for example.

Finally, OT represents the time a vessel is loading/unloading products through the pipeline system and depends on:

- Variations on the product pressure inside the pipeline
- Pump capacity: as this increase, OT decreases
- Pipelines' diameter: if a product operates in a pipeline with a higher diameter, OT tend to decrease

The 3 factors mentioned depend exclusively on the characteristics of the pipeline system and may only differ according to transportation efficiency. Generally, since the 3 terms mentioned have uncertainty associated, POT will be variable, which impact on terminal performance assessment.

Graphically, the relationship between POT and the vessel's path from its arrival to its departure from the terminal is explicit in Figure 5 (Rato, 2018).

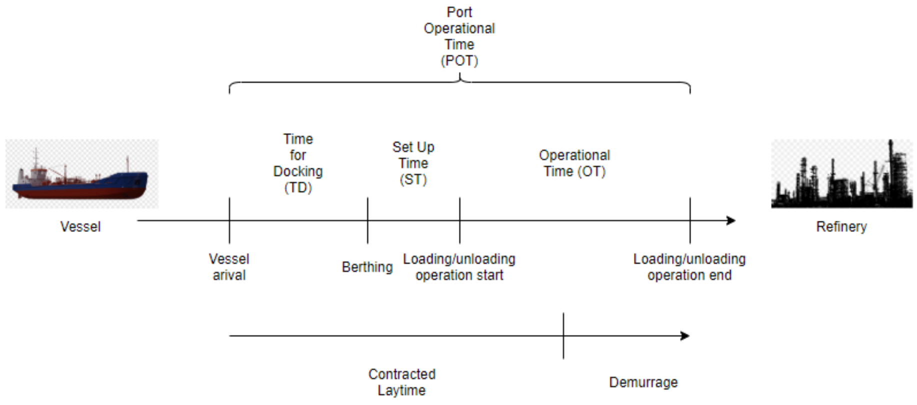

Figure 5: Relation between Port Operational Time and the vessel's path

Besides POT, the Demurrage is also an important performance indicator.
For each arriving vessel, a contract is stablished between port's management and the vessel's responsible, comprising all rules, operations, specific allocations, and the Contracted Laytime (CL). The latter works as the maximum time a vessel can stay at the terminal, and, if exceed, will have a financial penalty for the terminal. This overtime is called Demurrage and is a relevant performance indicator since it will measure operational and financial losses. It is calculated as follows in Equation (2):

$$\begin{cases} Demurrage = POT - CL, & if\ POT > CL \\ Demurrage = 0, & if\ POT < CL \end{cases} \tag{2}$$

Naturally, since CL is a fixed value for each vessel, Demurrages will only depend on variations of POT. If POT has variability, Demurrages will have and if **POT increases, Demurrages will increase as well.** With both Port Operational Time and Demurrages defined, the characteristics of Sines' Liquid Bulk Terminal are now described, and the operations will be evaluated according to these Key Performance Indicators.

2.2 Liquid Bulk Terminal of Sines

2.2.1 Characteristics

The Liquid Bulk Terminal of Sines was inaugurated in 1978 and is currently managed by CLT - *Companhia Logística de Terminais Marítimos*, which belongs to *Galp Energia* Group. It is the largest terminal of its type in Portugal and one of the largest in Europe, dimensioned to be a deep-water terminal and to possess a multiclient and multiproduct architecture. It has six berths and capacity to receive vessels up to 350000 Deadweight tonnes. It has a network of pipelines allowing the transportation of products within the port and linking it to the Sines refinery (Sines, 2020).
Besides the liquid bulk one, in Sines' Port there another 4 terminal types. Table 2 compares the handled cargo operated by terminal in 2017 and 2018 (ALGARVE, 2019):

Table 2: Quantities traded on Seaport of Sines' terminals in 2017 and 2018.

Terminals	**Quantity (kton)**		**Variation (%)**
	2017	2018	
Natural Gas	2853	2644	-7.33
Multipurpose	5317	6487	+22.00
Containers	22072	20912	-5.26
Petrochemical	398	536	+34.67
Liquid Bulk	17243	19307	+11.97

Based on the information of Table 2, the Containers terminal is the one with the biggest movement of goods, with 20912 kton in the past year of 2018. On the opposite side, the least representative terminal is the Petrochemical one, with only 536 kton in the same year. However, the Liquid Bulk Terminal has the second highest quantity operated in 2018, with 19307 kton, increasing 11.97% compared to the previous year. It was a high growth in relative and absolute values, showing that a study of its operation is relevant to assess if the operational efficiency is not jeopardized with the increase of product quantity handled.

Besides this quantity handled data, Liquid Bulk Terminal has some specific characteristics. It has 6 berths (denoted from 2 to 7) where vessels can dock and where they carry out their operations through the pipeline system, which, in turn, is connecting the terminal with the refinery. Each berth has its own specific characteristics, as demonstrated in Table 3 (Sines, 2016):

Table 3: Characteristics of Liquid Bulk Terminal berths

Berth	**Total vessel's length (m)**		**Capacity (ton)**	**Draft (m)**	**Size of the loading arm (m)**	
	Min	**Max**		**Max**	**Min**	**Max**
2	240	350	>70000	28	5.6	28
3	135	282	>7000 to 70000	17	3.8	18
4	135	295	>7000 to 70000	18	3.8	18
5	110	282	>7000 to 70000	17	3.8	18
6	70	110	<7000	10	2.5	9
7	70	106	<7000	10	2.5	9

The berth with the largest capacity is berth 2 which can receive vessels with more than 70000 tonnes of product transported. Simultaneously, berthing is permitted to vessels with a maximum of 350m, the longest ones permitted at the terminal. On the opposite side, berths 6 and 7 are exclusive for small product transactions, up to 7000 tonnes.

The draft characteristic (vertical distance between the water surface and the lowest part of the vessel's keel) and size of loading arm are directly proportional to the vessel length and the terminal capacity. Hence, when the capacity of the vessel increases, draft increases and, therefore, the size of the loading arm required becomes longer. These characteristics are verified for all berths on the Table 3.

These capacity and length restrictions constraint the allocation of vessels to berths.

2.2.2 Vessels' arrivals

The capacity of a terminal is also related to its capacity for receiving vessels. Then, it is relevant to note the total number of vessels at the Liquid Bulk Terminal and their distribution throughout the year. Statistics are shown in Figure 6 for year 2017 (Rato, 2018).

Figure 6 shows that the vessels' arrival had some variability. On one hand, November recorded the lowest value with 41 vessels (1 every 18 hours) and, on the other hand, in January the terminal operated 57 vessels (1 every 13 hours).

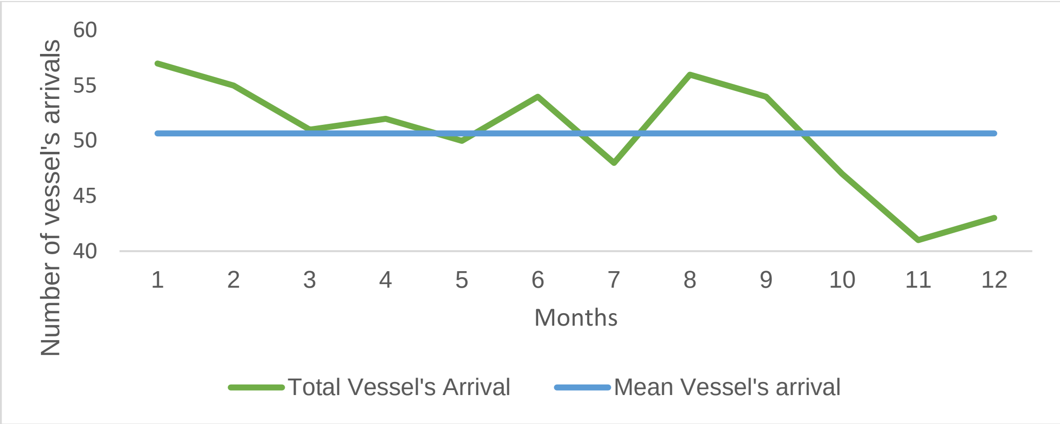

Figure 6: Vessels' arrival in 2017

Comprehensively, there is a variability in the arrival of vessels leading to an increase in the waiting time for each to dock, as there will be more in queue for each berth from month to month. This demonstrates that it is necessary to consider the variability of the data, especially on arrivals of vessels, since it will directly influence the terminal's operation.

2.2.3 Products

After the analyses of the vessel's arrival to the terminal and the characteristics of the same one in a general way, it is essential to know which products and in which quantities are allocated to berths. Sines' Liquid Bulk Terminal handle 6 types of products:

- Crude,
- Liquid Petroleum Gas (LPG),
- Fuel and Vacuum Gasoil Oil (VGO),
- Gasoline and Components,
- Gasoil
- Naphtha.

Although the *Galp Energia* Group's core business is the exploration of oil products and natural gas, its scope of refining and distribution operations leads it to produce for consumption and subsequent exportation. Therefore, Crude represents an important product for future transformation in several oil derivatives, being basically only received at the terminal. On the other hand, Gasoline and Gasoil are mainly shipped.

When a vessel arrives at the terminal, its allocation to berth will depend on the product transported, as displays Table 4.

Table 4: Allocation policy of products to berths

Products	Berths					
	2	3	4	5	6[1]	7[1]
Crude	x					
LPG		x	x	x	x	x
Fuel		x	x	x		
Gasoline		x	x	x	x	x
Gasoil		x	x	x		
Naphtha		x	x	x		

Table 4 shows that vessels transporting Crude are exclusively allocated to berth 2, as it is the one with highest capacity. Berths 3, 4 and 5 are used by vessels transporting all kind of products except Crude, while berths 6 and 7 are exclusives for quantities less than 7000 tonnes of LPG and Gasoline.

On the other hand, Figure 7 summarize the quantities of each product transacted per berth, divided into receptions and shipments, in the year of 2017.

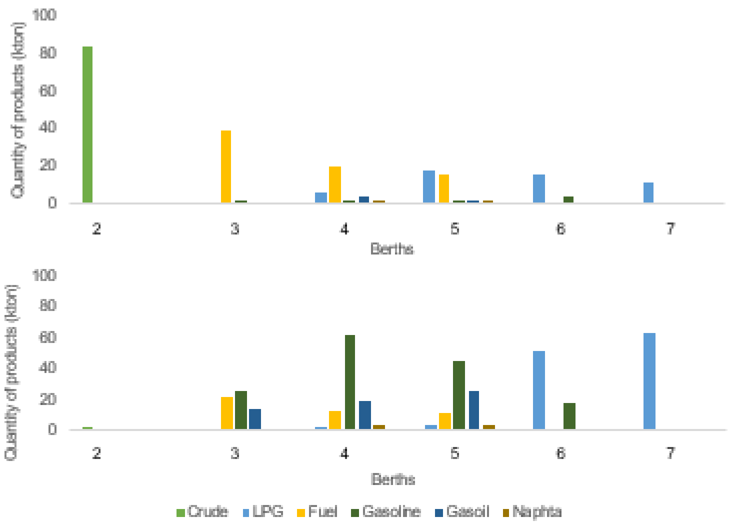

Figure 7: a) Quantities received by product by berth; b) quantities shipped by product by berth

In Figure 7 a), the receptions by product by berth are explicit. Crude transactions stand out, as it was received nearly 80 kton of product in 2017, exclusively on berth 2. It is also noticeable that Fuel is received in high quantities, operating on berths 3, 4 and 5. Finally, LPG receptions are made in relative small quantities on berths 3, 4, 5, 6 and 7. This last two berths, as mentioned, are exclusive for small quantities of this product and Gasoline.

On the other hand, Figure 7 b) displays the quantities shipped by product by berth, in 2017. In this, LPG stands out with nearly 50 and 60 kton in berths 6 and 7, respectively. Since these berths only operates

[1] Only for quantities less than 7000 tonnes

vessel up to 7000 ton, it appears that many LPG vessels are shipped from the terminal in small batches. Gasoline also reveals high quantities shipped, mainly on berths 3, 4 and 5. It follows that Gasoline shipments are taken in high quantities per vessel.

In general, Crude is mainly received while LPG, Gasoil and Gasoline are mainly shipped. This conclusion based on Figure 7 is in accordance with GALP core business: receiving Crude and processing it into derivates so they can be shipped for sale.

2.2.4 Pipelines

For the operation of the Liquid Bulk Terminal to be efficient, besides the capacity of the berths to operate the vessels, it is also fundamental that the pipeline system is appropriate for terminal's needs.

Sines' Liquid Bulk Terminal has a set of pipelines with different diameters with a length of 8 km connecting the refinery to the terminal. There are 6 pipelines, each one with distinct diameter. All 6 have loading arms that allow them to reach the berths. The loading arms have one operational restriction: if one is being used at some time, the remaining become unavailable until the end of the operation.

Table 5 shows the pipelines' loading arms available at each berth. For confidential reasons, their diameters are not available, assuming A-diameter pipeline as the largest and F-diameter pipeline the smallest one.

Table 5: Number of loading arms of each pipeline in each berth

	Berth 2	**Berth 3**	**Berth 4**	**Berth 5**	**Berth 6**	**Berth 7**
Pipeline A	2	2	2	2	0	0
Pipeline B	0	1	1	1	1	1
Pipeline C	0	1	1	1	1	1
Pipeline D	0	2	2	2	2	2
Pipeline E	0	1	1	1	1	1
Pipeline F	0	1	1	1	1	1

Based on Table 5, it is clear that each pipeline has loading arms where it is needed. For example, Pipeline A is the one with the highest diameter, and has 2 loading arms in berths 2 to 5 (even though, most of the times, it is only used berth 2). It can also be noticed the non-existence of Pipelines A in berths 6 and 7, because they are dedicated to small quantities, not requiring a high diameter pipeline.

Pipeline F, on the other hand, have 1 loading arm in all berths, except for berth 2, the one with highest capacity.

As an example, Figure 8 illustrates the arms and pipeline availability of Pipeline B.

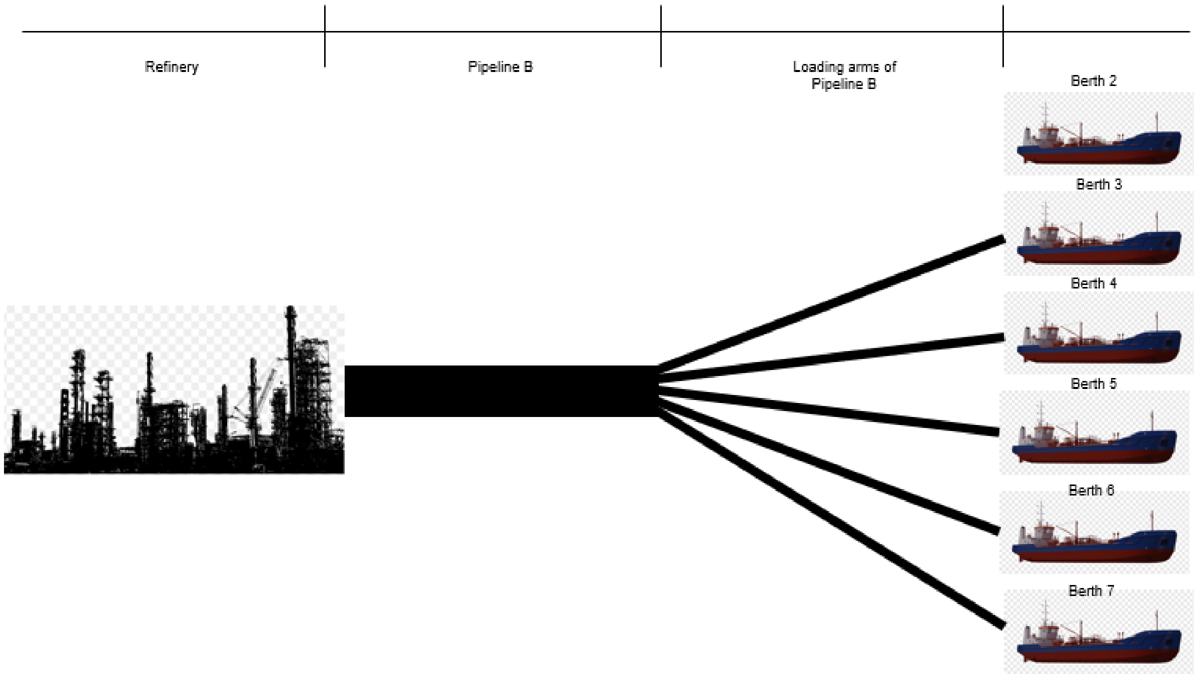

Figure 8: Distribution of loading arms of pipeline B to berths

Besides the restriction of pipeline usage when one loading arm is operating, there are also constraints concerning the product allocation to pipelines. These allocations are shown in Table 6, considering reception and shipment.

Table 6: Policy of products' allocation to pipelines, by reception and shipment

	Pipeline A	Pipeline B	Pipeline C	Pipeline D	Pipeline E	Pipeline F
Reception	Crude	Fuel	Gasoil	-	Gasoline+ Naphta	LPG
Shipment	Crude	-	Fuel + Gasoil	Gasoline	Naphta	LPG

Table 6 confirms same inferences made previously. Crude is allocated to Pipeline A since it is the product with the highest quantity operated at the terminal. LPG, on the other hand, uses Pipeline F for receptions and shipments, because it operates high quantities but in small batches. Finally, Gasoline is allocated to Pipeline E in receptions and Pipeline D in shipments. As it was mentioned when analysing Figure 7, Gasoline shipments are made in high batches, therefore, this operation needs a pipeline with higher diameter than reception for this product.

In general, an inefficient allocation of product to pipeline will impact the overall allocation of the terminal and the time each vessel stays in the system, leading to a performance decrease.

Based on every terminal characteristic defined since the beginning of this chapter, it is now important to assess the performance of the Liquid Bulk Terminal, to identify the existing problem.

2.2.5 Performance

The performance assessment will be divided by the two KPI defined: first, the Port Operational Time will be evaluated and then the Demurrage characteristics are reviewed. It will be considered, for both KPI, the month of January 2017, the one where the most vessels arrived.

Port Operational Time

Based on the information available, it was considered the month with the high vessels' arrival to be explored and characterized (January 2017).

Table 7: Quantity of each product handled by reception and shipment, and divided by berth

Product	Vessels Arrival	Quantity (ton)	Shipment (ton)	Reception (ton)	Quantity per berth (%)					
					2	3	4	5	6	7
Crude	9	1,070,469	0	1,070,469	100	0	0	0	0	0
LPG	18	58,674	17,078	41,596	0	0	12.96	43.65	12.06	31.34
Fuel	9	237,791	86,336	151,455	0	29.83	40.52	29.65	0	0
Gasoline	13	264,814	260,937	3,877	0	38.65	37.06	20.05	4.25	0
Gasoil	4	164,325	164,325	0	0	20.06	20.06	59.87	0	0
Naphtha	4	679,71	67,971	0	0	22.67	20.94	56.39	0	0
Total	**57**	**1,864,043**	**596,646**	**1,267,397**	**57.43**	**11.89**	**13.37**	**15.34**	**0.98**	**0.99**

Table 7 shows that a total of 57 vessels operated in January of 2017, with a total of 1,864,043 tonnes. There were more than twice as many receptions at the terminal when compared to shipments (1,267,397 compared to 596,646 tonnes) and, of these receptions, 84.46% (1070469 tonnes out of total 1,267,397 tonnes) were from Crude vessels. On the other hand, Gasoline has the highest quantity on shipments, with 43.73% (260,937 tonnes out of total 596,646 tonnes) of total.

From the information on Table 7 using LPG as an example, 18 vessels transporting this product arrived, totalizing 58674 tonnes handled at the terminal. Segregating, 17078 tonnes were shipped while 41,596 tonnes were receptions (70.89% of LPG total quantity). Moreover, the division by berth made explicit the allocation of this product to all berths except berth 2 (even though, in this month, berth 3 was not used). 43.65 % of the quantity handled in January 2017 were allocated to berth 5 while 12.06% were to berth 6.

On the other hand, it is interesting to notice that the 164,325 tonnes of Gasoil transacted refer to only 4 vessels and, inversely, LPG, even though 18 vessels transported this product, was traded in low batches, summarizing 58674 tonnes.

Despite the dedication of Crude vessels to berth 2 (Table 4), this summed up the highest quantity operated. It is noteworthy the homogeneous quantity handled of berths 3, 4 and 5 (ranging from 11.89 to 15.34 % of total quantity operated), evidencing the allocation of all products other than Crude with more than 7000 tonnes; similarly, berths 6 and 7 operated homogenous quantities of Gasoline and LPG with less than 7000 tonnes, resulting in total quantities around 18000 tonnes.

Table 8: Port Operational Time characterisation

Product	TD (h)	TD relative percentage (%)	OT (h)	OT relative percentage (%)	ST (h)	ST relative percentage (%)	POT (h)
Crude	170.0	33.40	276.3	54.28	62.7	12.32	**509.0**
LPG	241.1	36.52	303.0	45.90	116.0	17.58	**660.1**
Fuel	75.2	23.41	193.5	60.22	52.6	16.37	**321.3**
Gasoline	206.9	27.06	374.6	48.99	183.1	23.95	**764.6**
Gasoil	26.0	17.18	96.0	63.45	29.4	19.37	**151.4**
Naphtha	99.9	34.31	164.6	56.52	26.7	9.17	**291.2**
Total	**819.1**	**30.36**	**1408.1**	**52.20**	**470.4**	**17.44**	**Crude**

Port Operational Time on January 2017 summed up a total of 2697.6 hours (Table 8). The Operational Time has the biggest impact, with 52.20% of total POT, followed by Time for Docking and Setup Time, with 30.36 and 17.44%, respectively.

The analysis by product highlights the Gasoline, LPG, and Naphtha. The product with the highest POT is Gasoline with 764.7 hours, with the OT representing 48.99%, while TD weights 27.06%. This behaviour reveals two terminal's inefficient policies: poor allocation of vessels to berth and pipelines. It would be possible to solve these inefficiencies by allocating the product to pipeline with higher diameter, minimizing OT, or by developing a more appropriate allocation to berths, minimizing TD. Both solutions would be interesting to evaluate further on.

LPG has the second higher value of POT, with TD weighting 36.52% of the POT (Table 8). This result is partly due to the 18 vessels operated, and due to poor allocation of vessels to berths or even because LPG, contrasting with the other products, is allocated to pipeline F in receptions and expedition, increasing the competition within LPG vessels for pipeline allocation (Naphtha and Gasoil are also exclusively allocated to pipelines E and C respectively, but in January 2017 they do not perform receptions).

Finally, Naphtha is not a product with a high total POT, although, since only 4 vessels operated in the terminal on January, the mean value of POT is 72.79 hours, nearly 3 days. Clearly, allocation of this product to pipeline E is operationally inefficient.

Therefore, the poor allocation of vessels to berth and pipelines constrain the operational efficiency of the terminal. having a huge impact on POT. The month considered was the most constraining of 2017, highlighting the fragilities of the system. However, these policies, naturally, intend to maximize the efficiency of the terminal but fail by not considering the variability of system's parameters, evidenced by the variability of POT. Hence, it is important to study this factor in a deeper way.

The data variability is illustrated in Figure 9 through the representation of POT data distribution.

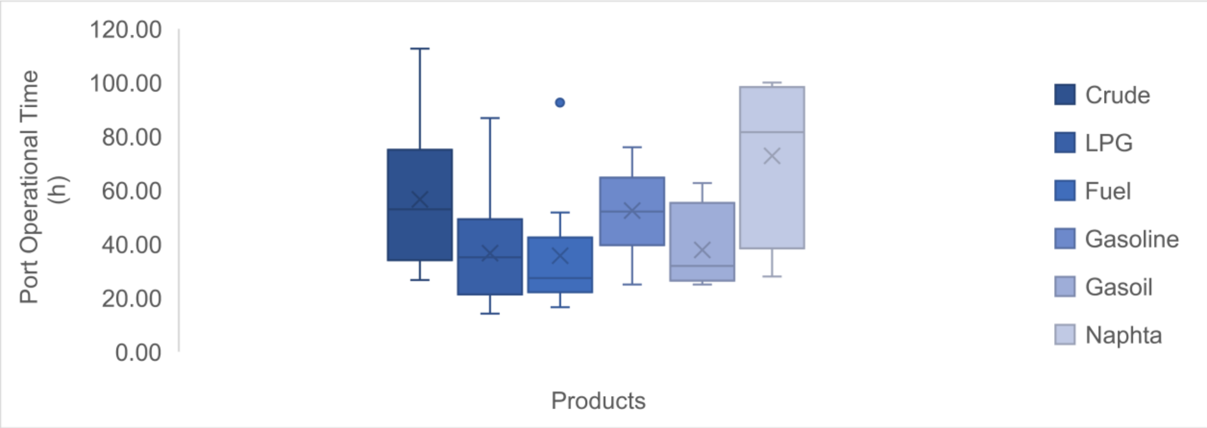

Figure 9: Port Operational Time boxplots by product

Table 9: Statistics of Port Operational Time boxplots

Products	P_{25} (h)	P_{50} (h)	P_{75} (h)	Inter quartile Amplitude (h)	Total Amplitude (h)
Crude	34.00	52.90	75.10	41.10	86.04
LPG	21.29	35.07	49.26	27.97	72.70
Fuel	22.13	27.40	42.43	20.30	35.20
Gasoline	39.65	52.14	54.76	15.11	51.05
Gasoil	26.43	31.84	55.25	28.82	37.67
Naphtha	38.42	82.58	98.37	59.95	72.00

As described in Figure 9 and supported by Table 9, Crude exhibit the wider amplitude of POT values, with Total Amplitude equal to 86.04 h. In addition, according to quartile 75, 75% of the data are below 75.10 hours while the median value stand at 52.90 hours. Similarly, Naphtha presents a high amplitude of values, with a median value of 82.58 hours. Finally, even though Fuel has the lowest median value, its vessels still have a 50% chance of having POT higher than 27.40 hours.

Table 10: Mean and Coefficient of Variation of Port Operational Time by product

	Crude	LPG	Fuel	Gasoline	Gasoil	Naphtha	Total
$\overline{POT}$ (h)	56.56	36.67	35.69	58.82	37.84	72.79	**47.32**
CV (%)	48.55	50.69	65.97	46.97	44.64	44.76	**55.22**

Table 10 presents the average and coefficient of variation (CV) of the POT for each product in January 2017. On one hand, POT mean value reaches its highest value for Naphtha (72.79 h), result of the 4 vessels operated. On the other hand, the lowest value corresponds to the mean time in system for Fuel, LPG, and Gasoil vessels, with 35.69, 36.67 and 37.84 h, respectively. On average, products remain at the terminal 47.32 hours.

The CV has its highest value for Fuel with 65.97%, followed by LPG with 50.69% (Table 10). Even Gasoil with the lowest CV has a value 44.64%. These variability on the data hinders the allocation policy, such as: if a vessel transporting Fuel is allocated to berth 3 for a reception operation, its POT will highly depend on the POT of the previous vessel and on the POT of the vessel that is using the loading arm to pipeline B.

However, POT variability does not explain himself where the allocation problem is. Therefore, it is interesting to deepen the analysis of terminal's performance by understanding if variability on the components that weight the most on POT (Table 8), Time for Docking (TD) or Operational Time (OT), explains its own variability.

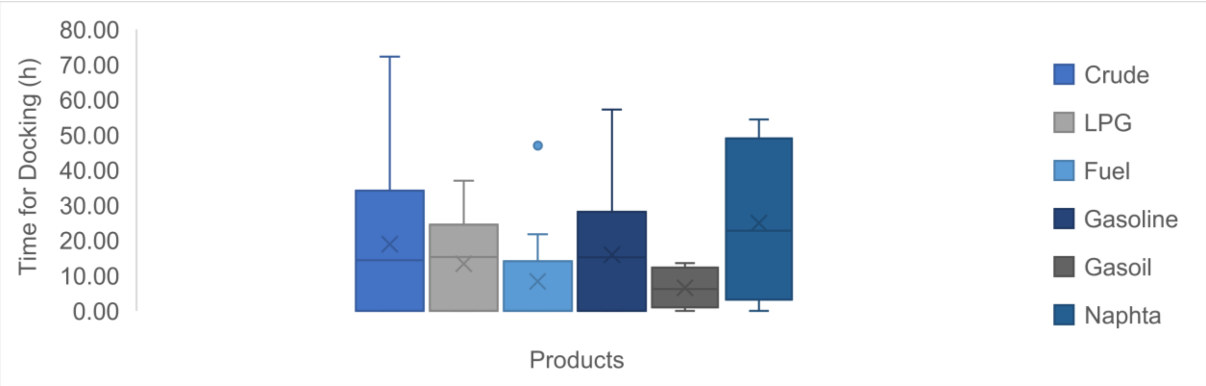

Figure 10: Time for Docking boxplots by product

Table 11: Statistics of Time for Docking boxplots

Products	P_{25} (h)	P_{50} (h)	P_{75} (h)	Inter quartile Amplitude (h)	Total Amplitude (h)
Crude	0.00	14.40	34.15	34.15	72.30
LPG	0.00	15.24	24.47	24.47	36.98
Fuel	0.00	0.00	14.10	14.10	21.80
Gasoline	0.00	10.69	22.67	22.67	33.40
Gasoil	0.00	6.19	12.28	12.28	13.58
Naphtha	3.12	22.73	49.05	45.93	51.28

The Fuel's Time for Docking is characterized in Figure 10 and denotes a total amplitude of 21.8 h. Vessels transporting this product are allocated to berth 3, 4 and 5, although, its TD is not as high as other products because:

- Pipeline B is exclusively allocated to Fuel's reception operation; for shipments, this product shares the allocation with vessels carrying Gasoil which, in January 2017, only arrived 4 vessels
- The arrival time of these vessels were at time intervals where berths were unoccupied

Nevertheless, Crude and Naphtha vessels had high variability on TD. On one hand, Crude has its high TD variability due to exclusive allocation to berth 2 only depending on other Crude vessels (vessels that usually had high operational time resulting of their enormous quantities operated). Naphtha, on the other hand, has its TD influenced by the allocation to berths 3, 4 and 5 and by enormous OT of previous Naphtha vessels on pipeline E.

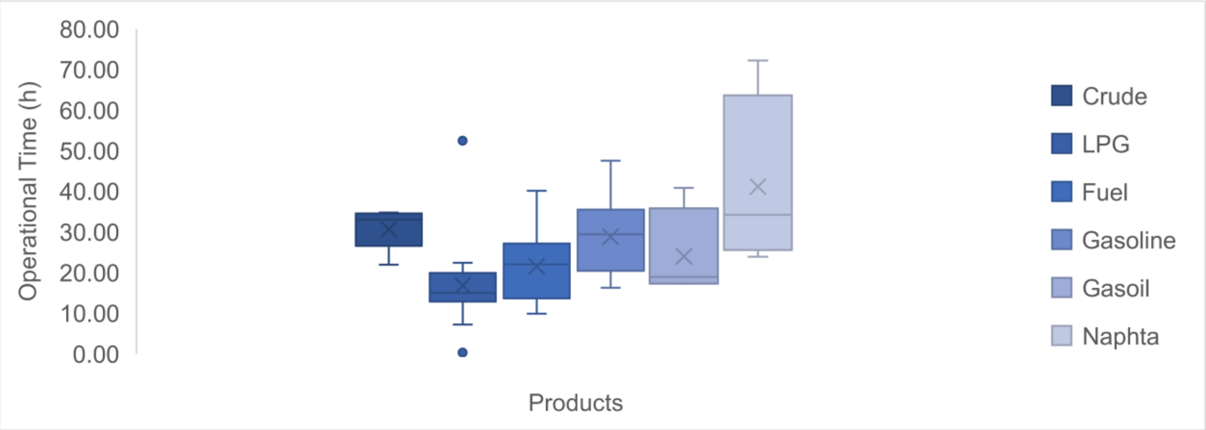

Figure 11: Operational Time boxplots by product

Table 12: Statistics of Operational Time boxplots

	P_{25} (h)	P_{50} (h)	P_{75} (h)	Inter quartile Amplitude (h)	Total Amplitude (h)
Crude	26.55	33.00	34.50	7.95	12.90
LPG	12.87	14.95	19.87	7.00	15.20
Fuel	13.65	22.00	27.10	13.45	30.20
Gasoline	20.42	29.40	35.45	15.03	31.27
Gasoil	17.30	18.95	35.78	18.48	23.53
Naphtha	25.53	34.25	63.65	38.12	48.27

In Figure 11 and supported by Table 12, the operational time of Naphtha stands out, not only due to its high values but also due to its variability. Naphtha is allocated to pipeline E, the second with the lowest diameter, meaning that quantities of this product are expected to be low. However, in January 2017, quantities operated were high, leading to pipeline overload and high values of OT (OT represented 56.52% of Naphtha's POT, with 164.6 hours (Table 8)). Moreover, the average and Coefficient of Variation (CV) of TD and OT for each product are shown in Table 13.

Table 13: Mean and Coefficient of Variation of Time for Docking and Operational Time, by product

		Crude	LPG	Fuel	Gasoline	Gasoil	Naphtha
TD	$\overline{TD}$ **(h)**	18.89	7.16	8.36	8.95	6.49	24.97
	CV (%)	129.34	180.58	193.76	197.20	89.92	95.62
OT	$\overline{OT}$ **(h)**	30.70	16.84	21.50	28.82	24.01	41.14
	CV (%)	15.71	61.61	43.75	35.21	47.17	52.22

The CV values for TD are very high, reaching 197.20% for Gasoline, with an average value of 8.95 h. This product is the third with highest CV for POT, with 58.82%.

On the other hand, CV values for OT are lower, reaching 15.71% for Crude. However, the remaining products range from 35.21% for Gasoline to 61.61% for LPG.

As conclusion, TD and OT impacts directly in POT variability. The product allocation to berths and pipelines requires a deeper analysis, considering the system variability to improve terminal's performance through an efficient allocation policy.

Demurrage

Another aspect reflected in the terminal performance is the Demurrage time and its costs. Demurrage is defined as the difference between the time a vessel spends at the terminal (POT) and the Contracted Laytime (CL) for that purpose. Despite being an operational indicator, allowing the quantification of how much time each vessel exceeds the contracted time at the terminal, it has a financial impact.

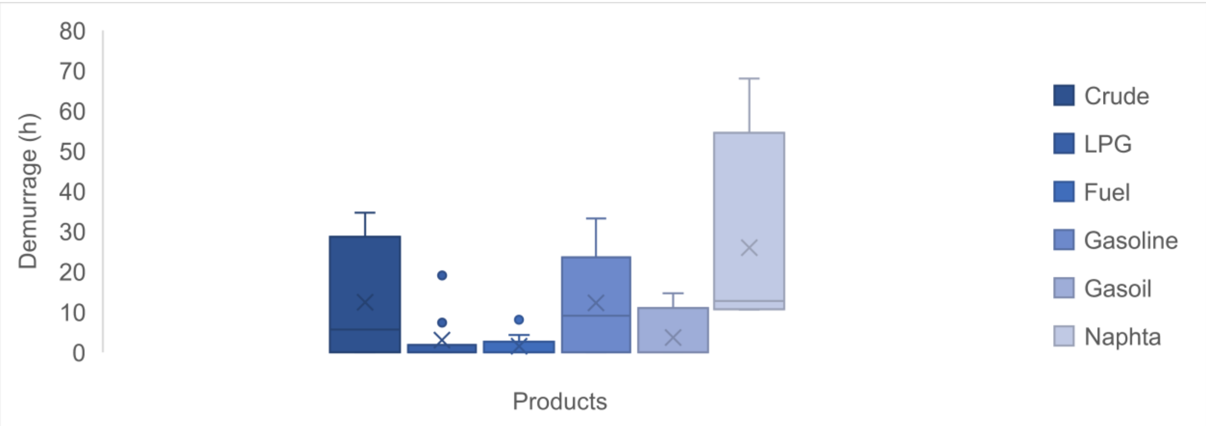

Figure 12: Demurrage boxplots by product

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Naphtha, Crude and Gasoline were previously referred to as the products with the highest and more variable Port Operational Time, by that order. The same pattern is illustrated in Figure 12, leading to conclude that products with high POT tend to have high Demurrages: **as POT increases and varies, Demurrages increase and varies**, and the inherent costs will get higher and more variable. Crude, as Figure 12 shows, has 75% of Demurrages in a total amplitude of 28.71 hours. However, its median value is 5.6 hours, which mean 50% will be higher than this value. On the other side, Fuel and LPG Demurrages are practically inexistent.

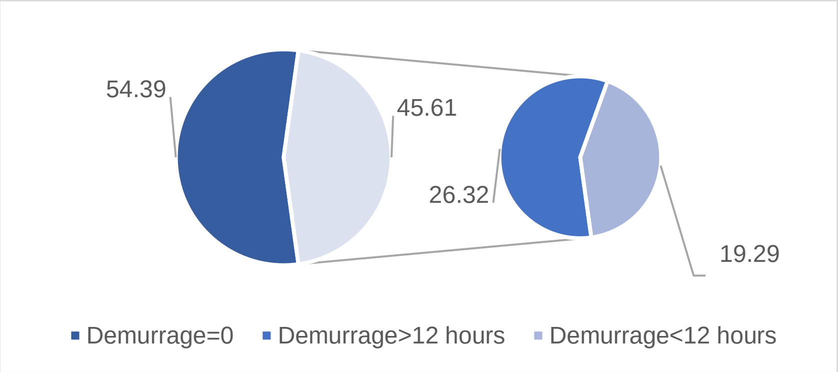


Figure 13: Comparison of vessels with Demurrage time equal to zero and higher than 12 hours

Figure 13 illustrate that 54.39 % of vessels had Demurrage equal to zero, therefore, does not incurring in financial costs for the company. However, from the 45.6% that incurred in financial costs, 26.32 % exceeded 12 hours of Demurrage, incurring high finance penalties, as shown in Table 14.

Table 14: Demurrage mean time and costs estimation by product

	Crude	LPG	Fuel	Gasoline	Gasoil	Naphta	Total
Demurrage (h)	112.1	54.0	13.4	278.6	14.7	104.0	**576.7**
Demurrage (€)	205599	21875	11061	201007	13444	63729	**516715**
Cost/hour (€/h)	1834	405	825	721	915	613	**-**

Table 14 demonstrates the Demurrage average values and an estimation of total cost by product in January 2017. The highest Demurrage time is for Gasoline, with 278.6 h and the lowest for Fuel with 13.4 h. Crude has the highest financial impact in costs with 205599 €., hourly costing 1834€ for the company.

Overall, 576.7 hours of Demurrage incurs in 516715€ of penalty costs for the company.

2.3 Final remarks

Throughout this chapter, the operations of a Liquid Bulk Terminal and performance indicators used, the Port Operational Time (POT) and Demurrages, to evaluate it were described in a first phase. In a second phase, the particular case of the Liquid Bulk Terminal at the Port of Sines was addressed. In this, the berths' characteristics, vessels' arrival, products handled, and pipelines system were explained, culminating in the evaluation of their performance considering the performance indicators previously defined.

That said, to detect the terminal limitation, it was concluded that the POT was high reaching a total of 2697.6 hours (Table 8). Its value becomes more evident, when it is divided by product. Vessels carrying Crude, LPG, Gasoline and Naphtha tend to have high POT. Similarly, when the variability of this indicator is analysed, the same products that had high POT, also show a high variability.

Afterwards, it was important to understand the origin of this variability, analysing the waiting Time for Docking and the Operational Time of each product. It is concluded that the TD of Crude and Naphtha are quite variable, introducing uncertainty in their POT. In the same way the OT proved to be variable for vessels transporting Naphtha, also influencing its POT.

Finally, Demurrage was analysed, and it was concluded that the products with the **highest POT tend to have higher values of Demurrage time.** The high values of Demurrage time incur in high costs, which should be mitigated. On the other hand, products with variable POT tend to have variable Demurrage.

Therefore, there is a chain of variability: products with higher and variable waiting, and operating times make the total time at the terminal and subsequently the time and cost of Demurrage higher and variable. However, these factors do not justify themselves, meaning there are root problems at the terminal. Such are:

- Bad allocation of vessels to berths
- Misallocation of products to pipelines
- Under-dimensioning of some berths, for example, berth 2 (although its resolution is not part of this dissertation)

In this way, and to overcome the aforementioned limitations, some solutions are proposed:

- Change Naphtha's from Pipeline E to Pipeline D, aiming with the increase of the pipeline' diameter, minimizing the Operational Time and consequent waiting time of the following vessels
- Vessels carrying LPG can use the pipeline E if their quantity exceeds 7000 tonnes
- Gasoline change its allocation to larger diameter pipelines, both for shipments and receptions
- All products may use berths 6 and 7 provided the quantity transported by their vessel is less than 7000 tonnes.

The aim of these solutions is not only to reduce the Port Operational Time of each product, but also to mitigate the variability by it and its constituents. In this way, it will also be possible to minimize the Demurrage, which represents the major problem for the terminal.

3. Literature Review

According to case study analyses, on one hand, it is relevant to know how the papers presented in the literature address the Berth Allocation Problem (BAP), to have a background on how to deal with terminal's problem (poor allocation of vessels to berths and to pipelines). On the other hand, it is also important to understand how to explore this problem with uncertainty associated. That said, it is expected to acquired knowledge to implement a methodology that improves the performance and minimizes the terminal costs.

The literature review timespan is from 2001 to 2019. This chapter is divided in four subsections. The first identifies methods to tackle the BAP, which are addressed in two subsection 3.1 and 3.2 for Container and Liquid Bulk Terminals, respectively. Afterwards, a statistical characterization of the literature review is presented in 3.3 followed by final remarks in section 3.4.

Despite the work addressed in the dissertation falls within Liquid Bulk Terminals problems, the increase importance of container terminals lead to the reference of these terminals as well in this literature review (de Oliveira et al., 2012).

3.1 Containers terminals

Optimization

In this first section the papers that solve the Berth Allocation Problem (BAP) using mathematical optimization models are reviewed. Usually, they formulate the problem as a Linear Mixed Integer Problem or even a Mixed Integer Non-Linear Problem, linearized later. These methods aim to achieve optimal solutions using appropriate computational software.

Raa et al. (2011) addressed the Berth Allocation Problem (BAP) and the Quay Crane Assignment Problem (QCAP) simultaneously. It was formulated a Mixed Integer Linear Programming (MILP), considering the minimization of three factors: handling time of vessels (considering the penalties for delays); berthing position, including penalty for the deviation of the vessel from the optimal position and penalty for the change of the number of cranes assigned to a vessel when the service is already undergoing.

In the same year, Du et al. (2011) tackled the continuous BAP and proposed a Mixed-Integer Non-Linear Programming (MINLP) model whose objective was the minimization of vessels delays in berths. Moreover, it adds a new objective to Raa et al. (2011) formulation: minimization of fuel consumption. By combining these goals, as well as the associated constraints, lead to a model computationally inefficient. To overcome this fact, the authors linearized the model using the Second-Order Cone Programming (SOCP). Two years later, Wang et al. (2013) took up this problem with the same objectives and applied the quadratic outer approximation approach reaching results as efficient as Du et al. (2011), with higher computational efficiency.

Hu et al. (2014) addressed the Berth Allocation and Crane Assignment Problem (BACAP), adding to the fuel consumption minimization of Du et al. (2011) the emissions minimization when vessels sailed and moored. A MINLP model was developed and linearized using SOCP. The authors concluded the port operation cost is inversely proportional to the fuel consumption. This paper adds to the work of Du et al. (2011) and Wang et al. (2013) the impact of quay-crane allocation on fuel consumption, as well as estimating vessels' emissions when docked.

Agra & Oliveira, (2018) addressed the BAP and Quay Crane Scheduling Problem (QCSP), considering heterogeneous set of cranes, through Mixed Integer Programming (MIP) formulation. Also developing a MIP model, Wang et al. (2018) studied the BACAP, and compared two policies of carbon emissions taxation rates. In the same year, Iris et al. (2018), developed another MIP allied to a Generalized Set-Packing (GSP) problem, in order to solve the Strategic Berth Allocation Problem (SBAP).

Correcher et al. (2019) also focused on the BACAP, specifically on its continuous variant with time-invariant crane assignment. The authors developed a MILP model to minimize the planning costs exploring the branch-and-cut algorithm for the iterative process.

Heuristics and meta-heuristic

However, it is not always possible through optimization to reach optimal solutions in useful computational time, so heuristic methods emerge as good solutions to solve problems of high complexity in good computational time, reaching optimal or near-optimal solutions.

In 2002, Guan et al. (2002) used a Generic Multiprocessor Task Scheduling (GMTS) model and applied it to the BAP with the objective of developing the schedule and sequencing for a given number of vessels that are worked on multiple consecutive cranes simultaneously, while minimizing the total weighted completion time. Five years later, Wang et al. (2007) solved the same problem combining three meta-heuristics: an improved beam search scheme, a two-phase node goodness estimation, and a stochastic node selection criterion. At the macro level, the problem was divided into multiple stage decision model, with the BAP being the centre of the system.

Imai et al. (2008) defined the BACAP in its discrete dimension. BACAP was then divided. BAP is formulated including the start and completion time of vessels' handlings. Considering that the size of the problem increases with the presence of these variables, the time gap variables were eliminated from the formulation with the objective of minimizing the total service time. To reach BACAP, only restrictions related to the crane's usage were added. Due to the complexity of the problem, a Genetic Algorithm (GA) was employed to approximate the solution providing good results even with additional restrictions. The only gap in this formulation is that it does not consider the relationship between the handling time and the number of cranes.

Golias et al. (2009) formulated the BAP as a combinatorial multi-objective optimization problem, where the total service time is minimized considering vessels priority agreements. The problem is solved using a GA, providing a set of solutions that allows the operator to evaluate several scheduling policies for the allocation of berths, ensuring costumers' satisfaction.

In the following year, Giallombardo et al., (2010) solved the Tactical Berth Allocation Problem (TBAP) together with a QCAP for a container terminal. It was formulated as Mixed Integer Quadratic

Programming (MIQP) (linearized later) and differs from the study of Imai et al. (2008), since it consider an hourly assignment of quay cranes. The objective is to minimize the yard-related housekeeping costs generated by the flows of containers exchanged between vessels. To overcome the model computational inefficiency, meta-heuristic approach was proposed combining Tabu Search with the MIQP formulation of the TBAP. Through real life data, it is concluded that the solution approach provides good upper bounds for the optimal solution.

In the same year, Chang et al. (2010) addressed on environmental issues as minimize the energy consumed in a container terminal, so as to improve the seaports efficiency and, consequently, terminals efficiency. The authors proposed the resolution of the BACAP, based on a definition of the problem as a multi-objective model seeking the minimization of the deviation between the actual and best berthing locations, minimize the penalty for delayed berthing and departure time of vessels, and minimize the energy consumed by the quay cranes. A Hybrid Parallel Genetic Algorithm (HPGA) was developed to solve the problem and a simulation experiment was performed to evaluate the algorithm results.

Lee et al. (2010) studied the continuous and dynamic BAP for a container terminal with the objective of minimizing the sum of weighted turnaround time for each incoming vessel. A Greedy Randomized Adaptive Search Procedure (GRASP) meta-heuristic was used, and two different allocation rules are followed in the construction phase of the algorithm. The results suggest that both GRASP approaches provide good results, being one better for smaller instance and the other for larger instances.

In the following year, Buhrkal et al. (2011) performed a computational comparison different formulations proposed in the literature for discrete and dynamic BAP. All models were tested under the same conditions and, using a greedy algorithm as initial solutions generator for all, it is concluded that the Generalized Set Partitioning Problem (GSPP) model is computationally more efficient than the remaining models.

In 2012, Oliveira et al. (2012), Yang et al. (2012) and Lalla-Ruiz et al. (2012) solved the BAP and BACAP with the objective of minimizing the total service time of vessels in the port. The first one considered the dynamic and discrete problem proposing a Clustering Search for resolution and Simulation Annealing (SA) as a solution generator. The second intends to solve the BACAP, with dynamic arrivals of vessels and continuous layout using a structured method with integrated cycles: first, one cycle aims to solve the BAP while the other solved the QCAP. Outside both, a cycle solves both simultaneously, trying to find the best approximate solution. Besides the objective mentioned, it also minimized the number of quay crane shifts. Finally, Lalla-Ruiz et al. (2012) focused on the same problem with the same characteristics as Oliveira et al. (2012). They proposed a hybrid meta-heuristic combining Tabu Search and Path Relinking. A comparison was made with GSPP, as the best model formulation for the problem, proved that the developed meta-heuristic reached the optimal solutions with a lower computational time.

In the following year, Elwany et al. (2013) addressed BACAP in dynamic and continuous terms and developed a heuristic, with the same objective proposed by Meisel & Bierwirth (2009), incorporating service quality and operational costs. In addition, SA was used to search the priority list.

In the same year, Lalla-Ruiz et al. (2014) sought to solve TBAP incorporating QCAP. The model formulation proposed by Giallombardo et al. (2010) is used which minimizes the yard-related housekeeping cost generated by the flows of container exchanged among the vessels. For its resolution, it was used a Biased Random Key Genetic Algorithm (BRKGA) which was benchmarked with existing optimizations in the literature that used the CPLEX software. The authors concluded that the computational time of BRKGA was much smaller than that of the optimizations and the model proved to be quite flexible, not varying the computational effort with sample size increases.

Ting et al. (2014) addressed the discrete and continuous BAP. First, the problem was modelled as a Vehicle Routing Problem (VRP) and was proposed a stochastic search technique called Particle Swarm Optimization (PSO). The conclusion was that this PSO presents excellent results, reaching all the optimal solutions for the problem in reasonable computational time.

Iris et al. (2015) addressed the BACAP developing a set partitioning model, reducing the number of variables by reduction methods. The authors also compared the use of time variant/invariant in QCAP and showed that the reduction of variables significantly improves the solutions and became computational efficiency, compared with previous works.

Hu (2015) focused on the BAP, extending the dynamic and discrete dimension, and, as in Hu et al. (2014), developed an optimization model to maximize operational efficiency and minimize costs. The innovation for this model relies on the existence of daytime preferences, i.e., minimizing night hours, increasing workers' comfort. It was solved with a multi-objective GA.

In the same year, Frojan et al. (2015) addressed the BAP differing from the state-of-art by addressing the problem considering multiple quays. This brings adjacent problems because, in addition to determining time and position for the vessel in the berth, it has the task of allocating the vessel to a quay. To define the problem, an Integer Linear Model was developed, but it only solved problem of small-medium size. Therefore, to solve real problems was used a GA with local search procedure to improve its solutions.

Mauri et al. (2016) proposed an Adaptive Large Neighbourhood Search for the resolution of the BAP in the discrete and continuous version. The authors compared the results with the Oliveira et al. (2012) and reached better results, not only than Oliveira et al. (2012), but also then all the existing methodologies, whether in continuous or discrete BAP, for several instances.

Kordić et al. (2016) intended to use combinatorial algorithms to solve a discrete and hybrid BAP. For its resolution it relied on the Sedimentation Algorithm and it is concluded that is possible to solve problems with up to 65 vessels. In the same year, Şahin & Kuvvetli, (2016) addressed the dynamic BAP, using a meta-heuristic called Differential Evolution. Statistical analysis was used to generate random samples and evaluate the meta-heuristic solutions. It was concluded that this reached the optimal solutions for the problem in reasonable computational time.

Lalla-Ruiz et al. (2016) extended the BAP with time-dependent limitations. The objective was to allocate and schedule vessels in the quay, also considering tidal and water depth constraints. The work solves the problem through one mathematical model based on the GSPP.

Correcher & Alvarez-Valdes (2017) solved the continuous and dynamic BACAP. To do so, the authors developed a BRKGA, minimizing the total cost. Computational tests showed that the proposed model was unable to find good quality solutions when the arrival time of several vessels were similar or even when vessels had preferred similar positions in the quay. Therefore, a Local Search procedure was

developed and improved the results quality. Local Search was able to find good solutions in less than 5 minutes for less than 60 vessels in a one-week horizon.
Venturini et al. (2017) solved the BAP considering different ports and several terminals. To accomplish that, it is considered cooperation between them to optimise the problem in question. This model cooperation approach shows to be economically and environmentally viable as, for instance, it reduces fuel consumption by 42%.
Dulebenets et al. (2018) focuses, for a multi-user terminal container, the collaborative approach between berths to solve the BAP, as Venturini et al. (2017), adding a higher demand than expected. To solve the problem, the authors proposed a Memetic Algorithm. The study showed that the collaborative policy presents a several cost savings during high demand periods. Xiang et al. (2018) solved the same problem applying a reactive strategy to deal with disruptions under uncertainty. Rolling Horizon Heuristic (ROH) was used to find good solutions, which was proven to be efficient and solve the problem in reasonable computational time.
Iris et al. (2017), as Mauri et al. (2016), intends to solve the BACAP using Adaptative Large Neighbourhood Search (ALNS), concluding that this outperforms the heuristics presented on state-of-art for many instances.
Wang et al. (2019) focused on the BAP in its dynamic aspect, aiming to minimize the cost of all vessels while staying in the port and produce the schedule for vessels in berths, considering multi-tidal planning horizons. To this end, it is used Levy Flight with Local Search procedure. Then, it was compared with PSO. Levy Flight presents solutions, both in quality and in computational times, superior to PSO. In the same year, Kramer et al. (2019), addressed the same problem with same characteristics for a container terminal, proposing two mathematical formulations: a time-indexed formulation and an arc-flow one. Existing instances in the literature were tested, and an optimal solution was found.
Wawrzyniak et al. (2019) developed a Portfolios Algorithm to choose, among several tested, those that fulfilled the run time that was limited. The Algorithm Selection Problem was applied and a trade-off is made between the computational time and the quality of the solutions obtained. Also in 2019, Barbosa et al. (2019) address the BAP and developed a Hybrid Evolutionary Genetic Algorithm for the discrete and dynamic version of the problem. On the other hand, Correcher et al. (2019) solved the same problem, but for terminals with irregular layouts. In this way, new space, and time limitations appear and, for its resolution, it presents a MILP and a heuristic, both with the objective of minimizing the total time in the port and the total assignment cost.
Finally, in the same year, an Evolutionary Algorithm was used by Kavoosi et al., (2019) to solve the Berth Scheduling Problem (BSP). The problem was modelled as MIP with the objective of minimizing the summation of waiting costs, handling costs and late departure costs of vessels in a container terminal. The experimental results showed the computational efficiency of the algorithm.

Among the Heuristics and Meta-heuristics works in the literature, only two were found that refer the stochastic nature of the input parameters to the system: Shang et al. (2016) and Xiang et al. (2017).
First, Shang et al. (2016) proposed a model considering the existence of data collected uncertainties, and a robust optimization model is designed. To solve the problem, the GA combined with an Insertion Heuristic is used, to obtain near optimal solutions. It is concluded that this methodology brings good

results for the intended objective. In the following year, Xiang et al. (2017) aims to solve the continuous BAP applying robust model with two objectives: minimizing the berthing costs and maximizing customers satisfaction. Realistic conditions were used considering characteristics of arrival times and handling times.

Simulation and Optimization-Simulation

The following four papers address the BAP with simulation or simulation-optimization, allowing to model the terminal system in a more intuitive and graphic way, testing different policies for the terminals to evaluate its performance.

Zeng & Yang (2009) proposed a simulation-optimisation model for loading operations in container terminals. It generates sequences through a GA and uses simulation to evaluate the objective function. It uses an optimization model to obtain an optimal solution for the schedule of each container on each vessel.

In 2014, Legato et al. (2014) integrate both tactical and operational models within the BAP through a Simulation-Optimization approach. For the TBAP it uses Beam Search heuristic to propose a tactical plan. This plan is then evaluated at the operational level using a Simulation approach. In an iterative approach, neighbour solutions are proposed by SA and evaluated again by simulation.

Budipriyanto et al. (2017) explored the BAP for a container terminal. This work uses a Discrete Event Simulation Model to deal with uncertainty, formulating two alternatives: non-collaborative response and collaborative response. For the later, and as in Venturini et al. (2017) and Dulebenets et al. (2018), it is assumed there is collaboration between berths to deal with the uncertainty of the parameters. It was concluded that the collaborative strategy allows waiting time reduction of vessels, as well as total vessel turnaround time.

Tasoglu & Yildiz (2019) focused on the integrated version of a BAP and QCSP. The authors addressed, for the first time, a multi-quay hybrid berth layout with dynamic arrival of vessels and stochastic handling times simultaneously. However, it is assumed that loading and unloading operations are unified in one and that the relationship between them is ignored. To solve the problem, the authors proposed a simulation-optimization methodology. Firstly, Conflict-Free Quay Crane Scheduling Algorithm was used and then it was represented the port operations of a typical container terminal through a simulation model. Simulated annealing is integrated in the simulation model. The main objective of this work was to minimize the latest vessel departure, i.e., makespan.

3.2 Bulk terminals

As with container terminals, mathematical optimization models are revised first and later the heuristics and meta-heuristic approaches.

Optimization

Robenek et al., (2014) solve the dynamic and hybrid BAP considering yard locations to specific cargo types and that each vessel only carries one type of cargo. The problem was formulated as a MIP, with the objective of minimizing the total service of each vessel. However, not even small size instances could be solved with this formulation. Therefore, the model was decomposed being the master problem formulated as a set partitioning problem, while the sub-problems provide information for each vessel with respect to a feasible assignment to the quay. In addition, a meta-heuristic was proposed which obtain near-optimal solutions in less computational time than the decomposition approach. Authors concluded that both the set partitioning model and the meta-heuristic achieve good results for up to 40 vessels, in reasonable computational time.

Heuristics and meta-heuristics

Umang et al. (2013) studied the dynamic and hybrid BAP for a bulk terminal to minimize total service time of vessels. There were proposed 3 different approaches to solve the problem, which latter on were compared based on computational results. The first one was a MIP, aiming to determine the vessels' berthing assignment along the quay terminal. The second was a set partitioning based approach (GSPP), which was also used by Buhrkal et al. (2011) to solve a discrete and dynamic BAP for a container terminal. In this one, the planning horizon is divided in discrete intervals and, within each interval, vessels should dock the nearest possible to pipeline facilities to minimize handling times and, subsequently, total service time. The last approach was a meta-heuristic based on Squeaky Wheel Optimization where, in each iteration, a solution is constructed, analysed and then prioritized to obtain the next solution. The results of these three methodologies were compared and was concluded that the GSPP and the meta-heuristic, in contrast to the MIP, could solve a large size problem, reaching near-optimal solutions.

Lastly, León et al. (2017) addressed the BAP for bulk terminals using machine learning to rank resolution approaches proposed in the literature so far. In the following year, Atencio & Casseres (2018) compared three meta-heuristics to solve the BAP: Genetic Algorithm, Ant Colony Optimization and Simulated Annealing. The objective was to minimize the penalty cost to the Port due to vessels' Demurrage in the berths, which, according to the authors is a consequence of poor vessel allocation. It is concluded that the three meta-heuristics showed good results for the proposed problem while minimizing computational effort.

To the best of author's knowledge, there are no papers applying simulation or simulation-optimization to Liquid Bulk Terminals.

3.3 Literature review characterization

The literature review characterization is provided considering the aforementioned studies. It is noteworthy that the set of studies mentioned are only a sample of a broad universe that exists on the subject. Therefore, in a first phase, it is interesting analyse the frequency distribution over the years.

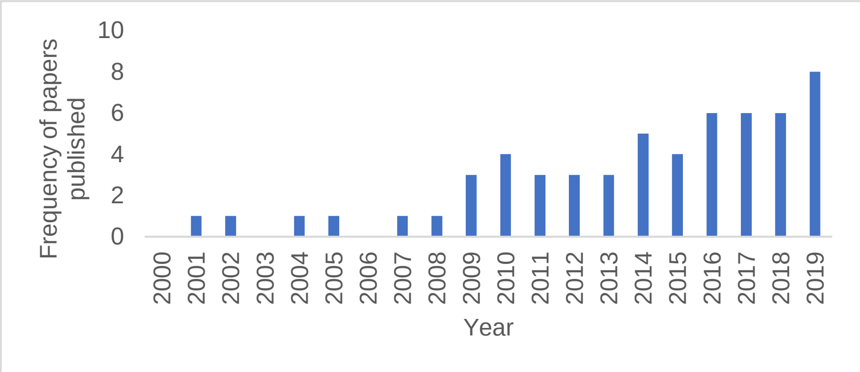


Figure 14: Frequency distribution on publications about the Berth Allocation Problem over the years

Figure 14 shows the upwards trend of papers published on the BAP, in the timespan of the literature review. This observation is mainly based on two factors. On one hand, in the last decades there has been a significant increase in global freight transport due to the enormous commercial trade. This fact has a direct influence on maritime transportation, leading to an increase of around 3.9 trillion tonnes in total freight transport between 2000 and 2015 (UNCTAD, 2016). Therefore, studies for a correct allocation of vessels on terminals are necessary for operational efficiency. On the other hand, the ambition to make profits by reducing costs and increasing the service level, leads ports to increasingly seek new ways to optimize the way vessels are served.

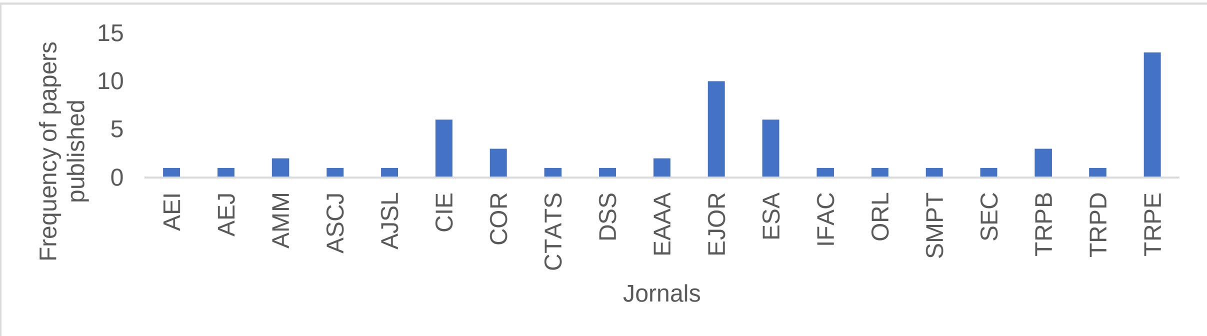


Figure 15: Frequency of papers published by journal

Figure 15 denotes the frequency distribution by journals, with the journal's acronyms being explicit in the List of Acronyms. It is noteworthy that the journals which frequently explore the Berth Allocation Problem are the Transportation Research Part E (TRPE), European Journal of Operation Research (EJOR), Computers and Industrial Engineering (CIE) and Expert Systems with Applications (ESA), with 13, 10, 6 and 6 respectively.

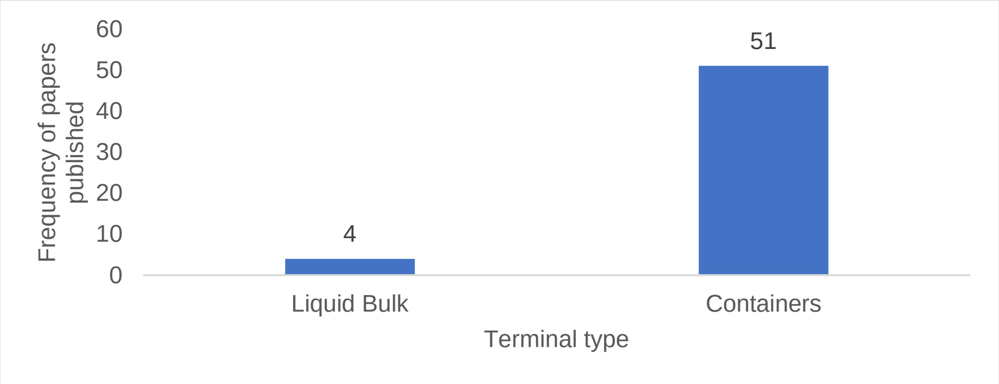


Figure 16: Frequency of papers published on liquid bulk and containers terminals

There are articles that refer specifically to container terminals while others refer implicitly (for example when solving QCAP or QCSP). There are also other articles, such as Umang et al., (2013), Robenek et al., (2014), León et al., (2017) and Atencio & Casseres, (2018) that refer exclusively to Bulk terminals. Figure 16 highlights the discrepancy that exists between the studies carried out on Container Terminals when compared to Bulk terminals, with 51 against 4. Therefore, based on that, it is possible to notice a clear gap in the literature that has every interest in being filled.

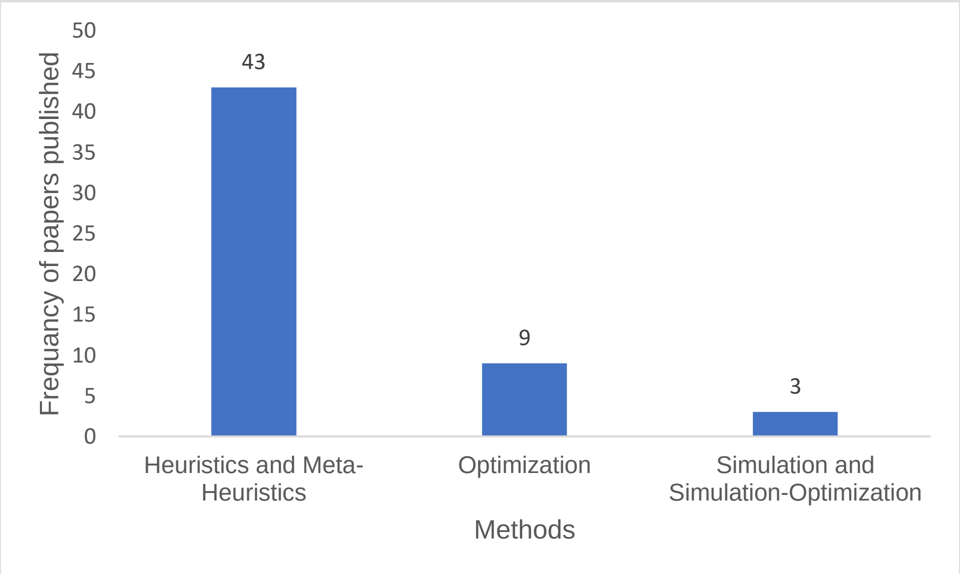


Figure 17: Comparison of the methods used to address the Berth Allocation Problem

Figure 17 highlight the difference between the methods used. Heuristics and Meta-heuristics, with 43 works, present a good tool to solve problems with several instances and relatively low computational time with Simulated Annealing and GSPP the most explored. Then, Optimization that aims to solve the problem by finding optimal solutions, with 9 papers. Lastly, it is shown Simulation and Simulation-Optimizations with 3 works performed, among them Budipriyanto et al., (2017), which applied Discrete Event Simulation.

Finally, it is notorious the lack of work dealing with the uncertainty of the input parameters in the system. There are, among the literature review presented, two papers that consider this factor: Shang et al., (2016) and Xiang et al., (2017).

3.4 Final remarks

The Berth Allocation Problem (BAP) study has been increasingly focused on literature. One of the factors for this increase, as mentioned in chapter 1, is the fact that the world population is growing exponentially, with their individual energy needs growing at equally alarming rates. Therefore, oil trades worldwide are increasing, emphasizing the terminals' role of be well organized to receive and ship products efficiently. On the other hand, costs always have a great impact on any company's finances, seeking to minimize them, while keeping the service level.

Allied to this growth is also the increasing importance of container terminals in the world maritime logistics. Throughout the literature review, the exhaustive exploration of papers related to this type of terminal was evident, as opposed to the reduced exploration of Liquid Bulk Terminals, with 4 of the 55 papers mentioned.

Further, within the exploration of terminal types, the use of Heuristics and Meta-Heuristics is exhaustive, while BAP resolution through Optimization or even Simulation and Simulation-Optimization is very little exploited (the latter being only tackled by Budipriyanto et al. (2017), Zeng & Yang, (2009) and Tasoglu & Yildiz, (2019)).

Even more obvious is the few papers exploring the variability of system parameters, with most papers studying the BAP with dynamic vessels' arrival and handling times. In the literature review referred to, only two papers considered this factor: Shang et al., (2016) and Xiang et al., (2017).

Therefore, it is possible to identify the following gaps in the literature:

- few studies focus on Liquid Bulk Terminals
- little exploration of Simulation and Simulation-Optimization
- nonexploitations of parameter variability.

All these gaps identified in the literature, fits the problem presented in the case study: the lack of study in the allocations of vessels to berths and pipelines, coupled with failure to consider and subsequently mitigate the effects of variability in system parameters.

It is possible to conclude that a simulation approach is suitable to explore the case study undertaken. Not only it is little addressed in the literature but also, among other advantages, it is adequate to study parameter variability. This is a very flexible technique, allowing to accommodate all complexities and particularities. On the other hand, this experimental approach is very intuitive and easy to apply. Finally, it can be extremely graphic, so the decision maker can easily see the progress of the system, transmitting transparency to the solution.

It is indeed evident that it will be a very useful method to evaluate alternatives to the allocation policies at the Sines' Liquid Bulk Terminal, seeking to understand and mitigate the effects of variability on system performance while allowing the evaluation of scenarios that minimize operational indicators.

4. Simulation Model

To propose a solution to Sines' Liquid Bulk Terminal problem a simulation methodology is proposed. This chapter will define the Key Performance Indicators and the Simulation Variables, as well as the conceptual model and the implementation of the model in the SIMUL8 software.

4.1 Key performance indicators

In Sines' Liquid Bulk Terminal there are several objectives proposed, operational or financial, to access its performance. In this dissertation, KPI Port Operational Time and Demurrages were considered to assess the achievement of the cost minimization and service level maximization:

- **Port Operational Time (POT)**: this KPI quantifies the total time, in hours, of each vessel in the system. It depends on the Time for Docking (TD), Setup Time (ST) and Operational Time (OT), as defined in Chapter 2
- **Demurrages**: the Demurrages evaluates the time that each vessel spends in the terminal after the Contracted Laytime. It is measured in hours, but is important to quantify in monetary units, as it represents a financial burden to the terminal.

4.2 Simulation variables

The variables associated with the simulation system should be standardized for a better understanding of data implementation. Firstly, the relevant sets associated with the terminal system are:

- $p \in P: set\ of\ products\ (1 = Crude;\ 2 = LPG;\ 3 = Fuel;\ 4 = Gasoline;\ 5 = Gasoil;\ 6 = Naphtha)$
- $m \in M: set\ of\ berths\ (1 = berth\ 2;\ 2 = berth\ 3;\ 3 = berth\ 4;\ 4 = berth\ 5;\ 5 = berth\ 6;\ 6 = berth\ 7)$
- $l \in L: set\ of\ pipelines\ (1 = A;\ 2 = B;\ 3 = C;\ 4 = D;\ 5 = E;\ 6 = F)$
- $o \in O: set\ of\ operations\ (1 = reception;\ 2 = shipment)$
- $v \in V: set\ of\ vessels\ (1 = Vessel\ 1;\ 2 = Vessel\ 2;\ \ldots;\ n = Vessel\ n)$

It is important to note that each vessel only carries one type of product, that is, whenever a vessel ***v*** is mentioned, the product ***p*** it carries is also mentioned.
With the sets defined, the relevant variables for the Liquid Bulk Terminal are now presented in Table 15.

Table 15: Terminal variables description

Variable type	Variable	Description
Decision	$\boldsymbol{D_{vm}}$	Allocation of vessel *v* to berth *m*
	$\mathbf{D_{plo}}$	Allocation of product *p* to pipeline *l* by operation *o*
Exogeneous	$\boldsymbol{X^1_{v1v2}}$	Time between consecutive vessels arrivals
	$\boldsymbol{X^2_p}$	Arrival of product *p*
	$\boldsymbol{OT_{po}}$	Operational time of product *p* by operation *o*
	$\boldsymbol{ST_l}$	Setup time on pipeline *l*

Table 15 characterize the variables of the terminal system. The first variables of interest are the **Decision Variables**, which are under management control, corresponding to the terminal allocation policies $\boldsymbol{D_{pm}}$ and $\mathbf{D_{plo}}$. $\mathbf{D_{plo}}$ is a matrix with binary inputs.

- $\boldsymbol{D_{vm}}$ represents the allocation of vessel ***v*** to berth ***m***
- $\mathbf{D_{plo}}$ represents the allocation of product ***p*** to pipeline ***l*** by operation type ***o***.

The second type of variables are **Exogeneous Variables** which are not under management control since they depend on external factors.

- $\boldsymbol{X^1_{v1v2}}$ represents the time between the arrival of consecutive vessels $\boldsymbol{v_1}$ and $\boldsymbol{v_2}$, measured in hours.
- $\boldsymbol{X^2_p}$ relates the arrival of each type of product ***p*** to the terminal
- $\boldsymbol{OT_{po}}$ represents the operational time by product ***p*** and operation ***o***, measured in hours.
- $\boldsymbol{ST_l}$ relates with the setup time of each vessel ***v*** on pipeline ***l***, measured in hours.

Finally, to access the performance of the Liquid Bulk Terminal system the **Output Variables** (the KPI), are presented:

- $\boldsymbol{POT_p}$ – Port Operational Time by product, in hours
- $\boldsymbol{Dem_p}$ – Demurrage by product, in hours

4.3 Simulation model implementation

For the construction of the simulation model, the **real system's observation** is started, intending to understand the interactions between the actors and the system's logic at a macro level. Based on this observation, a **conceptual model** that allows representing the real system is designed, as detailed as possible, to acquire a reasonable abstraction level related to the real system. Therefore, it allows the representation of the reality for analysis purposes. Finally, it is **implemented the conceptual mode**l in SIMUL8 software. These three steps together represent the first phase of the simulation model development characterized by **model building**.

It is noteworthy that this is not a strict methodology consisting only of these three steps; it is iterative, allowing to return to the observation of the system as often as necessary, to bring the conceptual model closer to reality and thereby improve implementation efficiency.

4.3.1 Real system

In Sines' Liquid Bulk Terminal, the vessels arrive and wait for their turn to dock outside the terminal. For berthing to be possible, two conditions must be fulfilled: a berth must be unoccupied, and the pipeline line affected to the product transported by the vessel must be free.

Whenever a vessel arrives, either for a reception or shipment operation, it is directed to the single queue for the 6 available berths. However, the allocation of products and vessels to berths currently follows the following policy (also presented in the Table 4):

- Berth 2, the one with the higher capacity, is exclusively dedicated to Crude transactions
- Berths 3, 4 and 5 are allocated to all remaining products: LPG, Fuel, Gasoline, Gasoil and Naphtha
- Berths 6 and 7 are only assigned to vessels carrying LPG or Gasoline, with a quantity less than 7000 tons.

Like the allocation of vessels to berths, the pipeline's selection to be used by each product is not arbitrary. There is a policy of allocating the higher quantities of products that arrive to larger diameter pipelines, to minimize the Operational Time (OT). The products allocation to pipelines considers these differences between the quantities shipped and received of products, as shown in the Table 6.

Hence, based on these policies and operations, the terminal operations can be summarized in a conceptual model. This model will allow the representation of the system with a sufficient level of abstraction so that it can be used and implemented in a computational software.

4.3.2 Conceptual Model

Sines' Liquid Bulk Terminal is characterized by activities and queues, with alternation between them. With respect to the system entities, they may be:

- Permanent: these are fixed in the system throughout the simulation, acting as resources. In this system, **Berths** and **Pipelines** are identified
- Temporary: entering and exiting the system, changing, and modifying its state. In the terminal's system, **Vessels** are identified

Based on the activities, queues, and entities, it is possible to build a conceptual model that represents the real system. This will be drawn through the following diagrams:

- Life Cycle Diagram (LCD): represents the process of each entity in the system, a sequence of activities (active states) and queues (passive states);
- Activity Cycle Diagram (ACD): represents through diagrams the processes of the entities simultaneously, displaying the interactions between them.

In both diagrams, activities are represented as rectangles and queues as ellipses.

4.3.2.1 Life Cycle Diagrams

Vessel

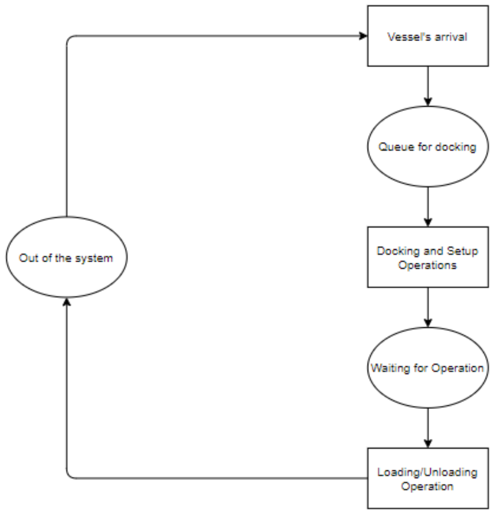


Figure 18: Life cycle diagram for entity "Vessel"

For the temporary entity Vessel, as shown in Figure 18, the following active and passive states were identified:

- **Activities**
  - *Vessel's arrival*: here it is represented the vessel arrival to the system
  - *Docking and Setup Operations*: this represents the vessels' docking at the berth and the subsequent setup operations
  - *Loading/Unloading operation*: finally, this illustrates the products' reception/shipment operations at the berth, through the pipeline lines
- **Queues**
  - *Queue for docking*: queue created by the arriving vessels at the terminal that are waiting to dock at the assigned berth
  - *Waiting for operation*: fictitious queue symbolizing the end of setup operations and the start of the receiving/shipping operations
  - *Out of system*: where vessels leave the system after their operations at the terminal

Berth

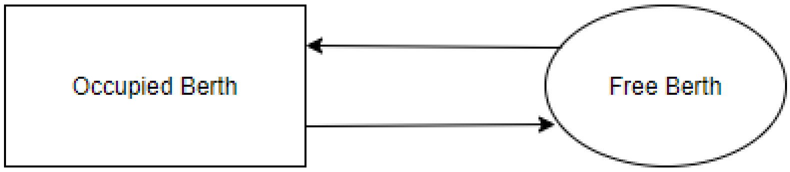


Figure 19: Life cycle diagram of entity "Berth"

For the permanent entity Berth it is identified two states, as shown in Figure 19:

- *Occupied berth*: active state which represent that the berth is being used
- *Free berth*: passive state representing a free berth

Pipeline

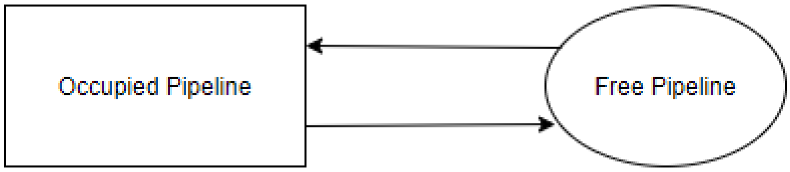


Figure 20: Life cycle diagram of entity "Pipeline"

For the permanent entity pipeline is identified by two states, as shown in Figure 20:

- *Occupied pipeline*: active state which represent that the pipeline is being used
- *Free pipeline*: passive state representing a free pipeline

4.3.2.2 Activity cycle diagram

The activity cycle diagram joins all Life Cycle Diagrams for a better understanding of the interaction among the entities, queues, and activities. It is presented in Figure 21.

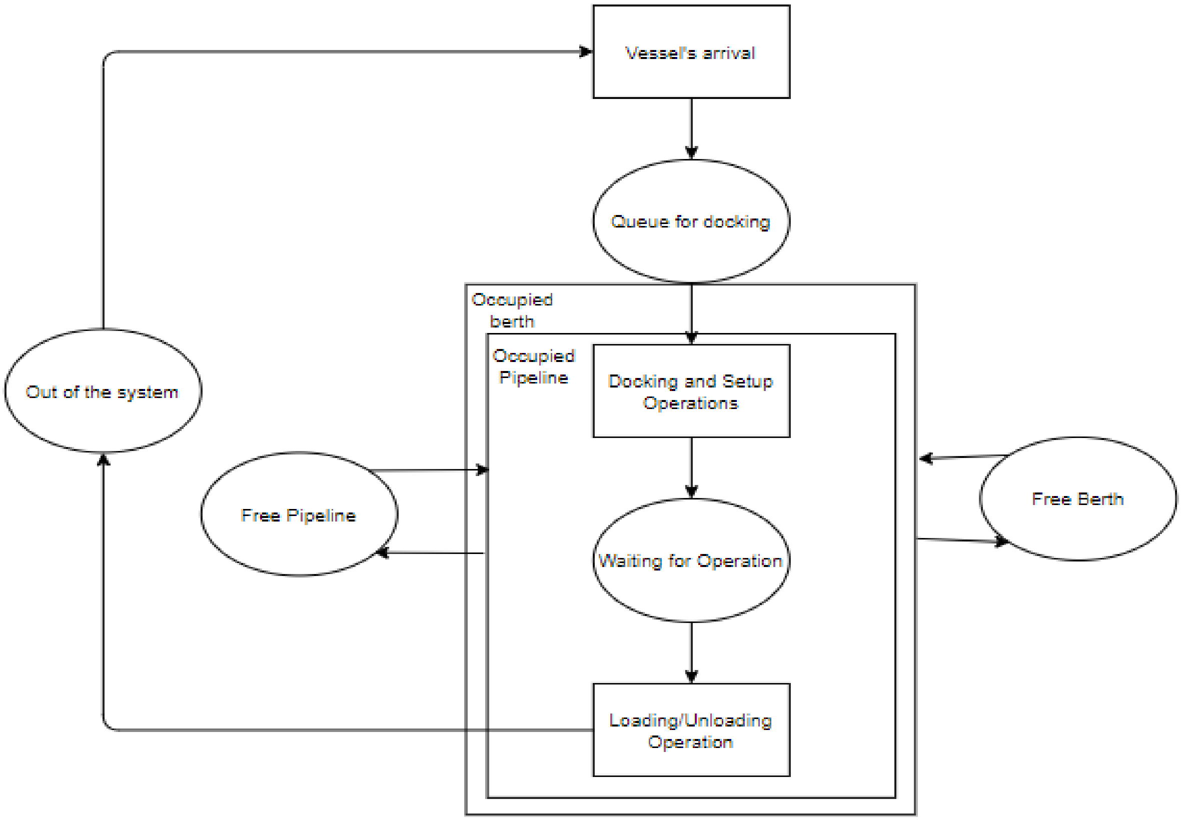


Figure 21: Activity cycle diagram of the terminal system

The Activity cycle diagram is described in the following pseudo code:

Pseudo code

i) Vessel's arrival

*Vessel **v** arrives at the terminal*

Generate the product's type according to exogeneous variable X_p^2

*Generate the pipeline **l** allocated to product type **p** and operation **o** according to decision variable* $\mathbf{D_{plo}}$

*Generate the berth **m** allocated to product **p** according to decision variable* $\mathbf{D}_{pm}$

Generate Setup time according to exogeneous variable $\boldsymbol{ST_l}$

Generate Operational Time according to exogeneous variable $\boldsymbol{OT_{po}}$

Determine the time of next arriving vessel, according to exogenous variable $\boldsymbol{X^1_{v1v2}}$

***If** Queue for Docking is empty:*

    ***If** pipeline **l** is free **and** berth **m** is free:*

        *Move vessel **v** from Queue for Docking to Docking and Setup Operation Activity*

        Determine the end of activity for T=Simulation Time + $\boldsymbol{ST_l}$

Else:

*Place vessel **v** in Queue for Docking*

Else:

*Place vessel **v** in Queue for Docking*

ii) End of Docking and Setup Operation

*Pipeline **l** and Berth remain allocated to vessel **v***

***If** Waiting for Operation is empty:*

*Move vessel **v** from Waiting for Operation to Loading/Unloading Operation activity*

Determine the end of activity for T=Simulation Time + $\boldsymbol{OT_{po}}$

Else

*Place vessel **v** in Waiting for Operation*

iii) End of Loading/Unloading Operation

*Remove vessel **v** from the system*

***If** there is a vessel in Queue for Docking*

***If** pipeline **l and** berth **m** are free*

*Move vessel **v** from Queue for Docking to Docking and Setup Operation*

Determine the end of activity for T=Simulation Time + $\mathbf{ST}_l$

Else

*Place vessel **v** in Queue for Docking*

Else

*Place vessel **v** in Queue for Docking*

End

4.3.3 Implementation

Based on the structure of the terminal, and the conceptual model and variables defined, the Liquid Bulk Terminal of Sines is implemented in SIMUL8 software.

Structural logic

Once the pre-sets on Appendix A are specified, the implementation is illustrated in Figure 22. The implemented model is divided in 4 blocks: A, B, C and Resources.

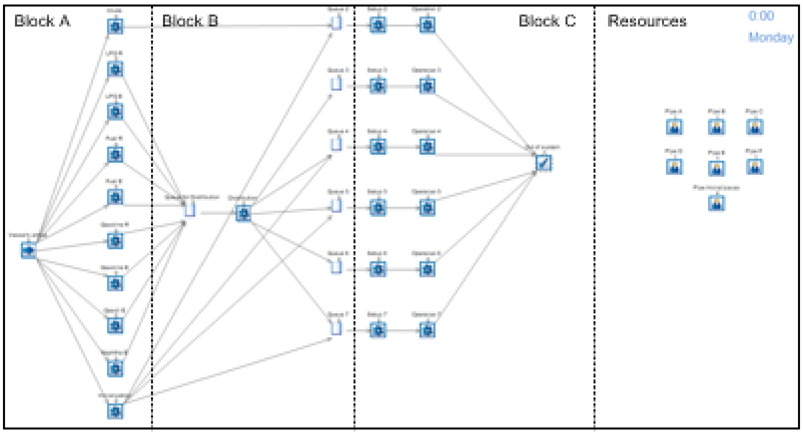


Figure 22: Simulation model implementation

Resources

Firstly, resources have been implemented in the system. The resources allow the allocation policies to be effectively implemented (berths and pipelines). However, for simplicity, in the implementation only pipelines are referred to, because whenever one “pipeline” is used, one “berth” is also used. Hence, berths are considered occupied when there is a "Vessel" entity in their setup or operation activity.

To accommodate initial conditions in the system, 4 pipelines were created, used exclusively for initialization purposes. Then, it was created six resources for 6 pipelines, each referring to each type of pipeline existing in the terminal (from A to F).

As it was mentioned, when a loading arm of a pipeline is being used in one berth, all the remaining loading arms of the same pipeline are unavailable for another berth. This characteristic was implemented considering the existence of only one pipeline arm of each type: if this is being used, the remaining ones are unavailable. These *"Pipeline"* resources were allocated to Setup and Operation activities, and the policy of allocating products to pipelines were made explicit to SIMUL8 through Block A activities, as it is explained further on.

Block A

Vessel entities arrive in the system through a single entry defined as "Vessel's arrival". Afterwards, the vessels are distributed to one of the 10 activities available, according to the product transported and the type of operation (reception or shipment). This latter division aims to facilitate the allocation of vessels to pipelines.

The activities' names of block A corresponds to the product's name, followed by the letter R or E, depending on whether the vessel will perform be a reception or shipment (expedition) operation. However, must be considered that:

- There are no "Crude E", "Gasoil R" or "Naphtha R" activities, because vessels carrying Crude do not carry out shipments, while Gasoil and Naphtha vessels do not carry out receptions, according to the data available from January 2017
- There is an activity called "Initialization" to assign the initial configuration to the simulation; it is not relevant whether it performs reception or shipping

These activities from Block A are fictitious activities with null duration, defined for the following objectives:

- to **recognize the product** that arrives at the terminal
- **recognize what type of operation** the vessel will perform
- assign the **Setup and Operation duration** of each vessel
- make the **allocation to pipelines** known to the program

To exemplify these objectives, "LPG R" activity is used as an example, with the procedure to be analogous for the remaining ones in Block A.

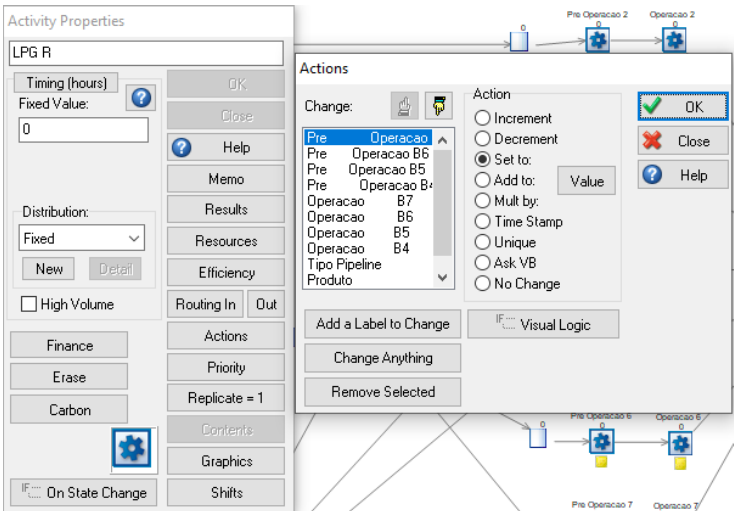


Figure 23: Actions on Block A activities

By selecting on the Actions option in "LPG R" activity properties, it can be noted all the corresponding labels. All "Vessel" entities that go through here will acquire these labels that will follow them in the remaining of the simulation. Among these, there are 4 pre-operation labels for berths 4, 5, 6 and 7 (note that, according to data from January 2017, there was no LPG reception operation in berth 3), 4 operation labels for berths 4, 5, 6 and 7, one *"Pipeline Type"* label and one *"Product"* label. Each of these labels is associated with a known or empirical distribution, or even a set of deterministic data, through the *"Set to"* option.

The *"Product"* label will let the system know which product reaches the terminal. This will not influence the logical structure of the system, but is helpful for the Key Performance Indicators (KPI) quantification at the end of the simulation (allows a more detailed result, e.g. by product). To transmit this information, fixed values were assigned to this label, giving the same value to the shipping, and receiving operations of the same product, as shown in Table 16.

Table 16: Values for label "Product"

Product	**Activity**	**Value**
Crude	Crude	1
LPG	LPG R and LPG E	2
Fuel	Fuel R and Fuel E	3
Gasoline	Gasoline R and Gasoline E	4
Gasoil	Gasoil E	5
Naphtha	Naphtha E	6

Furthermore, the label *"Pipeline"* indicates the subsequent products' allocation by operation type to pipelines. In this activity only these allocations are indicated, but the allocation is only performed when the entity "Vessel" reaches block C, where setup and the product transaction is made. Each scenario subsequently implemented will induce different values to this label on each activity, however, the values on Table 17 will be kept constant for each pipeline. For example, if a vessel transports LPG and performs a reception, it will proceed through the activity "LPG R" where it will have value 6 associated to the label *"Pipeline",* if it is allocated to pipeline F; takes the value 5 if it is allocated to pipeline E; and so on, as demonstrated by Table 17.

Table 17: Value for label "Pipeline"

Pipeline	**“Pipeline” Label value**
A	1
B	2
C	3
D	4
E	5
F	6

Finally, the four labels concerning the duration of setup operations and the four concerning the duration of product transfer operations are also present in Figure 23. To implement these in SIMUL8, setup and

operation times relative to each berth were associated to each activity, allowing the program to recognize them for each type of product and operation.
Therefore, the implementation for the setup and operation duration was carried out creating a Label based distribution. That is, a distribution that will depend on the label that is associated to the entity that goes through these activities and that enters the "Setup" and "Operation" activities. Through the *"Set to"* option, it is possible to assign to each of these labels, a distribution, whether empirical or known, or even a deterministic data set.
After the completion of this block of activities, all *"Vessel"* entities are directed to "Queue for distribution", with the exception of Crude vessels which, by performing the operations outside the other products, are allocated exclusively to "Queue 2", for berth 2.
These actions explained for Block A refer to the vessels arriving activity at the system, which is called, in the conceptual model, "Vessel's arrival".

Block B

The SIMUL8 default says that whenever two or more entities are in a queue for an activity, the first one to leave the queue will be the one that is first in the queue, that is, a First In First Out (FIFO) policy. However, it may be the case that each entity in the queue needs different resources to perform the next activity; here, the entity that has its first free resource enters the activity, regardless of its place in the queue.
To prevent this from happening, since the terminal uses a FIFO policy, Block B was created to simulate waiting to dock at the terminal. In this way, a single queue was created, through which all vessels must cross, followed by an activity (this activity is fictitious with a null duration, that exclusively serves the implementation of FIFO). This one does not need any resource to be carried out, so it receives the vessel that is first in the queue.
After that, this activity connects with 5 queues, one for each berth (except the queue for berth 2, because the allocation of berth 2 is made on the sideline). However, the same problem would occur for the exit of these queues and entry in the "Setup" activity in block C: the vessel that had the "pipeline" resource released in the first place would pass to this activity, regardless of its place in the queue. Hence, the queue of each berth was assigned the maximum amount of 1 vessel while the *"Wait until exit clear"* option was triggered in the *"Distribution"* activity. This way, a vessel in the queue "Queue for distribution" will only move to the "Distribution" activity when the queue for the berth corresponding to its allocation has 0 vessels, automatically moving to that berth queue because the duration of the "Distribution" activity is 0. If the berth has 1 vessel, the first in the queue for the "Distribution" activity will remain in the queue until the destination berth queue is empty.
Block B explained intends to implement in the program the queue to dock from the conceptual model, respecting the FIFO policy.

Block C

In C block, the operation activities in the berths are then divided into two components: Setup and Operation. Setup operation represents the time required to prepare the vessel and pipelines to transfer the product, corresponding to the setup time previously defined as ST. On the other hand, the operation is relative to product transfer with its time equal to the Operational Time (OT) previously defined.

The allocation to the pipelines is made considering the *"Pipeline"* label associated to the activities of Block A, missing only to transmit to the system that the choice of pipeline to berth at the terminal is dependent on this label. To do so, click on "*Resources*" in the *"Setup"* activity and select *"Resource by label"*, choosing the *"Pipeline"* label. For example, if a "vessel" entity in "queue 3", which has passed through the activity "LPG R", and which in this one has been associated to the *"Pipeline"* label number 6, it will only enter in the activity "Setup 3" if the resource "Pipe F" is available.

Once this is done, when a vessel is in queue to berth and this and the pipeline for the product are free, the vessel can berth. The "Setup" activity will be operated and then the "Operation" activity. However, in both the berth and the pipeline must exist to be performed, so the vessel does not discard these two resources when it leaves the setup and goes to the operation; the option present in the resources of the "Setup" activity "Require here but not release the resource" is selected, causing the resources to continue with the "vessel" entity to the next activity. Finally, the option "Only release the resource here" in the "Operation" activity is activated for the resource to be released.

When the "Operation" activity is finished, the "Vessel" entity exits the system and data related to it are collected, such as the total time in the system (Port Operational Time) and the value in hours of Demurrage.

5. Data analysis

This chapter is divided in two sections. In the first, it is demonstrated how the real data from the Liquid Bulk Terminal was processed to be implemented in the simulation model. In the second section, the simulation model is validated, comparing its outputs, Port Operational Time and Demurrage, with the outputs of the Sines' liquid bulk terminals. This latter section intends to validate the model, so it can replace the Liquid Bulk Terminal when alternative scenarios are evaluated.

5.1 Data treatment

To introduce values for the system variables, it was necessary to process data from the real terminal operations, mainly related to the setup and operation times of the vessels at the terminal, as well as on vessels' arrivals. This data processing aims at assessing the variability in the system variables.
As an example, consider the arrival of vessels in the system in January 2017. The time between arrivals of two consecutive vessels is calculated using the real data and a probability distribution is inferred from this. The StatFit program, which belongs to SIMUL8, infers directly from these data and returns the distribution that are statistically equal to it. Figure 24 compares the distribution of the data with the most similar distribution.

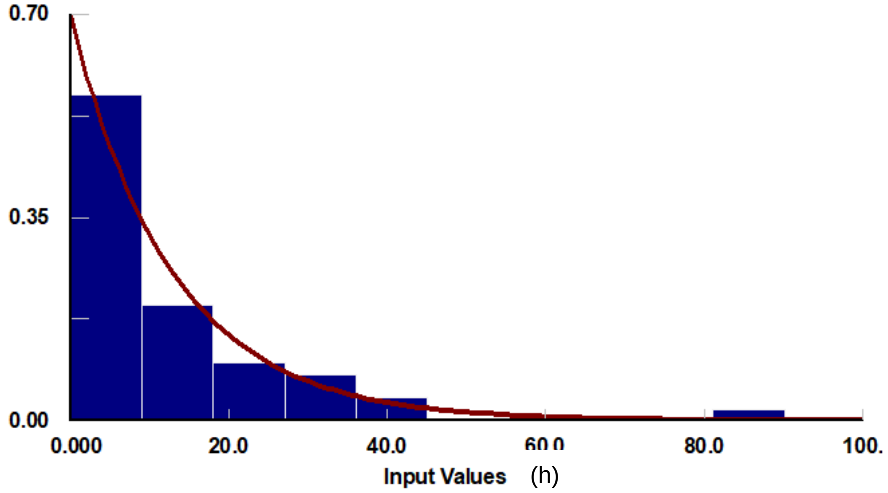


Figure 24: Graphic of time between consecutive vessels' arrival times empirical distribuiton and fitted exponential distribution

distribution	rank	acceptance	aicc prob
Exponential(0, 12.9)	100	do not reject	1
Lognormal(0, 1.9, 1.41)	21.6	do not reject	0.00218
Uniform(0, 90)	0	reject	0

Figure 25: Results for the goodness of fit of time between vessels' arrival

According to Figure 25, the distribution that is statistically equal to the data of vessels' arrival is an exponential distribution, with a parameter of 12.9 hours (one vessel arrives, on average, every 12.9 hours).

A similar data treatment was performed for the operation and setup times of the various scenarios described in the following Chapter. These OT and ST distributions are inferred from real terminal data of January 2017. However, in some scenarios, certain products will change their allocation to pipelines. Thus, the new OT of these products in the different pipelines are calculated in Rato (2018), considering the transfer rates and density of each product. From these values, distributions are inferred as new Operational Times.

Whenever it was not possible to associate a theoretical distribution, an equiprobable empirical distribution was used for input data in the simulated system.

5.2 Model validation

An important stage in a simulation model is the validation of its input-output transformation, by comparing the performance of the model with the real data. Hence, the real and simulated distributions of both Port Operational Time and Demurrages will be graphically and statistically compared. The assumptions for the statistical tests will be validated to perform a statistical validation of the model based on parametric or non-parametric tests.

In this way, the real data of the system, corresponding to the Decision and Exogenous Variables, have been introduced to the simulation model (available in Appendix C).

Besides the implementation of these variables, it is also necessary to determine the number of replications necessary for the simulation outputs to converge, that is, how many months of January 2017 need to be simulated for the system's outputs values to converge to the mean value within a 95% confidence interval. This number was calculated using SIMUL8 and resulted in **524 replications.**

Figure 26 presents the output results of both real and simulated scenarios, based on real data and on the 524 replications necessary for the system's output convergence.

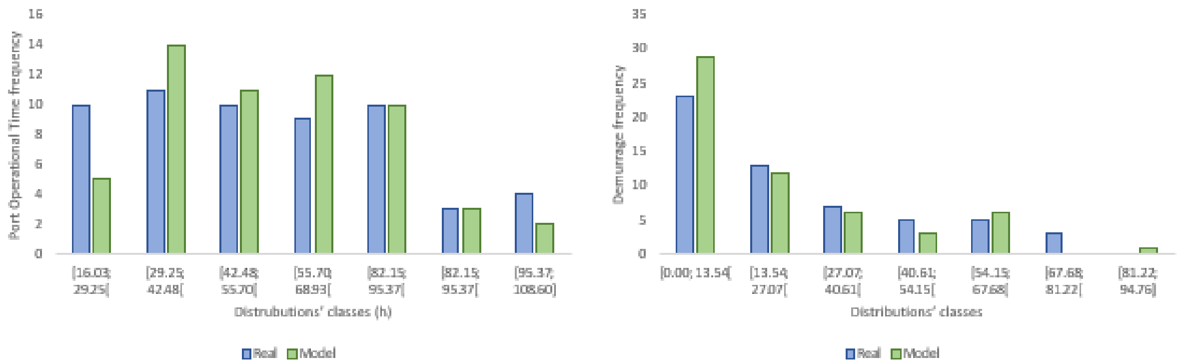


Figure 26: Comparison of real and simulated Port Operational Time and Demurrage

To validate the model is necessary to verify if the simulation results of Port Operational Time and Demurrage are statistically alike to the real terminal's data. Therefore, a t-student test for unpaired samples, with a significance level of $\alpha = 5\%$ is performed. This test assumes two assumptions that must be satisfied.

<u>First assumption</u> - Distribution of real and simulated Port Operational Time and Demurrages follows a normal distribution

For the first assumption, it is performed a **Shapiro test** to validate the normality of both real and simulated samples of POT and Demurrage. For this test, the following hypotheses are stated:

$$H_o: POT_{real} \sim N(\mu, \sigma) \qquad H_o: Dem_{real} \sim N(\mu, \sigma)$$
$$H_1: POT_{real} \neq N(\mu, \sigma) \qquad H_1: Dem_{real} \neq N(\mu, \sigma)$$

$$H_o: POT_{sim} \sim N(\mu, \sigma) \qquad H_o: Dem_{sim} \sim N(\mu, \sigma)$$
$$H_1: POT_{sim} \neq N(\mu, \sigma) \qquad H_1: Dem_{sim} \neq N(\mu, \sigma)$$

<u>Second assumption</u> - Real and simulated variances of Port Operational Time and Demurrages are homogeneous

For the second assumption, a **Levene test** is performed to prove the homogeneity of variances. The hypothesis for the second assumption are as follows:

$$\mathrm{H}_0: \sigma^2(POT_{real}) = \sigma^2(POT_{sim}) \qquad \mathrm{H}_0: \sigma^2(Dem_{real}) = \sigma^2(Dem_{sim})$$
$$\mathrm{H}_1: \sigma^2(POT_{real}) \neq \sigma^2(POT_{sim}) \qquad \mathrm{H}_1: \sigma^2(Dem_{real}) \neq \sigma^2(Dem_{sim})$$

All statistical tests described assume the same rejection conditions:

$$If\ p - value\ <\ \alpha,\ \mathrm{H}_0\ \text{ is rejected since there are significant difference}$$
$$If\ p - value\ >\ \alpha,\ \mathrm{H}_0\ is\ not\ rejected\ since\ there\ are\ no\ significant\ differences$$

Hence, the resulting p-values for all statistical tests as described in Table 18.

Table 18: Results of the assumptions of the hypothesis tests

Output Variable	Scenario	p-value		Result
		Shapiro	Levene	
POT	Real	0.1425	0.2555	Not rejected
	Simulation	0.2355		
Dem	Real	$1.14 * 10^{-5}$	-	Rejected
	Simulation	$7.89 * 10^{-6}$		

Through the results of Table 18, conclusions can be drawn on the validity of parametric t-student test assumptions:

- According to Shapiro test, there are no significant differences between real and simulated Port Operational Time distributions and a normal distribution, since p-values of POT_{real} and POT_{real} are equal to 0.1425 and 0.2355, respectively, both higher than 0.05, the significance level.

- Based on Levene test, there are no significant differences between the variances of POT_{real} and POT_{sim} since p-value for the comparison of homogeneous of variances is 0.2555: higher than 0.05.
- The p-values from Shapiro test for both Dem_{real} and Dem_{sim} are lower than the significance level, proving that **it is not possible to perform a parametric t-student test.**

Therefore, a t-student parametric test could be performed to evaluate if there are statistical differences between POT_{real} and POT_{sim}. Conversely, it is not possible to statistically compare the distributions of Dem_{real} and Dem_{sim} using the t-student parametric test since data are not normally distributed. Hence, the solution is to perform a non-parametric Mann-Whitney test for comparing independent and unpaired samples. This test, when compared to t-student test, relaxes the assumptions for use in any distribution whatsoever.

The hypothesis test for the parametric t-student and the non-parametric Mann-Whitney test are explicit as follows:

$$\mathrm{H}_0: \mu_{POT_{sim}} = \mu_{POT_{real}} \; vs \; \mathrm{H}_1: \mu_{POT_{sim}} \neq \mu_{POT_{real}}, \qquad \text{T-student test}$$

$$\mathrm{H}_0: \mu_{Dem_{sim}} = \mu_{Dem_{real}} \; vs \; \mathrm{H}_1: \mu_{Dem_{sim}} \neq \mu_{Dem_{real}}, \qquad \text{Mann-Whitney}$$

Hence, the statistical comparison of the POT_{real} and POT_{sim} through a t-student test and the comparison of $\mathrm{Dem}_{\mathrm{real}}$ with $\mathrm{Dem}_{\mathrm{sim}}$ through a Mann-Whitney test are presented in Table 19:

Table 19: Results for the hypothesis tests

Output variable	p-value	
	t-student	Mann-Whitney
POT	0.7786	-
Dem	-	0.8746

Both tests supported the conclusion that there is no statistical evidence that the two distributions of the POT_{real} and Dem_{real} are different from the respective simulation distribution (the p-values of both tests are higher than the significance level). Hence, the hypothesis that they are the same is not rejected.

Finally, is possible to conclude that the simulation model produces results consistent with reality. That said, the model can be used to predict the future behaviour of the Liquid Bulk Terminal, allowing the exploration of alternative scenarios.

6. Results analysis

This chapter will propose and evaluate the results of alternative scenarios to the Sines' Liquid Bulk Terminal operations. It is divided in two sections. First, scenarios are described. Then, the results of these same scenarios will be evaluated considering the KPI Port Operational Time and Demurrage.
In the scenario's evaluation, first it will be evaluated the scenarios of the terminating simulation of January 2017. Next, steady state scenarios are analysed, ending in scenarios where the queue policy is changed when compared to the real terminal one.

6.1 Scenarios description

This simulation study intends to evaluate new configurations with respect to the allocations of vessels to pipelines, aiming to minimize Port Operational Time and Demurrages.
To propose a solution to the problem identified at the Sines' Liquid Bulk Terminal, 15 scenarios are developed, hosting several operational research methodologies:

- **Optimization 1, Optimization 2, and Optimization 3** denominated O1, O2 and O3, where an optimization approach is used. These scenarios have been proposed and studied in Rato (2018) where the operations and allocations of vessels to berths and pipelines are optimized to minimize Port Operational Time
- **Simulation 1, Simulation 2, and Simulation 3** denominated S1, S2 and S3, where a stochastic simulation is performed. Sines' Liquid Bulk Terminal is simulated with data inferred from the real data of January 2017.
- **Optimization-Simulation 1, Optimization-Simulation 2, Optimization-Simulation 3**, denominated OS1, OS2 and OS3. In these, the vessels' allocation to berth are optimal solution for each optimization scenarios proposed by Rato (2018). This methodology is based on a Simulation-Optimization approach defined by Figueira & Almada-Lobo (2014) as **Solution by completion simulation**.
- **Steady State 1, Steady State 2, Steady State 3** denominated SS1, SS2 and SS3 where only simulation is used. The terminal is simulated in a long-term setting according to alternative allocation policies to berths and pipelines
- **Steady State – Queuing policy 1, Steady State – Queuing policy 2, Steady State – Queuing policy 1**, denominated SS-QP1, SS-QP2 and SS-QP3. These have the same specification as scenario SS3 and aims to evaluating different queuing policies for docking operations.

Each scenario has the characteristics described in Figure 27.

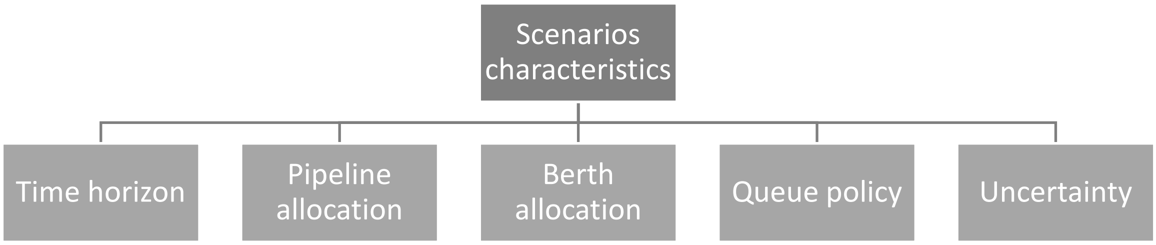


Figure 27: Scenarios' characteristics

Each scenario has distinctive characteristics, which one considering the different aspects depicted in Figure 28.

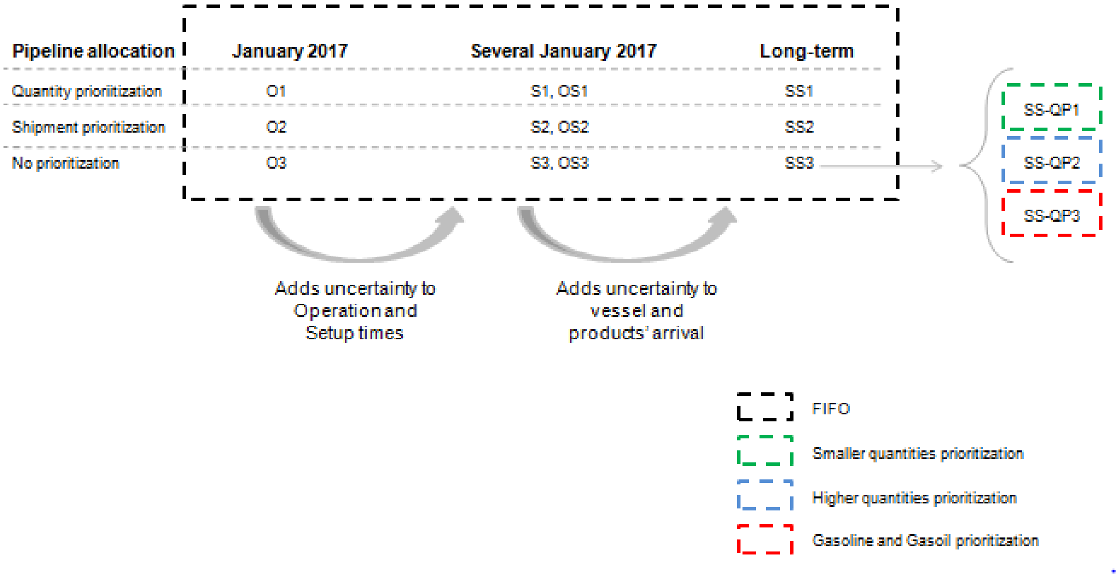


Figure 28: Scenarios' description according to its characteristics

Figure 28 illustrates the differences in the time horizons of all scenarios. Rato, (2018) studies the terminal improvements only for one month of January while scenarios S1, S2, S3, OS1, OS2 and OS3 perform a terminating simulation of January 2017. The remaining scenarios apply to a steady state simulation. Also, different pipelines allocations are investigated. As an example, scenarios O1, S1, OS1 and SS1 present the same prioritization rule (**quantity prioritization**) in the choice of pipeline. Two other rules are studied: **shipment prioritization** and **no pipeline prioritization**. However, in no-pipeline-prioritization rule there are differences between S3 and OS3. In S3, only Crude and LPG have a fixed allocation to pipelines, being allocated to pipeline A and F, respectively. The remaining products will use the pipeline with highest diameter that is available at the moment of its vessels' docking. On the other hand, OS3 uses the optimal solution for the allocation to pipelines of every vessel, found by Rato (2018). Only Crude and LPG have the pipeline allocation fixed, as in S3.

The queue policies used in each scenario are also described in Figure 28. Apart from SS-QPs, all scenarios use FIFO in queue for docking prioritization. The scenarios SS-QP1, SS-QP2 and SS-QP3 study three different queuing policies: **prioritization of small quantities**, **large quantities** and **Gasoline and Gasoil,** respectively.

Finally, the levels of uncertainty for each scenario are also depicted in Figure 28. The three optimization scenarios do not model uncertainty, as they use the real terminal data for all the variables and parameters. In the simulation and optimization-simulation scenarios for a terminating simulation of January 2017, uncertainty is added to the operation and setup times. Finally, in the six long term scenarios, uncertainty in the arrival of vessels is added, providing a random generation of vessels.

In addition to the description given in Figure 28, there is also a difference on the allocation of vessels to berths. In the optimization and simulation scenarios, for the terminating simulation of January 2017, the real allocations to berths of this month are used. This means that the allocation is the same as the one performed the Sines Terminal operators. For optimization-simulation, the allocation is done according the optimal solutions found by Rato (2018). Finally, in the long-term scenarios, a policy is adopted in which a vessel is allocated to the berth that is empty.

Besides the scenarios' description of Figure 28, Table 20 summarizes characteristics of all scenarios.

The input data for all scenarios is described in Appendix D.

The results and conclusions for all scenarios are presented in the following sections. The analysis is divided by time horizon, first analysing the scenarios that performed a terminating simulation of January 2017, moving on to steady state simulations, where it is also analysed the scenarios where the queue policy is modified.

Table 20: Scenarios description

Scenarios	Time horizon	Pipeline allocation			Uncertainty				Queue Policy			
		Quantity transported	Shipment Prioritization	No pipeline allocation	Vessels' arrival	Vessels to berths distribution	Operational Time	Setup Time	FIFO	Lower quantities prioritized	Larger quantities prioritized	Gasoline and Gasoil prioritized
Real	One month of January 2017								x			
Simulation												
S1	Terminating	x					x	x	x			
S2	Terminating		x				x	x	x			
S3	Terminating			x			x	x	x			
SS1	Steady state	x			x	x	x	x	x			
SS2	Steady state		x		x	x	x	x	x			
SS3	Steady state			x	x	x	x	x	x			
SS-QP1	Steady state			x	x	x	x	x		x		
SS-QP2	Steady state			x	x	x	x	x			x	
SS-QP3	Steady state			x	x	x	x	x				x
Optimization												
O1	One month of January 2017	x							x			
O2	One month of January 2017		x						x			
O3	One month of January 2017			x					x			
Optimization-Simulation												
OS1	Terminating	x					x	x	x			
OS2	Terminating		x				x	x	x			
OS3	Terminating			x			x	x	x			

6.2 Results

This section is divided in two subsections. The first presents the results of scenarios where terminating simulations are performed, a second one where steady state scenarios results are analysed and a third where queueing policy scenarios outputs are evaluated.

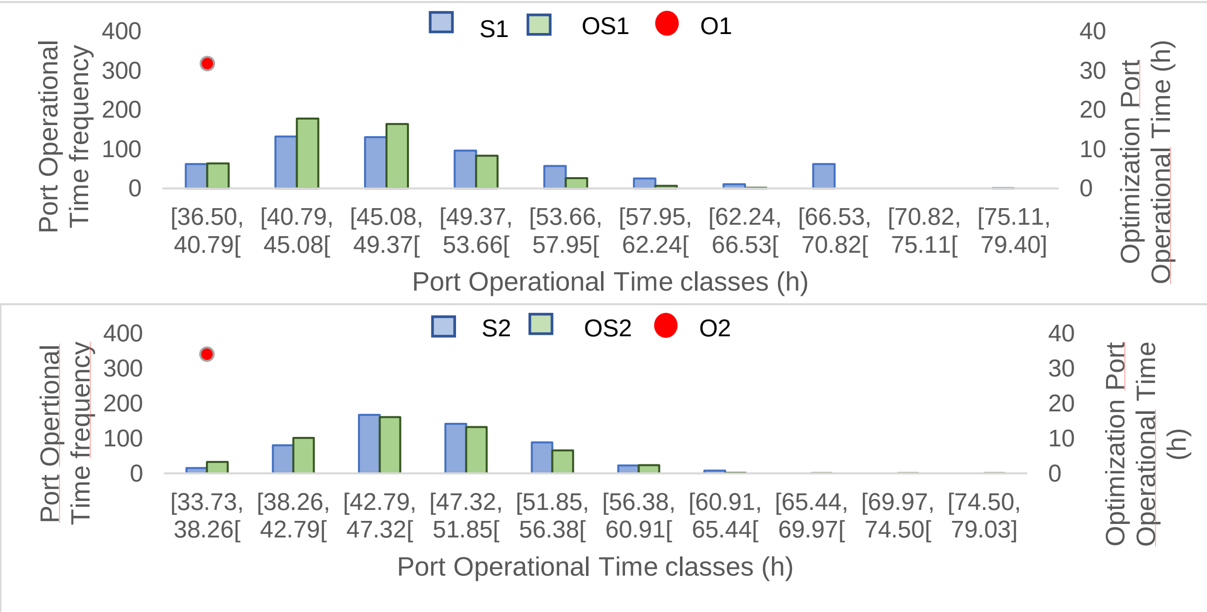
6.2.1 Terminating simulations

For the implementation of terminating scenarios, the Common Random Numbers technique was applied (Carson & Nicol, 2014). In this, the same set of random number is used in all six terminating scenarios for the results to be unbiased by the random numbers generator.

Before simulating each scenario, the number of simulations required for the average POT and Demurrages value of each product to converge to a 95% confidence interval was calculated. Moreover, the number of replicas used for all scenarios was the largest number among the number of simulations computed for scenario independently. Through SIMUL8, it was reached a value of **524 replication** for scenario S3. Therefore, this was the number of months of January 2017 simulated for all the terminating scenarios.

6.2.1.1 General results

In Figure 29, each value represents the average POT of each 57 vessels that performed operations at the terminal in January 2017, across the 524 replications (this value corresponds to the variable $\overline{POT}_{..}$ of Table 41 on Appendix E). Figure 29 presents the histograms of simulation and optimization-simulation scenarios grouped by pipeline allocation strategy (S1 and OS1, S2 and OS2, and S3 and OS3) . It also shows the optimal POT value from Rato (2018) (the red dot). The number of classes was calculated applying the Sturges Rule, with the horizontal axis is divided in 10 classes clustering the 524 replicas in intervals with width varying across the 3 scenarios.



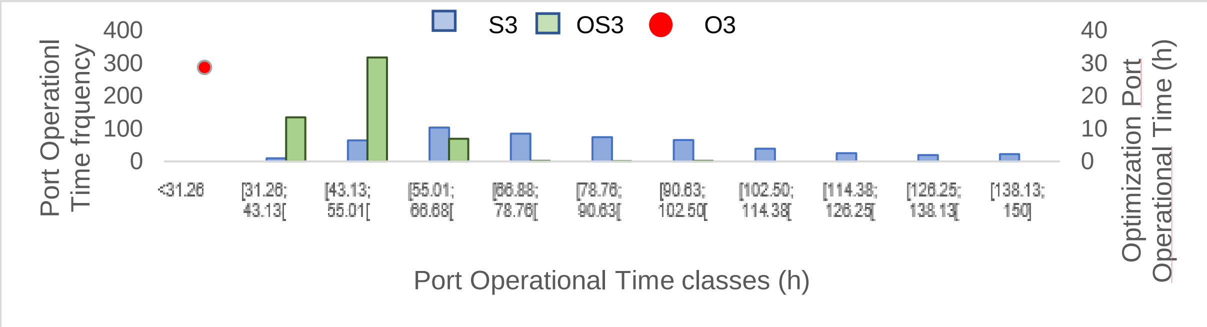


Figure 29: Port Operational Time data distribution of the terminating scenarios

Figure 29 shows that both Simulation and Optimization-Simulation for scenarios 1, 2 and 3 have their spike in classes [40.79, 45.08[, [42.79, 47.32[and [43.13, 55.01[hours, respectively. There is only one exception, scenario S3, where the mode is class [55.01; 66.68[. In fact, this scenario is the only one that does not have a graphical spike that stands out, showing an apparent plateau from class [31.26, 43.13[to [90.63, 102.50[hours. If the classes in the x axis were the same for all scenarios, the histograms would move to the left, and so their mode, specially the OS3 scenario.

Scenario S3 is, in fact, the scenario with more dissimilar results. Unlike scenarios 1 and 2, the policy of allocating products to pipeline is flexible for all products, except for Crude and LPG (which are allocated to pipelines A and F, respectively). This results in one operational problem. In this scenario, when a vessel berths, no matter the product or the quantity transported, it is allocated to whatever pipeline is free at the moment, among pipelines B, C, D or E. If more than one is available, it will be allocated to the pipeline with higher diameter, since it is the one that will provide lower Operational Time. However, this strategy does not consider the future arriving vessels. For instance, if a Naphtha vessel berths, with low quantity transported, it is allocated to pipeline B because it will minimize OT. However, the following vessel is a Fuel one with a higher quantity, being allocated to the second highest diameter pipeline available, pipeline C (if allocated to pipeline B, it would have a smaller OT). If the operator when deciding the allocation of the Naphtha vessel knew in advance that the Fuel vessels was coming, the pipeline choice would consider this fact and the Naphtha vessels would have been allocated to pipeline C, reserving pipeline B to the Fuel vessel. This strategy would have smaller Port Operational Time that the one used in S3. This “knowledge of the future” is modelled in scenario OS3, showing much better results, as the third chart on Figure 29 demonstrates.

Moreover, comparing Simulation to Optimization-Simulation approach across all scenarios, OS shows higher frequencies in lower value classes than S scenarios. This trend changes for higher value classes. Therefore, Optimization-Simulation, for this problem, presents better results on minimizing POT than Simulation approach.

Finally, all 3 charts compare the 524 replicas POT with the optimization approach of Rato (2018) for each scenario. As expected, optimization provides better results on minimizing POT on each scenario, but these results have low probability to happen. An optimization approach considers a determinist list of vessels that will arrive at the terminal, choosing the sequence of vessels that minimizes the POT. It also considers mean values, not considering the variability of the input data. Therefore, this optimal value is very difficult to achieve because it does not consider delays or inefficiencies in operations.

According to the simulations and optimization-simulations performed, the probability of occurring the optimal value of scenarios O1, O2 and O3 is 0.19%, 0.38% and 0.19%, respectively.

Besides the description of POT, analysing the waiting time for docking, TD, is also interesting. It is now analysed the variation of this factor for scenarios 1 and 2, for Fuel, Gasoline and Gasoil. Between these two scenarios, the vessels allocation to pipelines changes for these three products, and it will be interesting to assess the differences in weight that TD has in the POT.

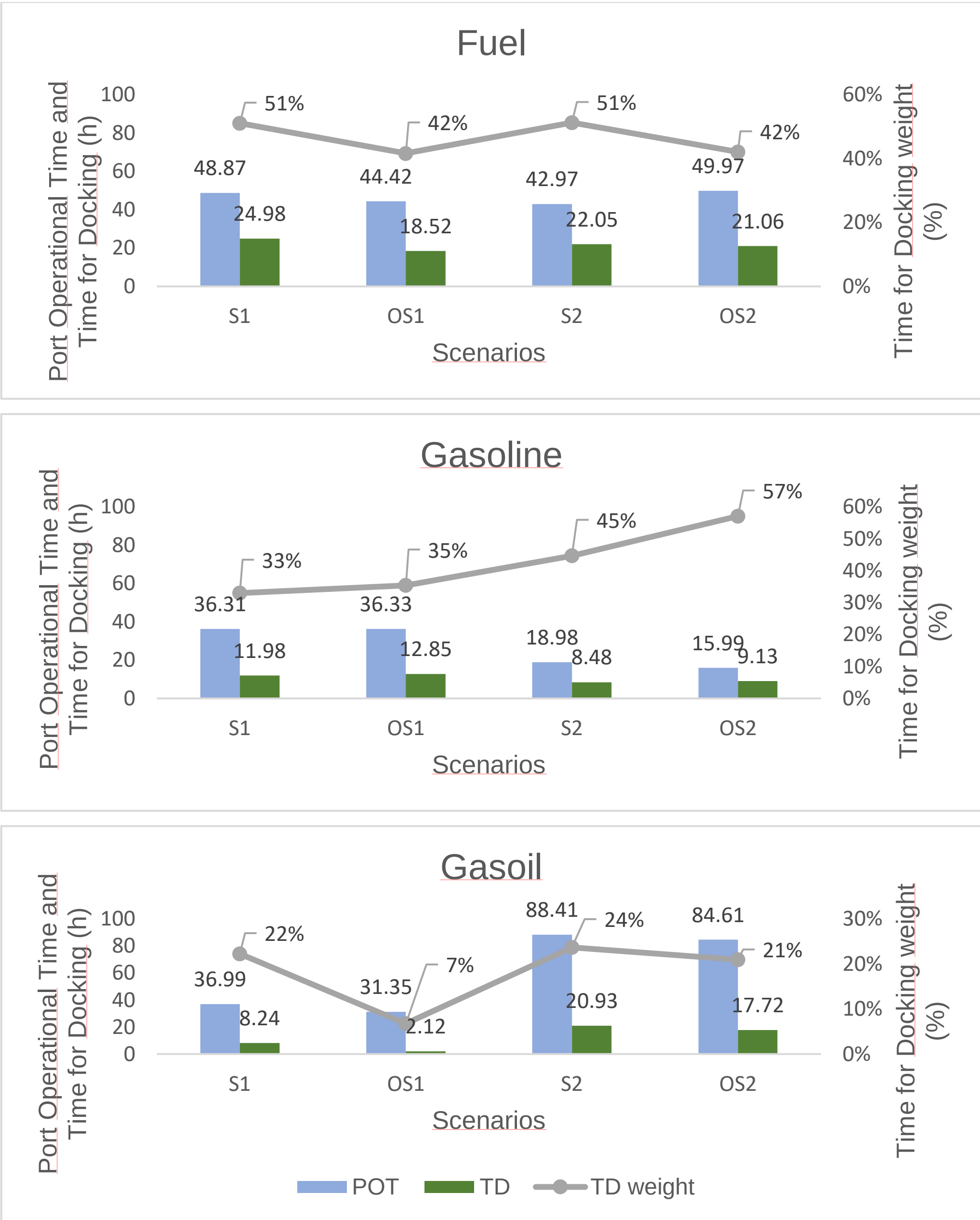


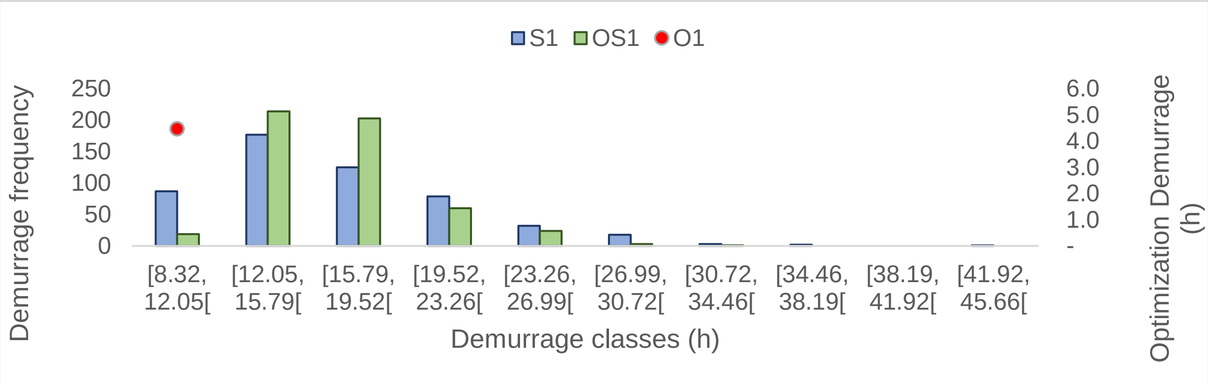
Figure 30: Time for Docking weight on Port Operational Time, for Fuel, Gasoline and Gasoil, on scenarios S1, OS1, S2 and OS2

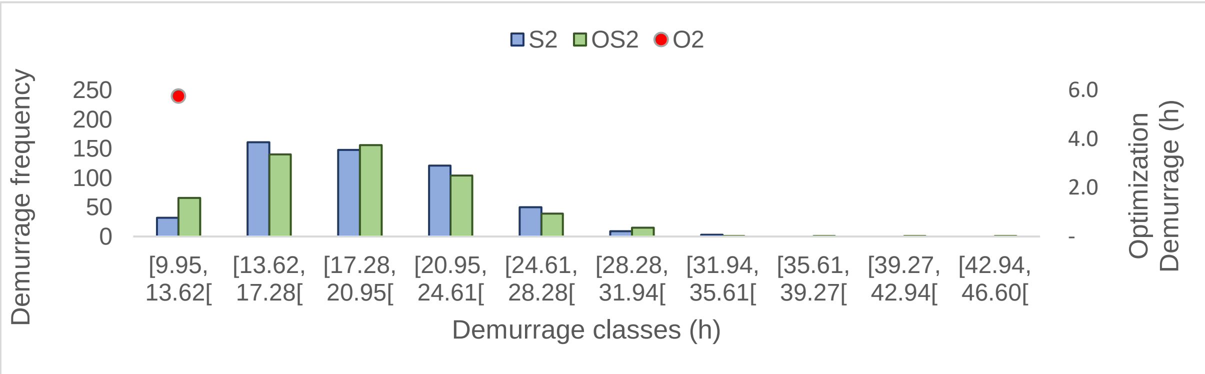
Figure 30 shows that vessels transporting Fuel present approximately the same weight of TD on POT for S1 and S2 (about 51%), and for OS1 and OS2 (about 42%). However, Optimization-Simulation scenarios results lead to lower TD weight compared to the Simulation ones.

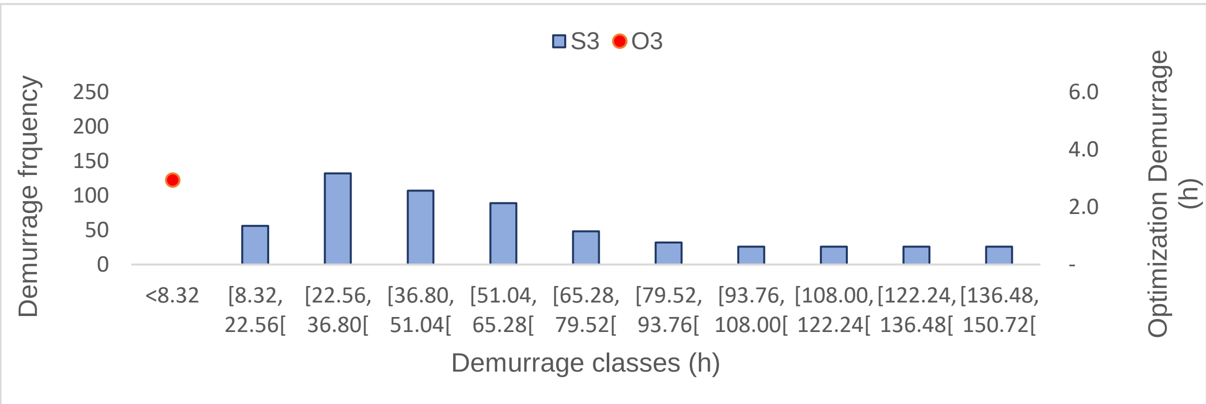
Gasoline vessels, on the other hand, lowers the POT from scenario 1 to 2, because it uses pipelines E and C instead of C and D, for reception and shipment, respectively. In S2 and OS2 the pipeline lines are practically exclusive to Gasoline unlike what happens in scenario 1. The Time for Docking ends up decreasing in absolute value but increasing its relative weight in the POT.

Finally, vessels transporting Gasoil registers a very low TD weight value for scenario 1, mainly for OS1, due to the allocation to pipeline C. On the other hand, in scenario 2, the POT increases abruptly with the allocation to pipeline E. Although, TD presents relatively low weight, proving that Operational Time and Setup Time increased with the alteration of pipeline allocation.

With respect to Demurrage Time it is expected, as analysed in Chapter 2, that the simulation results and patterns will be like those of POT in the corresponding scenarios.







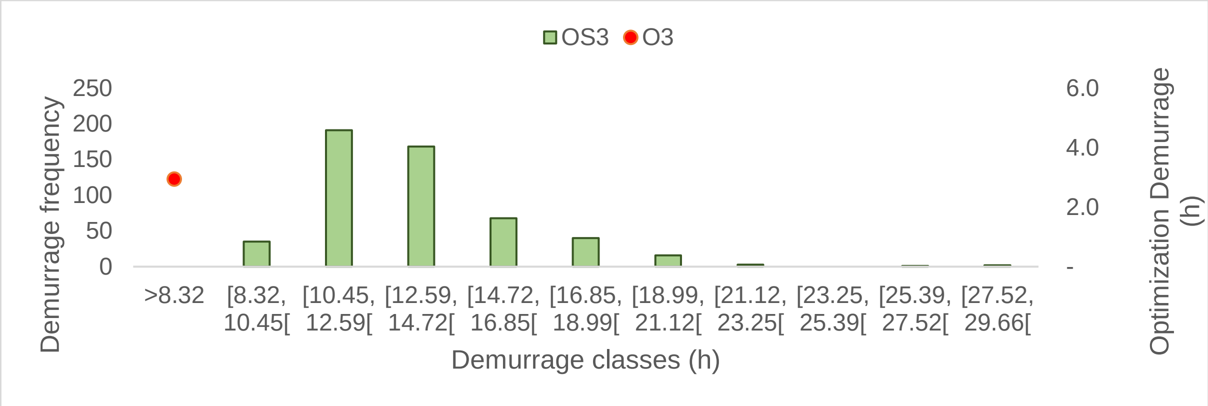


Figure 31: Demurrage time data distribution for terminating scenarios

Figure 31 presents 4 charts referring to all Simulation and Optimization-Simulation scenarios with respect to the different allocation policies. Scenarios S3 and OS3 are divided into two distinct histograms due to the pronounced difference in the value range of Demurrage time, allowing patterns to be distinguished more clearly. As for Port Operational Time, all scenarios are compared with Rato (2018), allowing it to be positioned in the values range.

The first observation drawn from the histograms concerns the class with the highest frequency (the modal class). The scenario with the leftmost peak is OS3, with 10.45 to 12.59 hours as the modal class interval. This is followed by S1 and OS1, with the peak in class [12.05, 15.79[hours, moving to S2 and OS2 with the mode in classes [13.62, 17.28[and [17.28, 20.95[hours, respectively. Finally, S3, as well as for POT, proves to be the scenario with the worst results, displaying its peak in class [22.56, 36.80[hours and with a range of values from 8.32 hours to 150.72 hours of Demurrage. As for Port Operational Time, if all graphics had the same x axis classes, for example, the histogram of scenario 1 would move to the right of scenarios 3, for example.

Comparing Simulation and Optimization-Simulation in their generality, it can be observed that in scenarios 1 and 3, the frequency of OS values is higher for lower value classes when compared to S, which indicates that OS presents lower POT than S. This pattern changes to the higher values, as well as visualized for Port Operational Time.

Finally, all scenarios were compared with Rato (2018) optimization value for Demurrage Time. In all scenarios this value occurs in the class with the lowest values, enabling the same conclusion as for the POT: optimization is indeed very advantageous in optimal conditions, but it does not consider the existence of variability in system's inputs. This characteristic is modelled by S and OS, with the mode of these methodologies for each scenario a step further to the right, however with realistically feasible results. Considering the optimization values, the probability of this event is quite low, with the values of 0.5%, 0.7% and 0.5% for scenarios O1, O2 and O3, respectively.

Since Demurrage Time represents a cost for the company, it is desirable that this value is as close to zero as possible. Figure 32 compares the frequency of vessels with Demurrage time equal to zero in all terminating scenarios to the vessels that had Demurrages time equal to zero in January 2017.

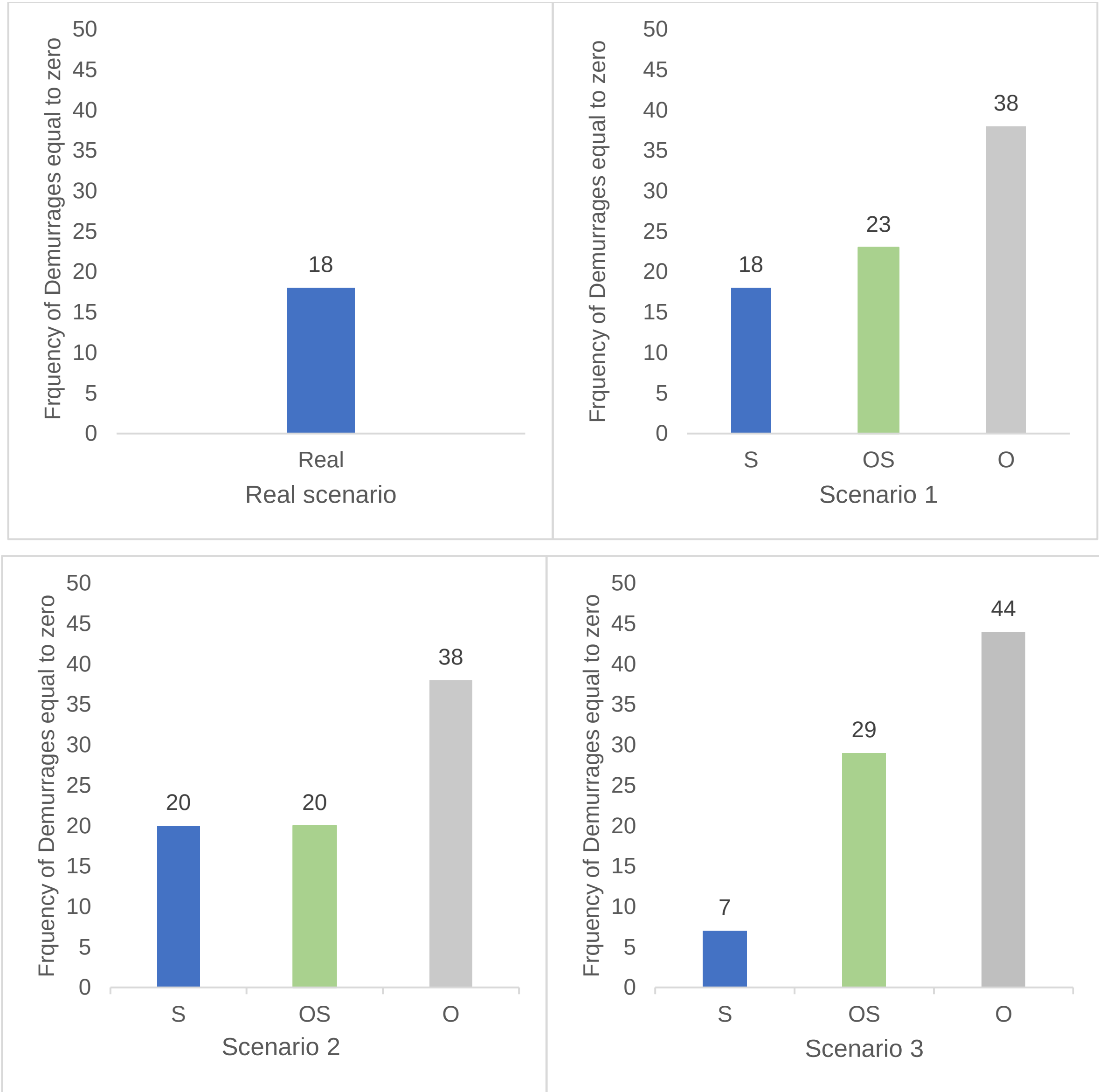


Figure 32: Comparison of vessels with Demurrage time equal to zero of each scenario

Scenario O3 shows the best result with 44 vessels with zero Demurrage Time among the 57 vessels. Optimization-Simulation also has its best result for scenario 3, with 29 vessels with Demurrage time equal to zero. Optimization-Simulation has better results than Simulation approach for scenarios 1 and 3, while in scenario 2 both methods present equal values, with 20 vessels with Demurrages time equal to zero.

Overall, all methods demonstrate better results than the real scenario, except for scenario S3, where only 7 vessels have a Demurrage time equal to zero.

It is also interesting to evaluate what happens to the vessels that had Demurrage time different from zero. Figure 33 shows the best and worst scenarios in this parameter: OS3 and S3, respectively.

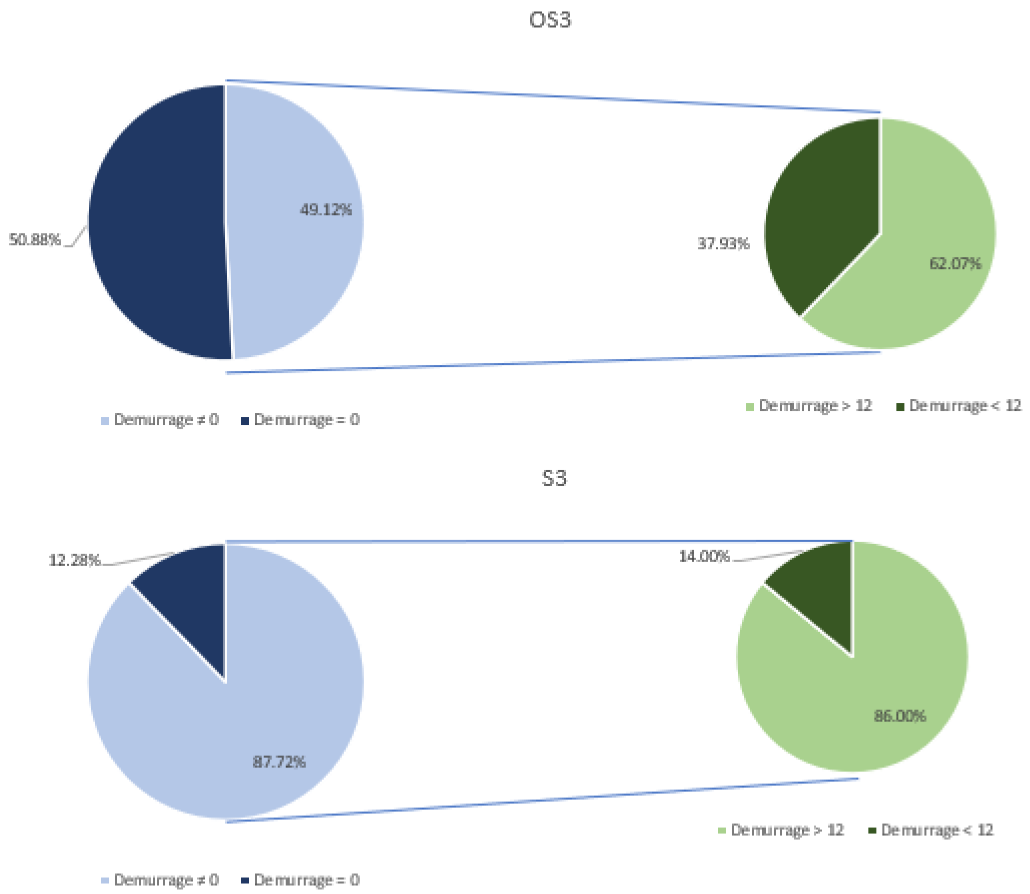


Figure 33: Comparison of vessels with Demurrages time equal to zero and higher than 12 hours, for scenarios S3 and OS3

According to Figure 33, on scenario OS3, among the 57 vessels, 49.12% had Demurrage time different from zero. From these vessels, 62.07% had Demurrage time values higher than 12 hours, which is heavily penalized in the contractual agreements' costs. With respect to scenario S3, 87.72% of the vessels had Demurrages time different from zero, from which, 86.00% had Demurrages time higher than 12 hours.

Finally, based on the vessels that had not Demurrage equal to zero, the variation of the Demurrage costs compared to the real terminal Demurrages costs are depicted in Figure 34, for all terminating scenarios. These costs were calculated using the hourly cost of Demurrage presented in Table 14.

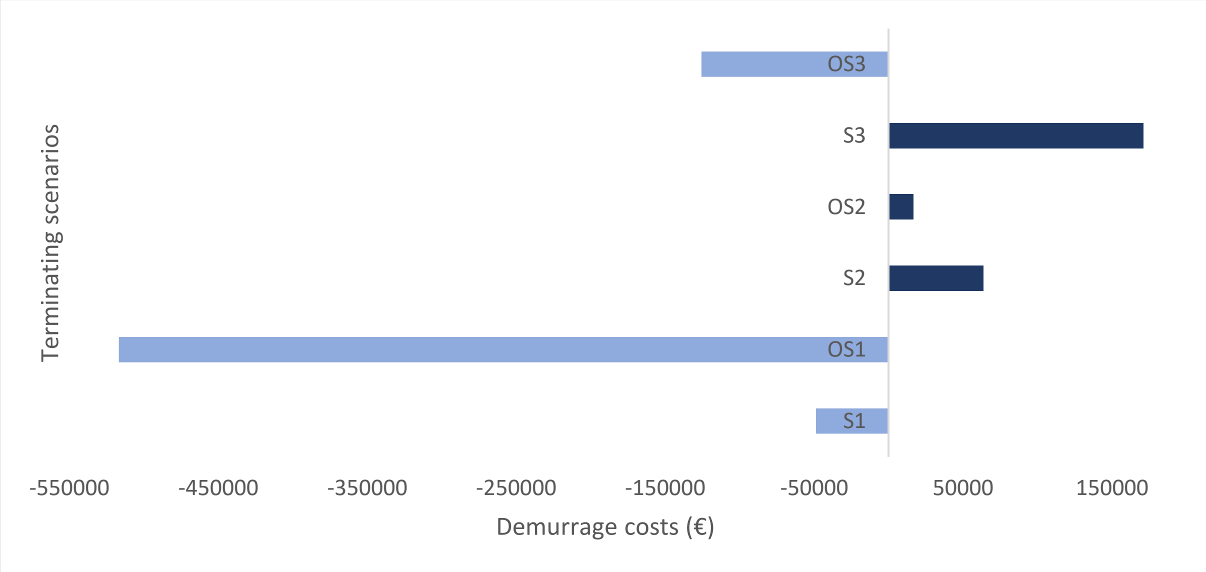


Figure 34: Comparison of Demurrage costs of terminating scenarios and real case study

Figure 34 illustrates that only scenarios S1, OS1 and OS3 decrease the costs associated with Demurrage when compared to what happened in the terminal in January 2017. Scenario OS1 is the one that provides the highest cost reduction. This scenario lowers the Demurrage time of Gasoil (as it will be analysed further on), a product with a high cost per hour of Demurrage.

Scenarios S2, OS2 and S3 increase the costs for the company. For S2 and OS2, this is due to the very high Demurrage of Gasoil. The S3 scenario shows poor results for almost all products, so it was expected to be the costliest scenario for the terminal.

6.2.1.2 Variability

The considerations of uncertainty in setup and operation times through Simulation and Optimization-Simulation of terminating simulations represents a very useful tool for the evaluation of changes on the policy allocations on the Liquid Bulk Terminal.

Figure 29 shown the POT for each simulation and compare the different scenarios and the optimization approach. In Figure 35 it is performed a deeper analysis on outputs variability, through boxplots. It is divided by products and scenarios, highlighting POT data distribution per product. It is used the output POT correspondent to the limit value of the 524 replicas of $\overline{POT_{p.}}$, for all p (Appendix E).

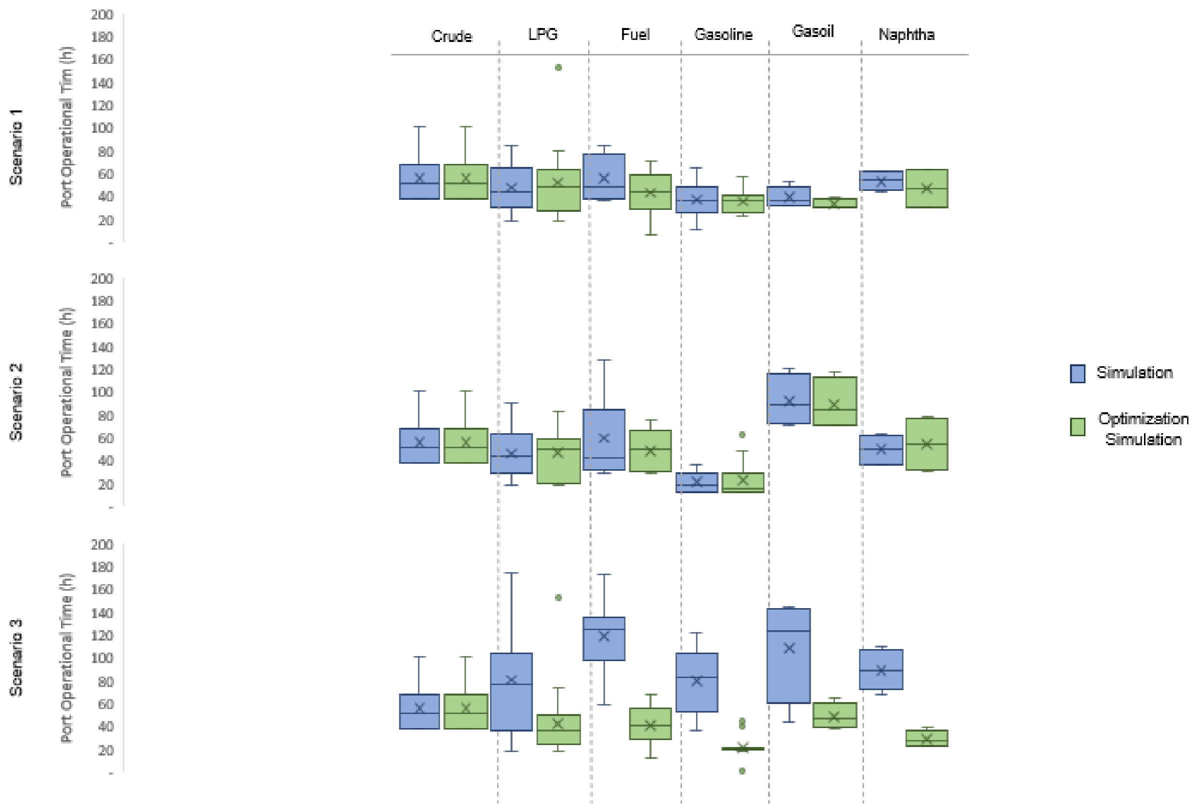


Figure 35: Port Operational Time boxplots of terminating scenarios, divided by product

Even with the division by product, the statistical patterns of scenarios 1, 2 and 3 are visible in their generality and when divided by Simulation and Optimization-Simulation. Figure 35 demonstrates that (supported by Table 43 on Appendix G):

- Optimization-Simulation scenarios present lower mean values when compared to Simulation scenarios, for almost all six products transacted at the terminal
- Median values (the cross symbol) are approximately homogeneous for Simulation and Optimization-Simulation on scenarios 1 and 2 for most products. In scenario 3, the results are different, with Simulation and Optimization-Simulation revealing higher medians when compared to the other scenarios
- By comparing all scenarios, it is possible to state that inter quartile amplitude is always lower for Optimization-Simulation approach than for Simulation. Among the three OS scenarios, OS3 presents the lowest inter quartile amplitude overall

The boxplot division by product made explicit how their POT change across scenarios. Some remarks are made based on Figure 35:

- Crude presents the same values in all scenarios, since its operations are performed parallelly to the other products and it has a dedicated pipeline: pipeline A

- Fuel, LPG, and Naphtha present better results in scenario OS3; the main reason being the products are allocated to the best pipeline available at the vessel arrival time (there is **no pipeline allocation** pre-established)
- Gasoline, due to the alteration from pipeline C to pipeline E, have **better results for scenarios S2 and OS2.** It also has **great results for scenario OS3**
- Gasoil have its **best results in scenario OS1**, since it is allocated to pipeline C (instead of pipeline D in scenarios S2 and OS2). It also presents good results in scenario OS3
- All products show **bad results for scenario S3**

After the analysis of POT variability through boxplot on Figure 35, a similar analysis will be made with respect to the Demurrage time variability. Figure 36 shows the boxplots for the Demurrage time per product, per Simulation or Optimization-Simulation.

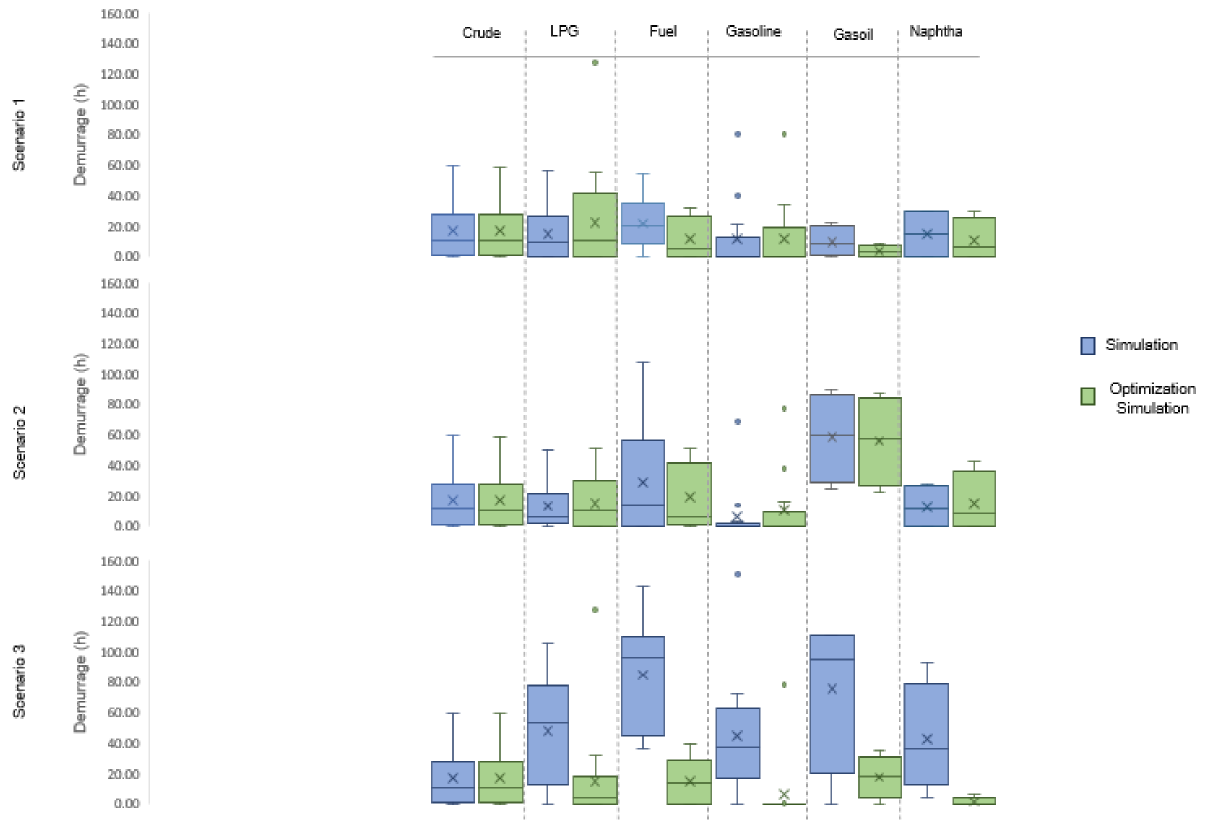


Figure 36: Demurrages boxplots of terminating scenarios, divided by product

Statistical patterns of scenarios 1, 2 and 3 are visible in their generality and when divided by Simulation and Optimization-Simulation. Therefore, conclusions can be drawn from Figure 36 supported by Table 42 on Appendix G:

- Regarding the average values of the six scenarios presented, the best results are in OS1, with 6.55 hours of Demurrage, followed by OS3 and S1, with 6.81 and 9.55 hours, respectively. The worst scenario in terms of average values is S3. It should also be noted that scenario 2, whether using Simulation or Optimization-Simulation, presents results that prove that the allocation policy is inefficient

- The OS3 scenario presents the smallest interquartile range. This is followed by S1 and S2 with 23.97 and 25.59 hours, respectively
- The OS scenarios show lower average values of Demurrage time than S ones, however, the Simulation reduces the variability more than OS, except for the case of the S3 scenario, which has the worst results for all evaluated parameters.

Deepening the analysis of Demurrage time, the boxplot reveals the influence that changes in allocations have on Demurrage time by product. Table 42 on Appendix G support the following conclusions:

- Crude, being exclusively allocated to pipeline A and berth 2 for all scenarios, does not change the Demurrage time across scenarios
- LPG gives low average values for the OS3 scenario when compared to scenarios 1 and 2
- Fuel shows its best results for scenarios OS1 and OS3
- Gasoline presents great results on scenario OS3
- Gasoil presents the best results for OS1 and is severely impacted by the change in product allocation to pipelines in scenario 2
- Naphtha presents the best results for scenario OS3

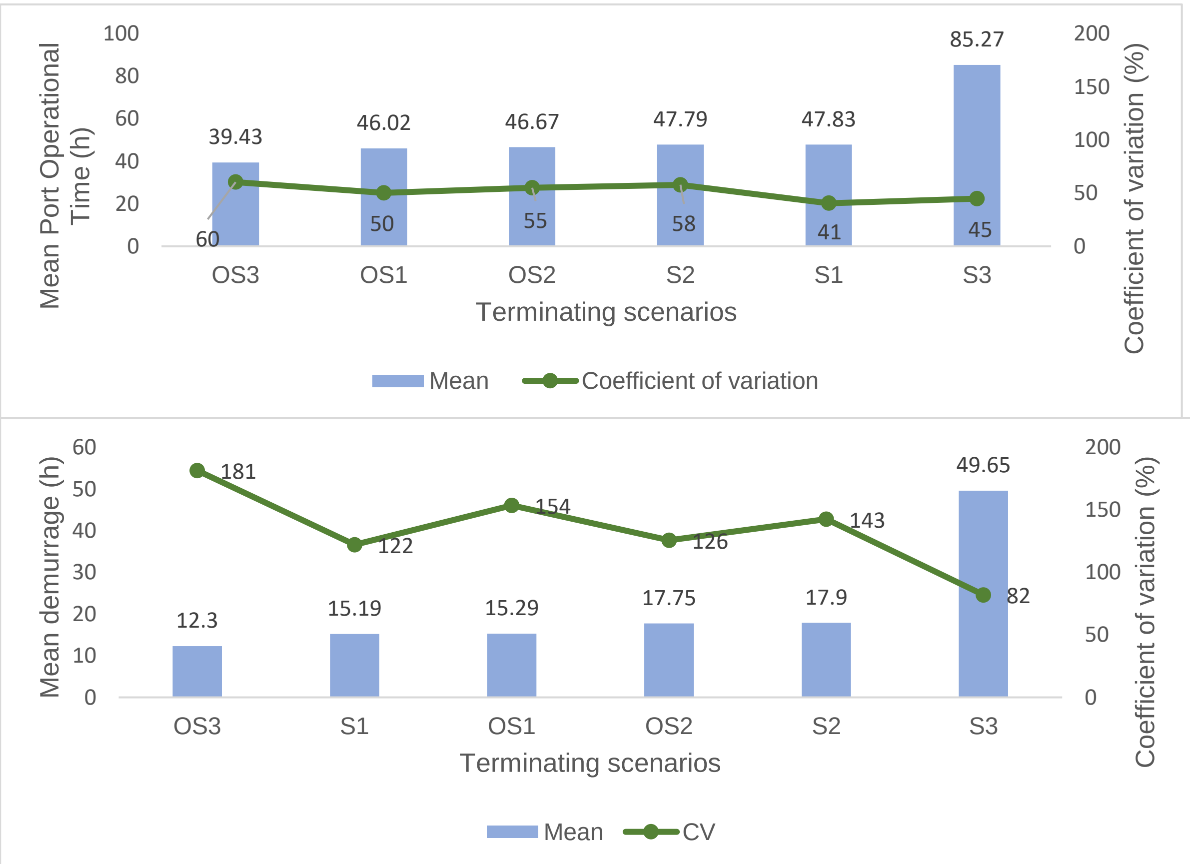


Figure 37: Coefficient of variation and mean values of terminating scenarios for a) Port Operational Time and b) Demurrage

Deepening the analysis of variability, Figure 37 depicts the coefficient of variation and mean values of terminating scenarios for Port Operational Time and for Demurrage Time, with the mean values in ascending order.

In Figure 37 it is visible that scenario OS3 has the lowest mean Port Operational Time and Demurrage time. Moreover, OS3 presents the highest CV among the six terminating scenarios, with 60 and 181%, for POT and Demurrage time, respectively. This shows that, even though the mean values of the KPI are low, the standard deviation is relatively high. In contrast, scenario S3 presents the highest mean POT and Demurrage time. Unlike scenario OS3, it presents the lowest CV value among the terminating scenarios for both POT and Demurrages time, with 45 and 82%, respectively.

In general, the coefficient of variation decreases when the mean value of the KPI increases. This suggests that with the increase of the KPI mean value, the standard deviation does not follow this increase. Therefore, outputs variability tends to increase when the mean value of the KPI decrease.

Another conclusion of Figure 37 is that Optimization-Simulation scenario show more variability than simulation ones. It is also noteworthy that Demurrage time have higher variability that Port Operational Time for all six terminating scenarios.

6.2.1.4 Computational times

The computational time associated with the six terminating scenarios are provided in Table 21.

Table 21: Computational time of terminating scenarios

	OS2	**S2**	**S1**	**OS1**	**OS3**	**S3**
Time	3' 40''	3' 50''	4' 11''	4' 27''	4' 33''	5' 17''

Scenario S3 is the one with the highest computational time, with 5 minutes and 17 seconds. On the opposite side, scenario OS2 only needed 3 minutes and 40 seconds. For scenarios 2 and 3, Optimization-Simulation had lower computational times than the Simulation ones. In scenario 1, scenario S1 have lower computational time than OS1.

6.2.1.5 Selection of the best terminating scenario

For the selection of the best allocation policy for the terminal, that is, the scenario that have the allocation policy of vessels to berths and pipelines that minimizes the Port Operational Time and Demurrage, it is now made a comparison between all scenarios and real terminal outputs, for both KPI (Figure 38).

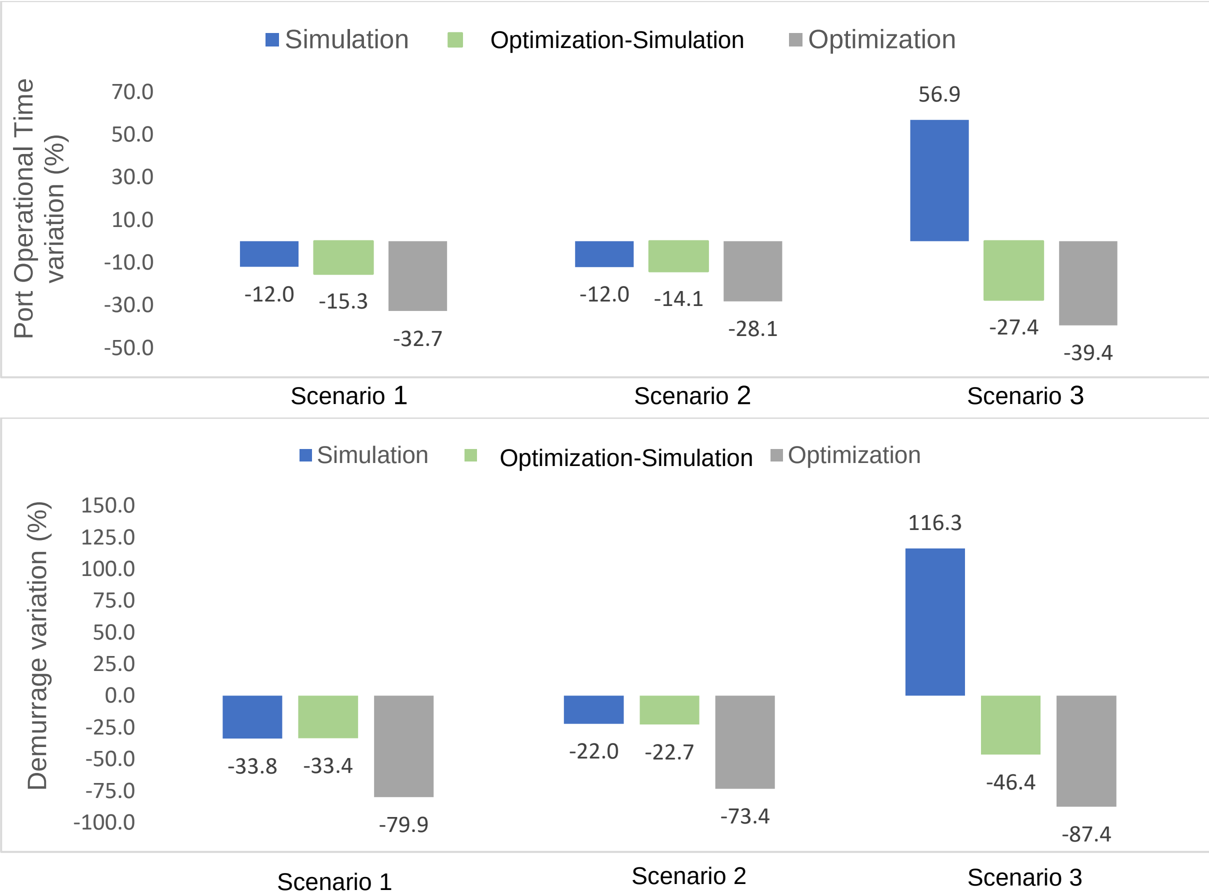


Figure 38: Variation of a) Port Operational Time and b) Demurrage time of terminating scenarios, compared to real terminal costs

Figure 38 shows the variation, for all scenarios, of Port Operational Time (the mean value of all $\overline{\mathrm{POT}_{..}}$) with respect to the real terminal values for January 2017. As it was mentioned, scenario S3 shows the least interesting results, increasing POT and Demurrage time by 56.9% and 116.3%, respectively. All other scenarios allow for an improvement, with optimization approaches presenting the best results (reaching 39.4 % for POT and 87.4 % for Demurrages, on scenario OS3). Although, as it was mentioned, this approach it very difficult to achieve since it needs to have the knowledge in advance of the arrival times of all vessels. Therefore, it does not consider the probability of delays or some problems associated with port activity. Therefore, a combination of optimization with simulation presents the second-best results overall, that is, this is the method that provide reliable results of both KPI, since it reflects very well the real terminal operations. This method also provides the best results for scenario OS3, where there is flexibility on pipeline allocation and the allocation of vessels to berths are the optimal solution found by Rato (2018). OS3 decreases POT by 27.4% and Demurrages times by 46.4%.

Moreover, Simulation approach also presents good results, decreasing the value of POT by 15.3% and Demurrage times by 33.4%, on scenario OS1. It is also noteworthy that Simulation-Optimization present better and more reliable results than Simulation approach, for both KPI.

It is also noteworthy that results of POT and Demurrage times are very similar.

In fact, this graphical comparison of scenarios' KPI is very useful to guess what the best scenario for the Liquid Bulk Terminal of Sines in January 2017. However, it is now performed a methodology for the selection of the best scenario, using the methodology on Appendix F for terminating simulations.

For the selection of the best terminating scenarios for the Liquid Bulk Terminal, it will only be considered the performance from the POT, since the conclusions for this KPI and Demurrage times were similar.
It starts by assuming the existence of $K = 6$ scenarios, with $R = 524$ replications and a practically significant difference of $\varepsilon = 5$ hours. The means and standard deviation of the POT for each scenario are presented in Table 22.
The scenario that presents the lowest mean POT is OS3, so this is the only constituent of subset A:

$$A = \{OS3\}$$

The screening thresholds is then calculated and the validity of the inequation is verified, as shown in Table 22.

Table 22: Results for the selection of the best procedure

Scenario i	S1	OS1	S2	OS2	S3	OS3
$\boldsymbol{POT_{.i}}$	47.83	46.02	47.79	46.67	85.27	39.43
$\boldsymbol{S_i^2}$	6.57	4.74	5.44	5.85	30.87	3.58
$\boldsymbol{W_{i,OS3}}$	1.28	1.02	1.12	1.17	5.32	-
$\boldsymbol{POT_{.i} \leq POT_{.4} + max(0, W_{i,OS3} - 5)}$	**35.71**	**35.45**	**35.55**	**35.60**	**39.75**	-
Validity	**False**	**False**	**False**	**False**	**False**	

The graphics of Figure 38 already induced what was the best scenario. Now, it was reached a conclusion. It is concluded that none of the scenarios presents the inequity as True, so none of them belongs to the new subset A. Hence, the only constituent, and therefore the **best terminating scenario, is OS3**, where Optimization-Simulation is used with the flexibility of product allocation to berths and pipelines.

6.2.2 Steady state simulation

In this section the results for the steady state scenarios SS1, SS2 and SS3 are presented. From the experience of Chapter 2 and the previous section of terminating simulations, POT and Demurrages have similar conclusions. Based on that, for this section, it will only be analysed the Port Operational Time results.

6.2.2.1 Steady state results

The three long-term scenarios were simulated using the Common Random Numbers (Carson & Nicol, 2014) allowing their trends to be effectively compared. As for terminating simulation, it was calculated number of replications needed for the mean POT converge to a 95% confidence interval. The high resulted in 20 simulations for scenario SS2. The need for replications in this steady state simulation is justified by the fact that every replica will produce results with different random numbers, allowing the variability of each scenario's output to be analysed when the set of random numbers change.

In addition, the same warm-up and collection data periods were considered, with 6500 hours and 65000 hours, respectively (approximately 9 months for warm up period and 7.5 years for collection data period). Figure 39 presents the trend of the average POT of all 20 replicas for all vessels that berthed, for the three scenarios.

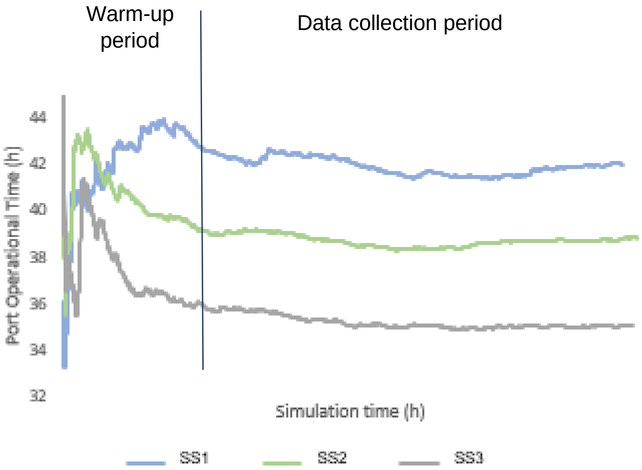


Figure 39: Mean Port Operational Time of steady state scenarios over time

Figure 39 demonstrates the POT data, converging to a value at the end of 65000 hours of collection data period. The POT value at the end of the simulation corresponds to a stationary state, representing the value at infinity of the KPI, estimating the limit of the averages series when it tends to infinity, that is, $\overline{POT} = \lim_{n\to\infty} \frac{1}{n} \sum_{v=1}^{n} POT_i$.

The following values were obtained:

$$POT_{SS1} = 42.002\ h \qquad POT_{SS2} = 38.847\ h \qquad POT_{SS3} = 35.064\ h$$

As depicted on Figure 39, scenario SS3 converges to the lower POT values, with 35.064 hours, followed by SS2 and SS1, with 38,847 and 42.002 hours, respectively. However, this is an average value for all vessels and does not accommodate the inherent and important variability to be considered when developing conclusions on the performance of the terminal. Hence, the boxplots in Figure 40 demonstrates the variability associated with scenarios' POT.

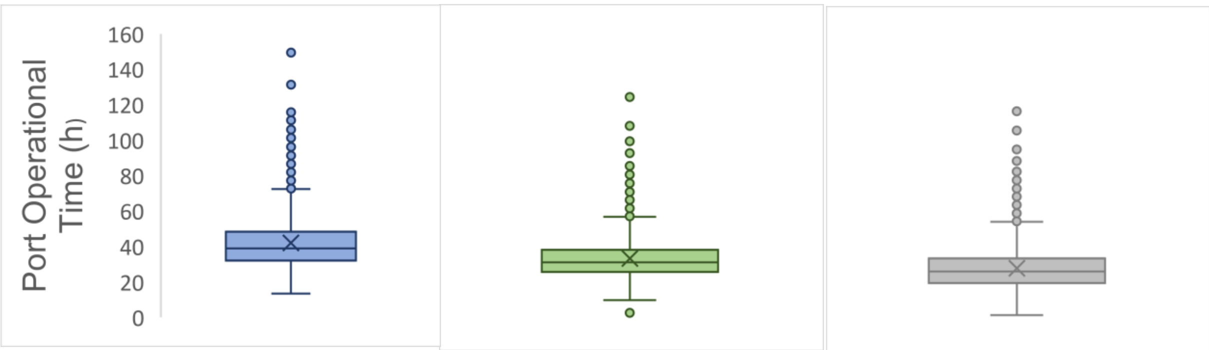


Figure 40: Port Operational Times boxplots of steady state scenarios

Table 23: Statistics of the boxplots of Port Operational Time, for steady state scenarios

Scenarios	Mean (h)	Median (h)	Inter-quartile amplitude (h)
SS1	42.002	38.951	16.240
SS2	38.847	36.990	11.225
SS3	35.064	33.345	12.451

Some conclusions can be reached through the boxplots of Figure 40, supported by Table 23. Scenario SS3 exhibits the lowest average and median of all scenarios while scenario SS2 presents the lowest interquartile range, followed by SS3 and SS1. However, even though SS3 has a slightly higher variability than SS2, it is noticeable that this is for lower values. In short, the scenario that presents worse Port Operational Time results for the 3 parameters, presented Table 23, is SS1. On the other side, the SS3 scenario shows the best results overall.

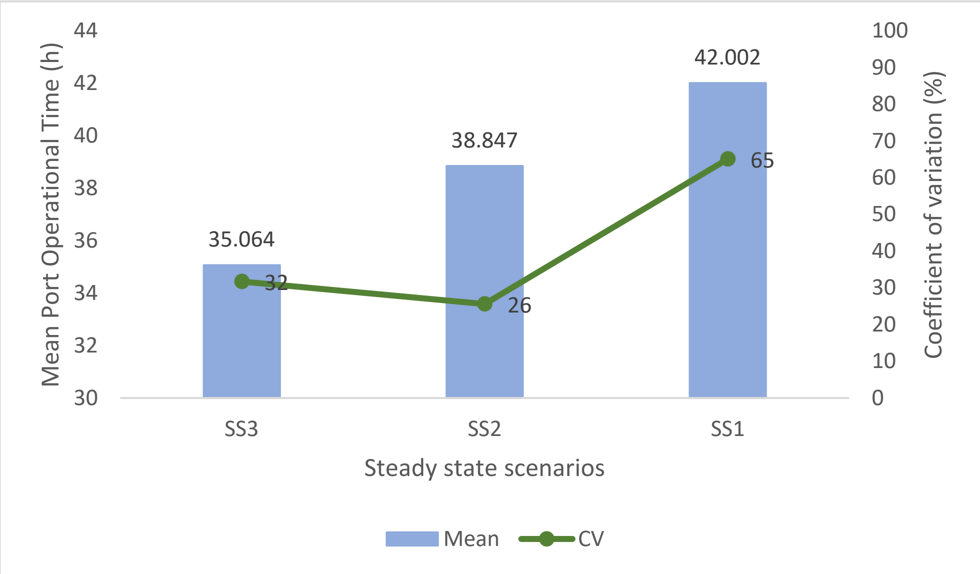


Figure 41: Mean value and coefficient of variation of Port Operational time of steady state scenarios

Considering Figure 41, scenario SS1 presents the highest mean POT and Coefficient of Variation, with 42.002 hours and 65%, respectively. These values demonstrate that this scenario output results with higher variability. On the other hand, scenario SS2 shows the lowest variability among the three, with 38.847 hours and 26% for mean POT and CV, respectively.

Table 24: Computational times of steady state scenarios

	SS1	**SS2**	**SS3**
Time	19' 31''	25' 12''	23' 07''

Finally, Table 24 demonstrate that scenario SS2 is the one the needed more computational time to perform, followed by SS3. Scenario SS1 presents the lowest computational time, with 19 minutes and 31 seconds.

6.2.2.2 Selection of the best steady state scenario

The steady state scenario with the allocation policy that minimizes the POT is now accessed. Based on the methodology proposed by Bonferroni for steady state scenarios (details in Appendix F), the construction of confidence intervals begins by describing the mean POT values resulting from each of the 20 replicates for scenarios SS1, SS2 and SS3, in Figure 42.

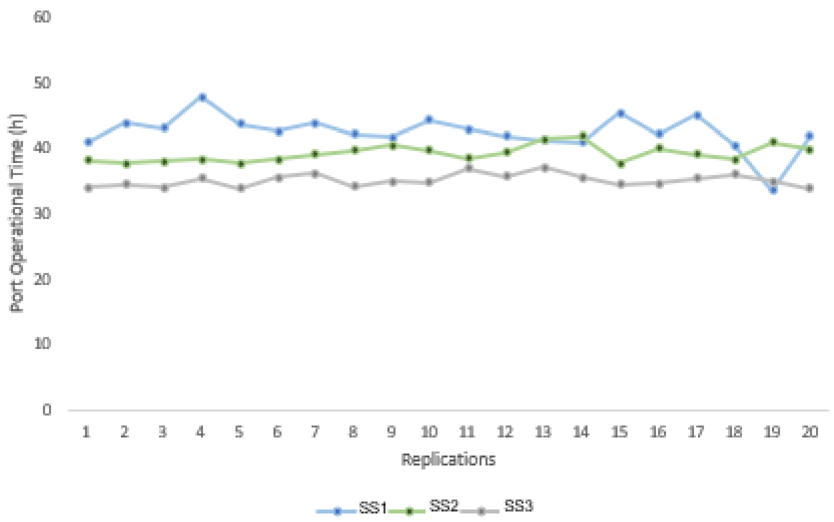


Figure 42: Port Operational Time mean values across the 20 replications

The values corresponding to Figure 42 are presented Table 44 on Appendix H.
The confidence intervals based on the Bonferroni method are displayed. Value needed for the construction of the confidence intervals can also be observed in Table 44 of Appendix H.

$$CI_{95\%}(SS1 - SS2) = [0.7817;\ 5.6814]$$

$$CI_{95\%}(SS1 - SS3) = [5.3095;\ 9.3517]$$

$$CI_{95\%}(SS2 - SS3) = [3.1638;\ 5.0344]$$

All confidence intervals are to the right of zero, so there is strong evidence that scenario SS2 has average POT values lower than SS1. The most important conclusion is the existence of statistical evidence that scenario SS3 has average POT values lower than the others. Therefore, this reveals that the best allocation strategy for the Liquid Bulk Terminal in a long-term horizon is no prioritization of pipelines to vessels transporting Fuel, Gasoline, Gasoil and Naphtha, with Crude and LPG being allocated to pipeline A and F, respectively. This result is aligned with the conclusions reached when considering terminating simulation scenarios.

6.2.3 Steady state simulation - Queueing policies scenarios

Based on the scenario SS3, the influence of queue policies on Port Operational Time will now be tested. For this purpose, as mentioned previously in this chapter, three scenarios derived from SS3 are developed: SS-QP1, SS-QP2 and SS-QP3.

It was considered the same warm-up period and data collection period as in the previous scenarios, 6500 and 65000 hours, respectively. However, based on the SIMUL8 results, 10 replicates were enough for the following scenarios to converge.

6.2.3.1 Queueing policy results

The results for these new scenarios are presented in Figure 43, comparing them with the SS3 scenario.

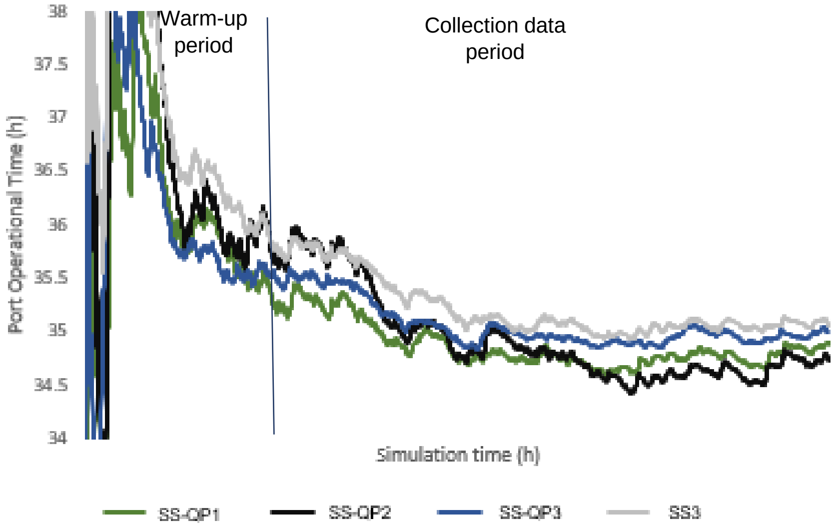


Figure 43: Mean Port Operational Time of Queueing policy scenarios over time

The simulations converge to following POT values:

$$POT_{SS-QP1} = 34.879\ h \qquad POT_{SS-QP2} = 34.736\ h \qquad POT_{SS-QP3} = 35.000\ h$$

There seems to be no significant differences between the POT averages of all scenarios. However, statistical analysis will be carried out later to prove or not this statement. This brings us to the analysis of the variability of the average values of all vessels for the 10 replicas.

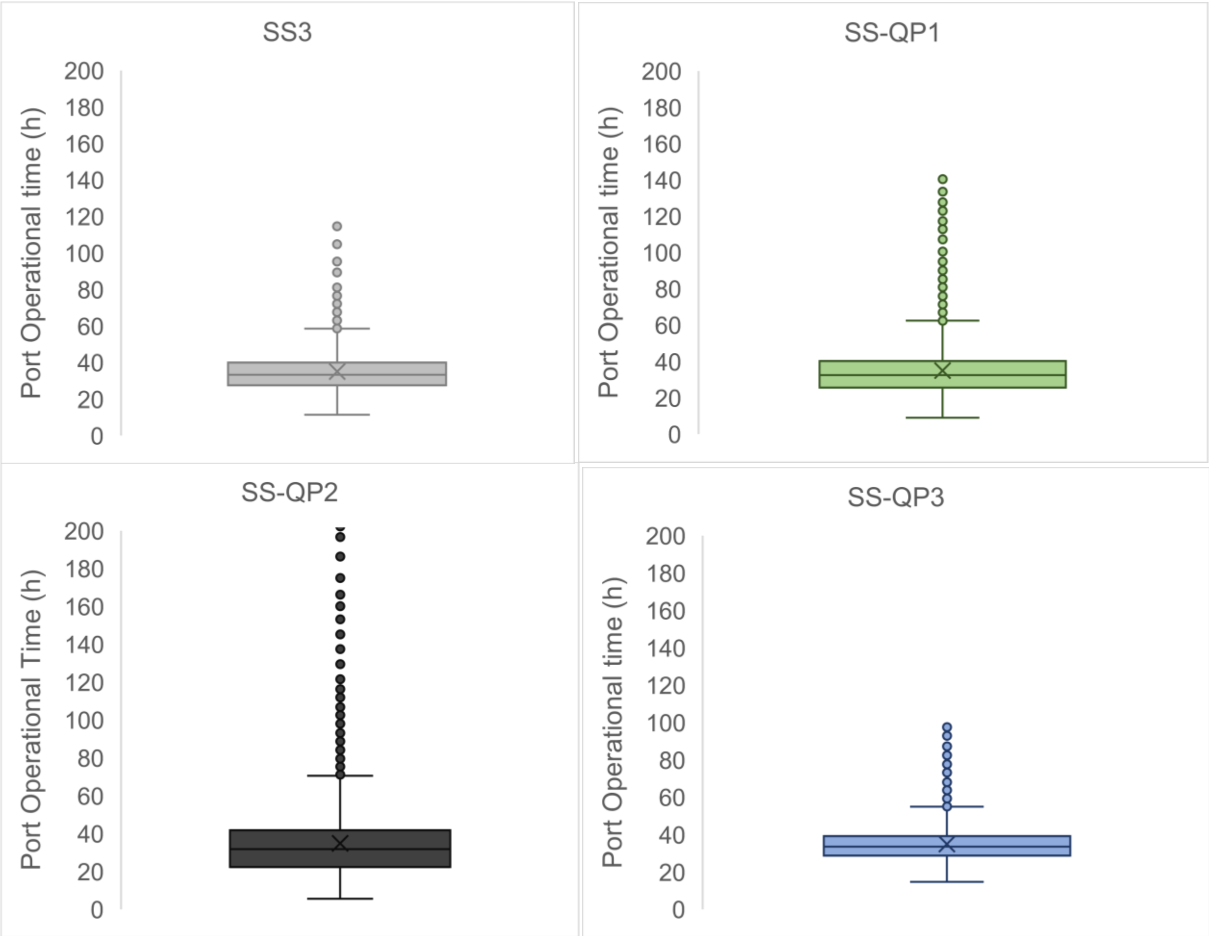


Figure 44: Port Operational Time boxplots of Queueing policy scenarios

Table 25: Statistics of the boxplots of queueing policy scenarios

Scenarios	Mean (h)	Median (h)	Inter-quartile amplitude (h)
SS3	35.064	33.345	12.451
SS-QP1	34.879	32.505	14.765
SS-QP2	34.736	31.838	19.493
SS-QP3	35.000	33.513	10.641

Based on Figure 44 and Table 25, it can be observed that scenario SS-QP2, where the highest quantities are prioritized, presents the smallest average and median values, but has the highest interquartile variability. It also presents the highest number of outliers. Among the four scenarios studied, SS-QP3, where Gasoline as Gasoil are prioritized in the queue for docking, presents a mean POT of 35.000 hours, with the lowest interquartile amplitude of 10.641 hours.

The queueing policy scenarios SS-QP1, SS-QP2 and SS-QP3 show lower POT mean value than the original SS3, although only SS-QP3 shows lower interquartile amplitude.

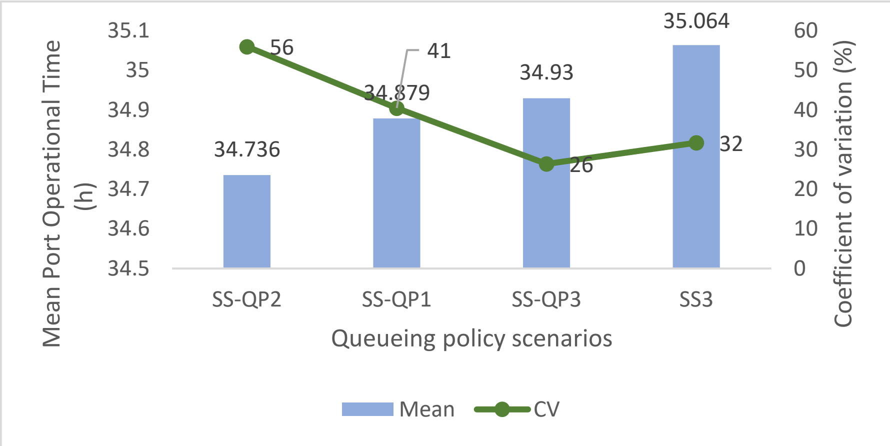


Figure 45: Mean Port Operational Time and coefficient of variation of queueing policy scenarios

Figure 45 shows the POT mean value and coefficient of variation of the three scenarios for the different queueing policies and SS3. Scenario SS-QP2, where the prioritization of higher quantities is made, reveals the smallest mean value with the highest CV, with 34.736 hours and 56%, respectively. On the other hand, SS-QP3 confirms itself has the scenario with the lowest variability in its outputs with a CV of 26.39%.

When compared to scenario SS3, where a FIFO policy is used, the only scenario that presents a lower variability is SS-QP3.

Table 26: computational times of queueing policy scenarios

	SS3	**SS-QP1**	**SS-QP2**	**SS-QP3**
Time	23' 07''	24' 04	24' 16	26' 34''

The scenario with the lowest computational time is SS3. On the other hand, the scenario with the highest one is SS-QP3, with 26 minutes and 34 seconds (Table 26).

6.2.3.2 Selection of the best queueing policy scenario

To assess the best queueing policy, the results obtained in all 10 replicas for all scenarios are now compared in Figure 46, with its data presented on Table 45 on Appendix H.

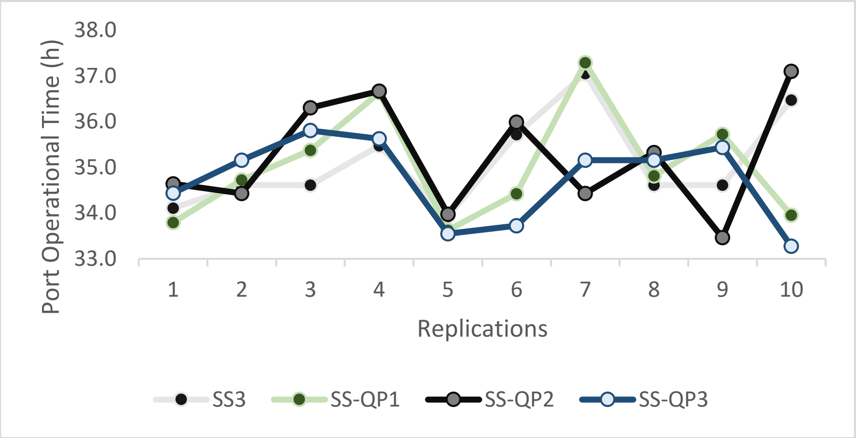


Figure 46: Port Operational Time mean values across all 10 replications

Using the t-student distribution when applying the Bonferroni method, the confidence intervals for the difference of mean POT are now presented:

$$CI_{95\%}(SS3 \; - \; SS - QP1) = [-1.071; \; 1.239] \qquad CI_{95\%}(SS3 \; - \; SS - QP2) = [-1.153; \; 1.153]$$

$$CI_{95\%}(SS3 - SS - QP3) = [-1.116; \; 1.890] \qquad CI_{95\%}(SS - QP1 - SS - QP2) = [-1.988; \; 1.591]$$

$$CI_{95\%}(SS - QP1 \; - \; SS - QP3) = [-0.576; \; 1.183] \qquad CI_{95\%}(SS - QP2 - SS - QP3) = [-1.170; \; 2.173]$$

It is concluded from the confidence intervals that there is no significant evidence that scenarios, SS-QP1, SS-QP2 and SS-QP3 show better results than scenario SS3. There is not also a statistical evidence that one of the queueing policy scenarios is better than another, since all these confidence intervals contain the zero. Therefore, these Confidence Intervals do not exclude the possibility that there are no differences between the queueing policy scenarios' Port Operational Time average values.

7. Conclusions

This dissertation involved seven chapters: Introduction, Case Study definition, Literature Review, Simulation Model, Data Analysis, Results, and Conclusion.

Firstly, a theoretical introduction was made on the Global, European, and Portuguese context of energy and oil industry. It was noted that this is an industry that grows from decade to decade and that it is increasingly important to be efficient in transportation operations. It is also important to note that around 90% of the world's oil is transported by vessels, and that, in this way, seaports are increasingly being overloaded operationally. In Portugal, as energetic dependency is very high, importations are a fundamental economical factor, requiring an efficient port organization for receive and ship products such as Crude, Gasoline, among others.

The second chapter was based on the description of the characteristics and operations of a Liquid Bulk Terminal in general, as well as the evaluation of its performance, and henceforth the description of the Sines' Liquid Bulk Terminal. This is of great importance for the Portuguese energy operation since it is the main doorway for oil products to enter the country. More deeply, its activities were described, referring to products handled, berths characteristics, vessels' arrivals, pipelines system, culminating in the evaluation of the terminal's performance. Here, it can be noted that, based on data from January 2017 (the most conditioning month of the same year), the total time in the system of each product, that is, the Port Operational Time (POT), was quite high. This leads to equally high Demurrages of the vessels arriving at the terminal, resulting in high costs for GALP.

Subsequently, the variability of the POT per product was evaluated, reaching the conclusion that not only were these values high but also quite variable, leading to variable values of the corresponding Demurrages. Thus, it became relevant to know the origin of this variability, analysing two components of the POT: Time for Docking (TD) and Operational Time (OT). Its values also proved to be quite high and variable, justifying the corresponding variability of the POT and the subsequent vessels Demurrage. However, this fact noted for these components reveals a root problem at the terminal: the poor allocation of vessels to berths, resulting in the increase of TD and the poor allocation of products to pipelines, increasing the value of OT (and TD, since, with the increase of OT, vessels wait longer to dock, increasing TD).

In this way, and based on the problem identified, a literature review was conducted on the problem found at the terminal, the Berth Allocation Problem (BAP), trying to find a basis for its resolution. This focused not only on Liquid Bulk Terminals but also on container terminals, due to their growth in recent years. Within each of these, the methods used to solve the BAP were described and analysed, focusing on Optimizations, Heuristics and Meta-Heuristics, and Simulation and Simulation-Optimization.

Throughout the characterization of the literature review, some gaps were found, such as the lack of study about Liquid Bulk Terminals, with only 4 of the 55 papers mentioned, the scarce use of Simulation and Simulation-Optimization as well as the little reference of papers that treat the variability of the parameters, summarizing Shang et al., (2016) and Xiang et al., (2017). Therefore, it can be confirmed that these gaps fit the problem presented in the case study: there are few studies on Liquid Bulk Terminals, combined with the failure to consider the variability of the system parameters. Hence, it was concluded that the use of simulation to solve the problem of poor allocation of vessels to berths and pipelines is appropriate, not only because it allows to fill the gap in the literature, but also because it enables to mitigate the variability of the parameters while testing alternative scenarios that minimize Port Operational Time and Demurrage costs for GALP.

In this way, the simulation model was developed. Firstly, the Key Performance Indicators Port Operational Time and Demurrage time already mentioned in the case study chapter are defined. Then, Decision Variables and Exogeneous Variables are presented. Both are very important in the definition of the variables of interest in the system and are also important for the standardization of the data implementation in the scenarios presented afterwards. A conceptual model, based on the real system of the Liquid Bulk Terminal, is then developed to simplify essential operations, and help the computational implementation of the simulation model. This representative model of the Sines' Liquid Bulk Terminal is implemented in the SIMUL8 software. To validate the model, the real data of the terminal was implemented to compare the outputs of the model with those that occurred on the terminal in January 2017. Through statistical tests, the model proved to be representative of the terminal's real operations, therefore making it possible to use for the test and analyse alternative scenarios.

Therefore, fifteen scenarios were developed, divided into three time horizons: one month of January 2017, several months of January 2017 (terminating) and Steady State (or Long term). Optimization was used for the first, simulation and optimization-simulation for the second and simulation for the third. In each of these, three pipelines allocation scenarios were tested: **quantity prioritization**, **shipment prioritization**, and **pipeline allocation flexibility**.

In the one month of January optimization scenarios, the flexibilization of pipeline allocation revealed significant improvements compared to the real terminal data in the same month, according to the work done by Rato (2018).

In the terminating simulations of January 2017, the flexibilization of the allocation to pipelines proved to be advantageous again, both in minimizing the POT and in minimizing Demurrage times. However, related with Demurrage costs, the scenario in which quantities were prioritized proved to be one that minimized it. Finally, a methodology for choosing the best policy was applied and it was concluded that the flexibility of allocation to pipelines is the best found.

It should be noted that optimization-simulation scenarios are more reliable for the evaluation of terminal performance, as they consider as input to simulation the optimal results found by Rato (2018) optimization model. On the other hand, it minimizes the POT and Demurrage time and costs in relation to the simulation, decreasing the variability of the results of the same KPI.

In the long-term horizon, the scenario where there is flexibility in pipeline allocation is again revealed as the one with the lowest POT. However, the scenario of expedition prioritization presents the lowest variability in the output of the same KPI. Through Bonferroni's methodology, the scenario of flexible pipeline allocations is again shown as the one that minimizes the POT.

Finally, based on the pipeline allocation flexibility scenario for the long term, three scenarios have been developed in which the queue policy is changed; FIFO is modified, and it is performed the **prioritization of small quantities, large quantities and Gasoil and Gasoline.**

The results demonstrate that, both in terms of average POT values and variability in their output data, the three new queue policy scenarios do not show significant improvements related with the FIFO one, neither between them. This is corroborated by the application of the Bonferroni's methodology.

Finally, it should be noted that the flexibility of allocation to pipelines is very beneficial for the terminal, both for the month of January and for terminating simulations in the same month, as well as in the long term. It is advantageous in terms of minimizing the time and costs of Demurrages, as well as in minimizing the Port Operational Time. Particularly, in the terminating simulations, this policy associated with the use of optimisation-simulation has enabled reliable and promising results of improvements on the operations of the Sines' Liquid Bulk Terminal.

Throughout this dissertation there were some limitations that could be overcome and others that limited the performance of the work. Within these, there is the little availability of data. It was only possible to use data for January 2017, which made the inference of operational and setup times quite difficult.

The lack of knowledge of the existence of operational restrictions was also an obstacle. The lack of knowledge of the working shifts of the workers at the terminal, the weather conditions necessary for the operation at the terminal to take place safely or even the size of the vessels arriving at the terminal removed the possibility of introducing more complexity into the system and thus bringing it closer to the reality experienced in the Liquid Bulk Terminal at the Port of Sines.

There is a future work on the problem addressed in this dissertation. The first corresponds to the consideration of a hybrid terminal, where vessels can berth in more than one berth at the same time, if their size so justifies, or even the sharing of one berth by two vessels.

Regarding the selection of best scenarios, it would be very interesting to use a decision support model that considers more than one objective.

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9 Appendix

Appendix A - Initial conditions of the simulation model

Before implementing the system's structural logic, it is important to consider some initial aspects. Firstly, the simulation clock features are defined, as illustrate Figure 47.

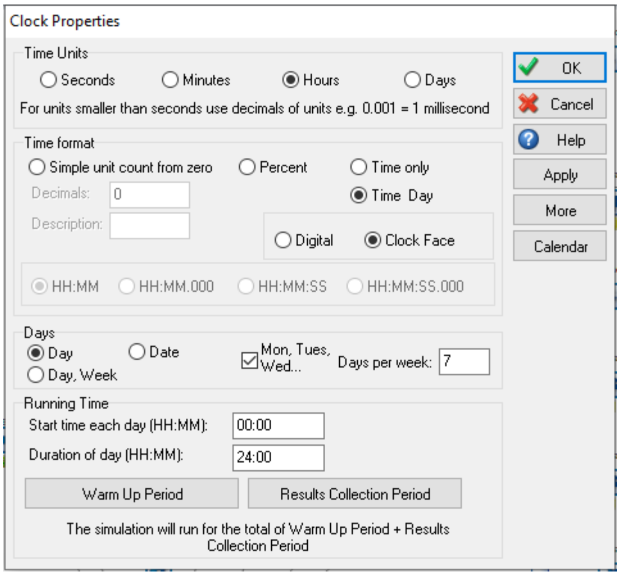

Figure 47: Simulation clock initialization

As the time interval between vessels arrivals is measured in hours, the clock was programmed to advance in hour units of time, and the terminal operates 7 days a week, 24 hours a day.

The Warm-up Period and Results Collection Period are only considered when a steady state simulation is performed.

On the other hand, the default for resource travel times is set to 0, considering that pipeline and berth resources do not move between vessels. These features have been implemented through the *"Set to zero"* option, as shown in Figure 48.

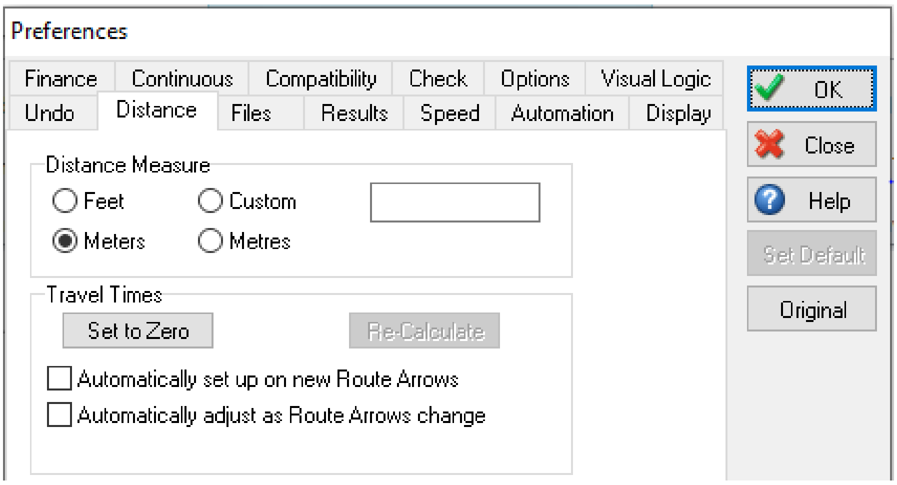

Figure 48: Travel times setup

Appendix B – Data implementation

All data implemented in the simulation model will be divided by the variables defined in Chapter 4.

Decision variables

Decision variable $\boldsymbol{D_{vm}}$ is implemented by associating a number for each vessel that arrived at the terminal. Values are described in Table 27:

Table 27: Assignment of values to variable $\boldsymbol{D_{vm}}$

Variable value	Berth
1	3
2	4
3	5
4	6
5	7

On the other hand, $\mathbf{D_{plo}}$ decision variable is defined as two matrices, one for reception and another for shipment. Number 1 is associated with the allocation of pipeline l to product p, while 0 means the no allocation. The matrices are represented as follows:

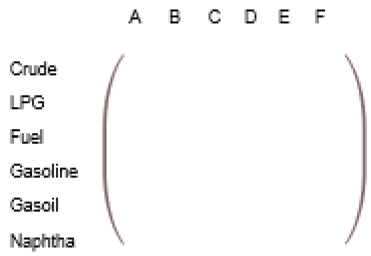

Figure 49: Variable $\boldsymbol{D_{plo}}$ display

Exogeneous variables

The first exogeneous variable $\boldsymbol{X^1_{v1v2}}$ is defined as a list of the times between arrival of two consecutive vessels *v*.

The second $\boldsymbol{X^2_p}$ refers to the arrival of products. This variable is defined as a list of consecutive number associated with the arriving product and operation, as Table 28 defines:

Table 28: Assignment of values to variable X_p^2

Product	Operation	Value
Crude	Reception	1
LPG	Reception	2
	Shipment	3
Fuel	Reception	4
	Shipment	5
Gasoline	Reception	6
	Shipment	7
Gasoil	Shipment	8
Naphtha	Shipment	9
Initialization	-	10

Operational times and setup, defined by variables $\boldsymbol{OT_{po}}$ **and** $\boldsymbol{ST_l}$, respectively, are defined of deterministic set of values, or even empirical or known distributions.

Appendix C – Real data

Decision variables

Table 29: Input data for vessel allocation to berth of real scenario

Decision variable	Distribution	Values
$\boldsymbol{D_{vm}}$	Deterministic	(4; 3; 2; 3; 5; 4; 5; 3; 2; 1; 4; 2; 1; 5; 2; 5; 4; 3; 4; 1; 5; 4; 2; 4; 3; 1; 1; 3; 2; 5; 3; 5; 1; 2; 3; 5; 1; 5; 3; 2; 2; 2; 1; 3; 2; 5; 3; 3)

$\boldsymbol{D_{plo}}$ – Allocation of product *p* to pipeline ***l*** by operation *o*

$$D_{pl1} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} ; \; D_{2pl2} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

Exogeneous variables

Table 30: Input data for time between consecutive vessels arrival and products' arrival of real scenario

Variable	Distribution	Values (h)
$\boldsymbol{X^1_{v1v2}}$	Deterministic	(0.0; 0.4; 9.3; 21.0; 29.1; 34.4; 25.1; 42.4; 8.5; 2.7; 16.3; 1.0; 7.7; 0.4; 7.4; 8.5; 3 4.0; 1.4; 3.4; 10.6; 0.0; 16.0; 18.5; 11.5; 12.9; 0.1; 37.0; 29.2; 4.8; 10.5; 6.2; 25.3 8.2; 9.8; 6.4; 8.3; 2.0; 6.0; 1.7; 0.3; 24.0; 12.0; 6.2; 34.8; 1.0; 90.0; 8.0; 3.0; 6.0; 18.3; 4.7; 8.6; 0.0; 2.4)
$\boldsymbol{X^2_p}$	Deterministic	(3; 7; 1; 1; 7; 6; 3; 1; 1; 1; 2; 2; 8; 7,; 5; 3; 2; 7; 3; 4; 3; 7; 9; 7; 9; 3; 3; 4; 3; 7; 1; 1; 4; 5; 9; 7; 3; 2; 3; 7; 8; 5; 2,; 8; 2; 2; 1; 4; 7; 9; 7; 8; 7; 3; 4; 5; 1)

Table 31: Input data of Operational Time of real scenario

	Distribution	Values (h)
OT_{11}	Deterministic	(30.60; 34.80; 21.90; 33.00; 34.60; 29.10; 33.90; 34.40; 24.00)
OT_{21}		(19.00; 20.30; 22.40; 14.50; 7.20; 19.80; 52.50)
OT_{22}		(20.10; 14.00; 10.00; 12.20; 15.40; 13.40; 0.30; 18.50; 13.10; 16.83; 13.50)
OT_{31}		(40.10; 25.10; 29.10; 22.00; 22.60)
OT_{32}		(17.40; 9.90; 10.90; 16.40)
OT_{41}		21.33
OT_{42}		(47.50; 36.90; 31.00; 34.00; 19.50; 17.70; 22.10; 21.97; 45.00; 29.40; 32.00; 16.23)
OT_{52}		(40.83; 17.30; 20.60; 17.30)
OT_{62}		(31.12; 18.19; 14.11; 16.79)

Table 32: Input data of Setup Time of real scenario

	Distribution	Values (h)
ST_1	Deterministic	(7.90; 6.10; 4.73; 7.37; 7.80; 9.40; 7.10; 6.80; 5.50)
ST_2		(5.50; 5.40; 3.70; 4.00; 4.85)
ST_3		(8.25; 5.1; 6.65; 7.1; 6.5; 6.1; 7.7; 10.85)
ST_4		(10.00; 6.10; 15.78; 7.6; 5.25; 24.55; 7.00; 10.83; 12.5; 12.20; 5.40)
ST_5		(3.62; 8.83; 7.50; 6.30; 4.10)
ST_6		(4.40; 6.80; 7.50; 8.55; 4.10; 9.00; 4.47; 4.50; 6.35; 4.20; 3.30; 2.93; 5.25; 6.83; 4.65; 11.13; 17.40; 4.60)

Appendix D – Scenarios' input data

Decision variables

Table 33: Input data for vessel allocation to berth of terminating scenarios

Variable	Scenarios	Values	
		Simulation	**Optimization-Simulation**
D_{Vm}	**1**	(4; 3; 2; 3; 5; 4; 5; 3; 2; 1; 4; 2; 1; 5; 2; 5; 4; 3; 4; 1; 5; 4; 2; 4; 3; 1; 1; 3; 2; 5; 3; 5; 1; 2; 3; 5; 1; 5; 3; 2; 2; 2; 1; 3; 2; 5; 3; 3)	(5; 3; 2; 5; 4; 5; 5; 1; 2; 1; 4; 3; 2; 4; 3; 4; 5; 2; 5; 1; 4; 4; 2; 5; 1; 3; 1; 2; 3; 5; 2; 4; 3; 1; 2; 4; 3; 5; 1; 3; 2; 1; 2; 3; 1; 4; 3; 2)
	2		(4; 1; 1; 5; 4; 4; 5; 1; 2; 3; 5; 2; 3; 5; 2; 4; 5; 1; 5; 1; 5; 5; 2; 5; 3; 1; 3; 2; 1; 1; 4; 3; 4; 2; 1; 3; 4; 1; 4; 2; 2; 2; 1; 3; 2; 3; 4; 1; 2)
	3		(5; 1; 1; 4; 5; 5; 4; 1; 3; 2; 5; 3; 2; 5; 2; 5; 4; 3; 4; 2; 5; 4; 1; 5; 2; 3; 1; 2; 1; 4; 3; 4; 2; 1; 3; 5; 1; 4; 3; 1; 3; 2; 1; 3; 2; 5; 2; 1)

$D_{plo,S1} = D_{plo,OS1} = D_{plo,SS1}$ – Allocation of product *p* to pipeline *l* on operation *o*, for scenarios S1, OS1 and SS1.

$$D_{pl1} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix} \; e \; D_{pl,2} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

$D_{plo,S2} = D_{plo,OS2} = D_{plo,SS2}$ – Allocation of product *p* to pipeline *l* on operation *o*, for scenarios S2, OS2 and SS2.

$$D_{2pl1} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \; e \; D_{2pl2} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

Table 34: Input data of products allocation to pipelines on the pipeline allocation flexibilization

Variable	Distribution	Values
$D_{plo,S3}$ $D_{plo,OS3}$ $D_{plo,SS3}$ $D_{plo,SS-QP1}$ $D_{plo,SS-QP2}$ $D_{plo,SS-QP3}$	Deterministic	(6; 2; 1; 1; 2; 2; 6; 1; 1; 1; 6; 6; 3; 2; 2; 6; 5; 2; 6; 2; 6; 4; 3; 4; 2; 6; 6; 2; 6; 2; 1; 1; 3; 2; 4; 2; 6; 5; 6; 4; 3; 2; 6; 2; 6; 5; 1; 2; 2; 4; 3; 2; 2; 6; 2; 3; 1)

Exogeneous variables

Table 35: Input data for time between consecutive vessels' arrival of all scenarios

Variable	Scenario	Distribution	Values (h)
X^1_{v1v2}	S1 OS1 S2 OS2 S3 OS3	Deterministic	(0.0; 0.4; 9.3; 21.0; 29.1; 34.4; 25.1; 42.4; 8.5; 2.7; 16.3; 1.0; 7.7; 0.4; 4.0; 1.4; 3.4; 10.6; 0.0; 16.0; 18.5; 11.5; 12.9; 0.1; 37.0; 29.2; 4.8; 10.5 8.2; 9.8; 6.4; 8.3; 2.0; 6.0; 1.7; 0.3; 24.0; 12.0; 6.2; 34.8; 1.0; 90.0; 8.0 18.3; 4.7; 8.6; 0.0; 2.4)
	SS1 SS2 SS3 SS-QP1 SS-QP2 SS-QP3	Exponential	12.9

Table 36: Input data of products' arrival of all scenarios

Variable	Scenario	Distribution	Values (h)
X^2_p	S1 OS1 S2 OS2 S3 OS3	Deterministic	(3, 7, 1, 1, 7, 6, 3, 1, 1, 1, 2, 2, 8, 7, 5, 3, 2, 7, 3, 4, 3, 7, 9, 7, 9, 3, 3, 4, 3, 7, 1, 1, 4, 5, 9, 7, 3, 2, 3, 7, 8, 5, 2, 8, 2, 2, 1, 4, 7, 9, 7, 8, 7, 3, 4, 5. 1)

Table 37: Input data of Operational Time of scenarios S1, OS1 and SS1

	Distribution	**Values (h)**
$\boldsymbol{OT_{11}}$	Empirical	(30.60; 34.80; 21.90; 33.00; 34.60; 29.10; 33.90; 34.40; 24.00)
$\boldsymbol{OT_{21} = X_{22}}$	Empirical	(20.10; 14.00; 19.00; 20.30; 10.00; 22.40; 12.20; 15.40; 13.40; 0.30; 18.50; 13.10; 14.50; 16.83; 7.20; 19.80; 52.50; 13.50)
$\boldsymbol{OT_{31}}$	Empirical	(40.10; 25.10; 29.10; 22.00; 22.60)
$\boldsymbol{OT_{32}}$	Empirical	(17.40; 9.90; 10.90; 16.40)
$\boldsymbol{OT_{41}}$	Fixed	3.7
$\boldsymbol{OT_{42}}$	Uniform	[11.75 , 26.19]
$\boldsymbol{OT_{52}}$	Empirical	(40.83; 17.30; 20.60; 17.30)
$\boldsymbol{OT_{62}}$	Empirical	(31.12; 18.19; 14.11; 16.79)

Table 38: Input data of Operational Time of scenarios S2, OS2 and SS2

	Distribution	**Values (h)**
$\boldsymbol{OT_{11}}$	Empirical	(30.60; 34.80; 21.90; 33.00; 34.60; 29.10; 33.90; 34.40; 24.00)
$\boldsymbol{OT_{21} = X_{22}}$	Empirical	(20.10; 14.00; 19.00; 20.30; 10.00; 22.40; 12.20; 15.40; 13.40; 0.30; 18.50; 13.10; 14.50; 16.83; 7.20; 19.80; 52.50; 13.50)
$\boldsymbol{OT_{31} = X_{32}}$	Empirical	(40.10; 25.10; 29.10; 22.00; 22.60; 31.10; 7.44; 31.10; 7.09)
$\boldsymbol{OT_{41}}$	Fixed	21.33
$\boldsymbol{OT_{42}}$	Exponential	4.85
$\boldsymbol{OT_{52}}$	Empirical	(99.99; 48.84; 48.84; 44.66)
$\boldsymbol{OT_{62}}$	Empirical	(31.12; 18.19; 14.11; 16.79)

Table 39: Input data of Operational Time of scenarios S3, OS3, SS3, SS-QP1, SS-QP2 and SS-QP3

	Distribution	**Values (h)**
$\boldsymbol{OT_{11}}$	Empirical	(30.60; 34.80; 21.90; 33.00; 34.60; 29.10; 33.90; 34.40; 24.00)
$\boldsymbol{OT_{21} = OT_{22}}$	Empirical	(20.10; 14.00; 19.00; 20.30; 10.00; 22.40; 12.20; 15.40; 13.40; 0.30; 18.50; 13.10; 14.50; 16.83; 7.20; 19.80; 52.50; 13.50)
$\boldsymbol{OT_{31}}$	Empirical	(48.44; 28.93; ; 37.06; 38.85; 12.09)
$\boldsymbol{OT_{32}}$	Empirical	(30.18; 9.25; 30.10; 37.19)
$\boldsymbol{OT_{41}}$	Fixed	10.95
$\boldsymbol{OT_{42}}$	Exponential	81.5
$\boldsymbol{OT_{52}}$	Empirical	(47.48; 28.22; 26.67; 24.34)
$\boldsymbol{OT_{62}}$	Empirical	(21.79; 13.92; 18.66; 22.83)

Table 40: Input data of Setup Time of all scenarios

	Distribution	**Values (h)**
$\boldsymbol{ST_1}$	Empirical	$(7.90;\ 6.10;\ 4.73;\ 7.37;\ 7.80;\ 9.40;\ 7.10;\ 6.80;\ 5.50)$
$\boldsymbol{ST_2}$	Empirical	$(5.50;\ 5.40;\ 3.70;\ 4.00;\ 4.85)$
$\boldsymbol{ST_3}$	Empirical	$(8.25;\ 5.1;\ 6.65;\ 7.1;\ 6.5;\ 6.1;\ 7.7;\ 10.85)$
$\boldsymbol{ST_4}$	Empirical	$(10.00;\ 6.10;\ 15.78;\ 7.6;\ 5.25;\ 24.55;\ 7.00;\ 10.83;\ 12.5;\ 12.20;\ 5.40)$
$\boldsymbol{ST_5}$	Empirical	$(3.62;\ 8.83;\ 7.50;\ 6.30;\ 4.10)$
$\boldsymbol{ST_6}$	Exponential	4.44

Appendix E – Simulation perspectives

Terminating simulation

A terminating simulation runs for a given time T_E where *E* is a time limit for the simulation or simply an event that dictates its end. In these terminating simulations performed in this work, it is the end of operation of the last vessel of January 2017. The system is simulated in the time interval [0; T_E] under well-defined initial conditions (the vessels that were already operating in the terminal in 1st January 2017, for example) and based on *n* observations in each *R* replication its performance is evaluated (Carson & Nicol, 2014).

In Sines' Liquid Bulk Terminal, due to the division by the type of product each vessel carry, *n* becomes n_p specific to each product corresponding to the number of vessels that docked in January 2017. For all simulations to be carried out under the same conditions, n_p must be constant for each product so the definition of the terminating point T_E must be large enough for all 57 vessels that arrive at the terminal in the month under consideration to have enough time to finish their operation. It was then considered T_E =1000 hours (1 month and 10 days, a sufficient gap for all vessels end their operations).

Table 41 presents in a general way the data collected in each *R* simulation replica for the two KPI, Port Operational Time and Demurrage, generically denoted by Y. It will be collected $\mathrm{n_p}$ observations of each product in each replica, also represented in Table 41, calculating the average of each product in each replica in the variable $\overline{\mathrm{Y_{p.}}}$, achieving the average of each KPI for all products, in the variable $\overline{\mathrm{Y}}_{..}$.

Table 41: What happens in each replication

Product	Within-Replication Data (Y_{p,n_p})	Across-Replication Data ($\overline{Y_{p.}}$)
Crude	$Y_{11}\ Y_{12}\ Y_{13}\ Y_{14}\ Y_{15}\ Y_{16}\ Y_{17}\ Y_{18}\ Y_{19}$	$\overline{Y_{1.}}$
LPG	$Y_{21}\ Y_{22}\ Y_{23}\ Y_{24}\ Y_{25}\ Y_{26}\ Y_{27}\ Y_{28}\ Y_{29}\ Y_{2,10}\ Y_{2,11}\ Y_{2,12}\ Y_{2,13}\ Y_{2,14}\ Y_{2,15}\ Y_{2,16}\ Y_{2,17}\ Y_{2,18}$	$\overline{Y_{2.}}$
Fuel	$Y_{31}\ Y_{32}\ Y_{33}\ Y_{34}\ Y_{35}\ Y_{36}\ Y_{37}\ Y_{38}\ Y_{39}$	$\overline{Y_{3.}}$
Gasoline	$Y_{41}\ Y_{42}\ Y_{43}\ Y_{44}\ Y_{45}\ Y_{46}\ Y_{47}\ Y_{48}\ Y_{49}\ Y_{4,10}\ Y_{4,11}\ Y_{4,12}\ Y_{4,13}$	$\overline{Y_{4.}}$
Gasoil	$Y_{51}\ Y_{52}\ Y_{53}\ Y_{54}$	$\overline{Y_{5.}}$
Naphtha	$Y_{61}\ Y_{62}\ Y_{63}\ Y_{64}$	$\overline{Y_{6.}}$
		$\overline{Y}_{..}$

Steady state simulation

A steady state simulation consists in two phases: a first, characterized by a transient regime, where the KPI average value is quite dispersed from its real value, usually called initialization bias; a second where the system's KPI is converging to the limit value of the KPI. For the value of the KPI to be consistent with the characteristics of long run simulation, it is necessary to have an intelligent initialization of the system.

One of the most accepted methodologies is to divide the simulation into these two parts, considering a warmup period from time 0 to T_0, followed by data collection from T_0 to T_E. The key step is the choice of T_0 because the system state at that time must be representative of the system steady state. T_E must be large enough to guarantee accuracy in the estimation of long-term behaviour. With this T_0 chosen, data collection should be eliminated up to that point, just collecting in the interval $[T_0, T_E]$.

Considering the eliminated *d* observations and that the total number of observations *n*, a rough way to calculate the value of T_E is to assume that $n - d$ (number of observations not eliminated) must be at least 10 times larger than d $(n - d = 10d)$ (Carson & Nicol, 2014).

If a single replica is used in the long-term simulation, it could be the case that the observations of a given KPI may be correlated. One way to escape this fact is to make R replicas of the same simulation and in each one of them eliminate the same initial data collection time. This will also show the variability on the KPI across replicas.

Appendix F - Selection of the best procedures

Terminating simulation

Procedure

1. The probability of correct selection is specified $\frac{1}{k} < 1 - \alpha < 1$, with *R* replicas, *K* scenarios, and practically significant difference ε>0, which is the acceptable deviation so that one scenario presents a better KPI value than the other. Then, it is calculated the t-student value of:

$$\boldsymbol{t = t}_{\boldsymbol{1-(1-\frac{\alpha}{2})^{\frac{1}{k-1}}, R-1}}$$

2. For each scenario, the mean and standard deviation of the KPI values is calculated for the *R* replicas, corresponding to $\overline{Y}_{..}$
3. Computation of screening thresholds:

$$\boldsymbol{W_{ij} = t}\left(\frac{S_i{}^2 + S_j{}^2}{\boldsymbol{R}}\right)^{\boldsymbol{1/2}}, \text{ com } i \neq j$$

4. For the two KPI defined (POT and Demurrages), the lower their value the better. Therefore, start by forming a subset A with the scenario with the lowest average value of KPI
5. From subset A, denote the mean value of the selected scenario $Y_{.j}$. Compute:

$$Y_{.i} \leq Y_{.j} + max\{0, W_{ij} - \varepsilon\}$$

6. If the inequality is True, then add scenario i to subset A, and return to step 1, increasing R. Otherwise, scenario j is the best one.

This methodology will provide the selection of the best scenario sturdier and more precise than only graphical display of results.

Long term simulation

In the Bonferroni method, it is assumed that *C* confidence intervals in total for all possible combinations between the scenarios, where $C = \frac{K\,(K-1)}{2}$, with *K* equal to the number of test scenarios. The goal is that all confidence intervals contain the true difference between the averages of two scenarios, with confidence coefficient $1 - \alpha_i$. However, with increasing scenarios, the total confidence coefficient of all *K* scenarios decreases, so there is less certainty that all statements, S_i, produced by the confidence intervals are true. Therefore, the method states the following:

$$P\ (all\ statements\ S_i\ are\ true, i = 1, \ldots, C) \geq\ 1 - \sum_{j=1}^{C} \alpha_j = 1 - \alpha_E$$

The probability of all confidence intervals producing the right results must be greater than or equal to $1 - \alpha_E$, where α_E is the overall error probability, with α_j being the error for each confidence interval *C*. So:

$$\alpha_E = \sum_{j=1}^{C} \alpha_j <=> \alpha_E = \alpha_1 + \alpha_2 + \ldots + \alpha_C, \qquad with\ \alpha_1 = \alpha_2 = \ldots = \alpha_C$$

Therefore:

$$\alpha_E = C\alpha_j <=> \frac{\alpha_E}{C} = \alpha_j$$

Hence the confidence coefficient of each interval corresponds to the overall error probability divided by the number of confidence intervals.

Based on these confidence intervals, three potential outcomes are reached:

- If the confidence interval for $\overline{POT_i} - \overline{POT_j}$, with $i \neq j$, is totally to the left of zero, there is strong evidence that the hypothesis $\overline{POT_i} - \overline{POT_j} < 0$, or $\overline{POT_i} < \overline{POT_j}$ is true
- If the confidence interval for $\overline{POT_i} - \overline{POT_j}$, with $i \neq j$, is totally right to zero, there is strong evidence that the hypothesis $\overline{POT_i} - \overline{POT_j} > 0$, or $\overline{POT_i} > \overline{POT_j}$ is true
- If the confidence interval for $\overline{POT_i} - \overline{POT_j}$, with $i \neq j$, contains zero, it indicates that there is no statistical evidence that one scenario is better than the other.

Appendix G – Boxplots' data

Demurrage

Table 42: Demurrage boxplot data for all terminating scenarios

Products	Scenario 1					
	Simulation			Optimization-Simulation		
	Mean (h)	Median (h)	Inter quartile amplitude (h)	Mean (h)	Median (h)	Inter quartile amplitude (h)
Crude	11.03	17.17	26.78	11.03	17.17	26.78
LPG	9.44	15	26.16	10.36	22.03	41.69
Fuel	20.44	21.61	32.17	5.37	11.99	26.05
Gasoline	0	11.51	13.1	0	11.91	18.9
Gasoil	7.99	9.52	19.09	3.11	3.55	7.54
Naphtha	14.74	14.74	29.55	6.72	18.8	25.67
TOTAL	**9.55**	**15.19**	**23.97**	**6.55**	**15.85**	**28.15**
	Scenario 2					
Crude	11.1	17.19	26.66	11.1	17.19	26.66
LPG	6.36	13.12	19.69	10.16	15.06	29.67
Fuel	13.75	28.79	56.15	6.24	18.75	40.83
Gasoline	0	6.61	1.65	0	10.35	9.78
Gasoil	60	58.34	57.79	56.97	56	57.51
Naphtha	11.8	12.8	26.59	8.61	14.95	36.24
TOTAL	**10.97**	**17.90**	**25.59**	**10.55**	**17.77**	**28.84**
	Scenario 3					
Crude	11.01	17.18	26.99	11.01	17.18	26.99
LPG	53.49	47.91	64.98	4.52	14.5	18.25
Fuel	96.46	84.61	65.86	14.09	14.53	28.72
Gasoline	36.79	44.5	46.5	0.8	6.08	0
Gasoil	95.26	75.42	89.69	17.57	17.5	27.62
Naphtha	36.38	42.53	66.84	0	1.52	4.55
TOTAL	**51.49**	**49.63**	**56.77**	**6.81**	**12.31**	**16.82**

Port Operational Time

Table 43: Port Operational Time boxplot data for terminating scenarios

Products	Scenario 1					
	Simulation			Simulation-Optimization		
	Mean (h)	Median (h)	Inter quartile amplitude (h)	Mean (h)	Median (h)	Inter quartile amplitude (h)
Crude	52.04	56.07	30.13	52.04	56.07	30.13
LPG	44.04	47.73	34.86	48.45	52.35	36.13
Fuel	48.87	55.77	38.26	44.42	43.22	30.17
Gasoline	36.31	37.56	21.99	36.33	35.87	15.14
Gasoil	36.99	39.54	16.57	31.35	33.42	6.4
Naphtha	53.94	53.52	16.5	46.76	46.76	32.22
	Scenario 2					
Crude	52.04	56.07	30.11	52.04	56.07	30.11
LPG	43.61	46.19	34.39	50.02	47	41.2
Fuel	42.97	59.95	52.11	49.97	48.56	35.9
Gasoline	18.98	21.52	16.18	15.99	22.84	16.6
Gasoil	88.41	92.14	43.37	84.61	89.49	41.15
Naphtha	50.14	50.00	55.59	54.36	54.36	45.63
	Scenario 3					
Crude	52.04	56.07	30.11	52.04	56.07	30.11
LPG	76.78	80.82	67.46	36.15	42.88	25.6
Fuel	124.31	118.81	37.35	41.79	41.24	26.31
Gasoline	82.75	79.96	51.1	20.15	21.4	1.94
Gasoil	123.11	108.59	82.86	46.56	49.01	23.63
Naphtha	89.36	38.34	34.19	27.07	29.05	13.71

Appendix H – Confidence intervals

Scenarios SS1, SS2 and SS3

Table 44: Data for the construction of confidence intervals

	Average Port Operational Time			Differences		
Replication	**SS1**	**SS2**	**SS3**	**SS1-SS2**	**SS1-SS3**	**SS2-SS3**
1	41.072	38.309	34.109	2.763	6.963	4.200
2	43.854	37.861	34.613	5.993	9.240	3.248
3	43.143	38.080	34.103	5.062	9.040	3.977
4	47.838	38.366	35.472	9.472	12.366	2.894
5	43.731	37.861	33.928	5.870	9.803	3.933
6	42.687	38.399	35.717	4.289	6.971	2.682
7	43.958	39.126	36.247	4.832	7.711	2.879
8	42.268	39.816	34.284	2.452	7.983	5.532
9	41.747	40.611	35.080	1.137	6.667	5.531
10	44.327	39.742	34.914	4.585	9.413	4.828
11	42.974	38.491	37.055	4.483	5.919	1.436
12	41.900	39.480	35.814	2.420	6.087	3.666
13	41.284	41.522	37.101	-0.238	4.184	4.421
14	40.958	41.988	35.652	-1.030	5.306	6.336
15	45.376	37.861	34.613	7.515	10.763	3.248
16	42.299	40.064	34.792	2.235	7.507	5.272
17	45.201	39.190	35.518	6.011	9.683	3.672
18	40.493	38.474	36.177	2.019	4.317	2.297
19	33.689	41.039	35.097	-7.350	-1.408	5.943
20	42.002	39.892	33.904	2.110	8.098	5.988
Sample mean	42.540	39.308	35.209	3.232	7.331	4.099
Sample variance	7.491	1.583	0.927	12.726	8.661	1.855
Standard error				3.567	2.943	1.362

With the mean values and standard deviations of the difference of means calculated, only the value of the t-student function for the necessary confidence coefficient is left. Hence, as number of scenarios $K = 3$, the number of confidence intervals C is equal to 3. So, as the value of the function is $t_{\frac{\alpha_j}{2},R-1}$:

$$\alpha_j = \frac{\alpha_E}{C} = \frac{0.05}{3} = 0.0167$$

Therefore:

$$t_{\frac{0.0167}{2},20-1} = t_{0.0083,19} = 3.07$$

Table 45: Data for the construction of confidence intervals for queueing policy scenarios

Replications	**Scenarios POT (h)**				**Differences (h)**					
	SS3	**SS-QP1**	**SS-QP2**	**SS-QP3**	**SS3-SS-QP1**	**SS3-SS-QP2**	**SS3-SS-QP3**	**SS-QP1-SS-QP2**	**SS-QP2-SS-QP3**	**SS-QP2-SSQP3**
1	34.109	29.957	34.644	34.435	4.152	-0.535	-0.326	-4.687	-4.478	0.209
2	34.613	31.644	34.431	35.157	2.969	0.182	-0.544	-2.787	-3.513	-0.726
3	34.613	31.964	36.307	35.807	2.649	-1.693	-1.194	-4.342	-3.843	0.500
4	35.472	33.261	36.670	35.629	2.211	-1.198	-0.158	-3.409	-2.369	1.041
5	33.928	30.150	33.979	33.546	3.778	-0.051	0.381	-3.830	-3.397	0.433
6	35.717	30.824	35.992	33.727	4.893	-0.276	1.989	-5.168	-2.903	2.265
7	37.055	33.888	34.431	35.157	3.167	2.624	1.898	-0.544	-1.269	-0.726
8	34.613	29.859	35.329	35.157	4.754	-0.716	-0.544	-5.470	-5.298	0.172
9	34.613	31.644	33.464	35.441	2.969	1.149	-0.828	-1.820	-3.797	-1.977
10	36.471	33.052	37.101	33.276	3.419	-0.630	3.195	-4.049	-0.224	3.825
Sample mean	35.120	31.624	35.235	34.733	3.496	-0.115	0.387	-3.611	-3.109	0.502
Sample variance	1.058	2.074	1.514	0.848	0.787	1.520	2.139	2.350	2.247	2.645
Sample Standard deviation					0.887	1.233	1.462	1.533	1.499	1.626

Again, using the Bonferroni method, the confidence coefficient is calculated. Assuming again $\alpha_E = 5\%$, although this time it is compared 4 scenarios, that is, K=4. So:

$$C = \frac{4(4-1)}{2} = 6$$

To construct all six Confidence Intervals, each one with confidence coefficient:

$$\alpha_j = \frac{\alpha_E}{C} = \frac{0.05}{6} = 0.0083$$

Therefore, the t-student function assumes the following value, also calculated by linear interpolation on its table values:

$$t_{\frac{0.0083}{2},10-1} = t_{0.004167,9} = 3.25$$