Maritime logistics with berth and pipeline allocation: A case study

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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

1. Introduction

The global energy sector directly influences the competitiveness of modern economies. Excluding the electricity share, energy production has dramatically increased in the last two decades, as result of developing countries' industrial and economic growth.

Related to 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 (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, on crude oil. Europe had 88.4% of dependence, in 2016 (Dias et al., 2016). This indicator shows the necessity of European seaports, where the oil arrives from the exporting countries, to be well organized and operationally efficient to receive it.

The Portuguese case follows the European trend. From 2012 to 2017 the energy dependency level remained stable. It was verified a minimum value of 72.4% in 2014 and a maximum of 79.7% in 2017 (DGEG, 2020).

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, 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' berths 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.

This is the motivation for this work. The objective is to applicate an operational research methodology to Sines' Liquid Bulk Terminal operations, to provide recommendations of improvements on its operational policies and financial issues. To achieve it, the minimization of terminal's performance indicators such as Port Operational Time and Demurrages, which will be defined latter on, are crucial. As intermediate objectives, the search in the literature of a proper methodology to address the problem, searching for a gap in the state of art and the evaluation of variability of system parameters, are also important aspects of this work.

2. Case Study

2.1 Liquid Bulk Terminals

In a Liquid Bulk Terminal, there are specific aspects and operations that characterize 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 depend 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.
The allocation of vessels to berths and pipelines is a major problem in this area of study. In fact, this is addressed in the literature as Berth Allocation Problem (BAP). It is widely studied, and Bierwirth & Meisel (2015) divided its characteristics according to three attributes: **Spatial, Temporal and Performance measures.**
These Performance Measures are very important for the management of terminals activities, since they could indicate whether and where exists an operational problem. Therefore, it is relevant the definition of two of them: Port Operational Time (POT) and Demurrages.
POT is defined as 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):

$$POT = TD + ST + OT \qquad (1)$$

TD represents how long a vessel waits to dock at a terminal, i.e, the time it remains at a queue to dock in a berth. On the other hand, ST refers to the time interval since the vessel docks and starts its operation, of reception or shipment, at the berth, considering all inherent vessel and pipeline preparations. Finally, OT represents how long a vessel is transferring product through the pipeline system.
An illustrative example of how POT and its constituents relate with the vessel's path at the Liquid Bulk Terminal is presented in Figure 1.

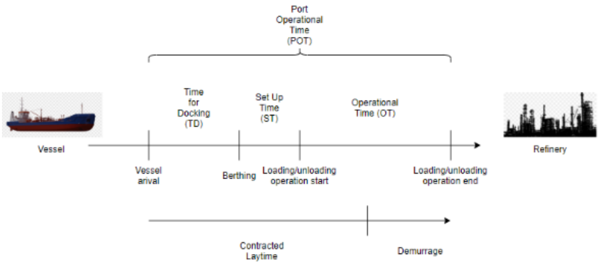

Figure 1: Relation between Port Operational Time and vessel's path

[1] Only for quantities less than 7000 tonnes

Closely related with POT is the concept of Demurrage. 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):

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

With the terminal operations and the performance measures characterization, it is now described the operations and performance of the Liquid Bulk Terminal of Sines.

2.2 Liquid Bulk Terminal of Sines

2.2.1 Operations

The liquid bulk terminal 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. The berth with the largest capacity is berth 2 which can receive vessels with more than 70000 tonnes of product transported. On the opposite side, berths 6 and 7 are exclusive for small product transactions.
The capacity of the terminal is also related with its capacity to receive vessels. At the Liquid Bulk Terminal, in the year of 2017, a mean of 51 vessels arrived every month, with January being the month with more operations, with 57 vessels. Comprehensively, there is some variability in the arrival of vessels.
Another aspect very important to analyse are the products handled at the terminal and its allocations to berths and pipelines. Sines' liquid bulk terminal handles 6 types of products: Crude, LPG, Fuel, Gasoline, Gasoil and Naphtha. The policy of allocation of products to berths is presented in Table 1.

Table 1: 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		

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 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.**
The distribution of the loading arms of pipeline B is explicit in Figure 2, as an example.

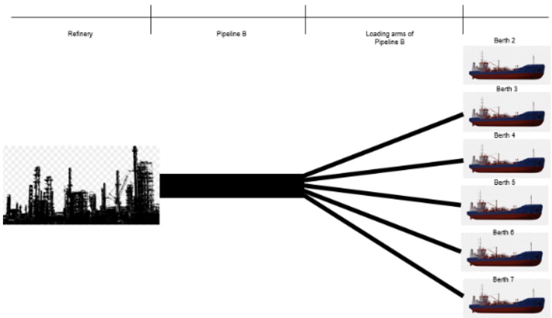

Figure 2: Distribution of loading arms of pipeline B to berths

Pipeline B has one loading arm in each of berths 3, 4, 5, 6 and 7.
As for berths, there is also an allocation policy of products to pipelines, shown in Table 2.

Table 2: Policy of products' allocation to pipelines, by reception and shipment

[2]	Pipeline					
	A	**B**	**C**	**D**	**E**	**F**
R	C	F	Goil	-	G+N	LPG
S	C	-	F+Goil	G	N	LPG

In general, an inefficient allocation of products to pipelines will impact the overall allocation of the terminal and the time each vessel stays in the system, leading to a performance decrease.
Based on the operations performed at the Liquid Bulk Terminal of Sines and on the performance indicators defined previously, the terminal performance is now assessed.

2.2.2 Performance

Port Operational Time

Based on data from January 2017, POT and its constituents were analysed.
The product with the highest POT is Gasoline with 764.6 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. On the other hand, 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. It is clear, that the 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.
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.

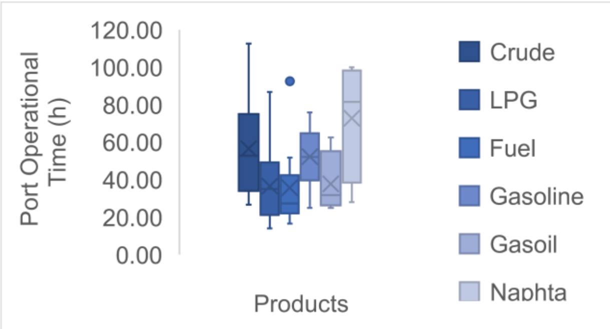

Figure 3: Port Operational Time boxplot by product

In Figure 3, Crude exhibit the wider amplitude of POT values, with Total Amplitude equal to 86.04 hours. 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, it still has a 50% chance of being higher than 27.40 hours.
POT's components TD and OT have a high variability, somehow explaining the Port Operational Time's variability.

Demurrage

Finally, Demurrage is analysed. 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. First, its variability is analysed in Figure 4.

[2] R-Reception; S- Shipment; C-Crude; F-Fuel; G-Gasoline, Goil-Gasoil; N-Naphtha

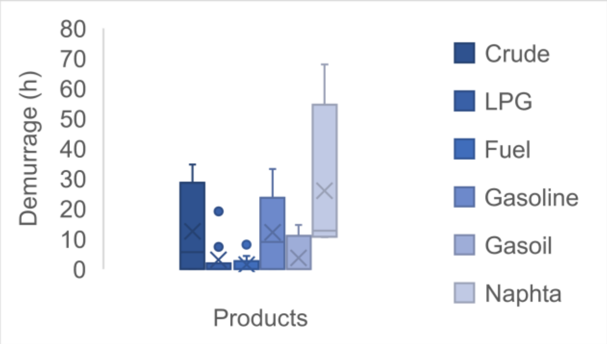

Figure 4: Demurrage boxplot by product

Naphtha, Crude and Gasoline were previously referred to as the products with the highest and more variable Port Operational Time. The same pattern is illustrated in Figure 4, leading to conclude that product 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.

For this indicator, it is desirable that it is equal to zero. However, sometimes it is not possible, so it should be as lower as possible, for the costs be equally lower. In fact, 54.39 % of vessels had demurrage equal to zero, therefore, does not incurring in financial cost for the company. However, from the 45.61% that incurred in financial costs, 26.32 % exceeded the 12 hours of Demurrage, incurring in high finance penalties.

In January 2017, there were 576.7 hours of Demurrages in total, incurring in more than 500000€ in costs.

As a conclusion, POT was quite high in January 2017, with Crude, Gasoline and Naphtha to have the highest. Analysing the variability of this indicator, the same products with higher POT tend to have higher associated variability. The origin of this variability is somehow explained by the variability on TD and OT. Finally, Demurrages were also quite high, and products with the highest POT tend to have the highest Demurrages. It is concluded that there is (1) bad allocation of vessels to berths and (2) bad allocation of products to pipelines.

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 case study problem (poor allocation of vessels to berths and 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 acquire knowledge to implement a methodology that improve the performance and minimize the terminal costs.

Despite this literature review focuses on the liquid bulk terminals, the exponential growth of the importance of container terminals leads to the reference of these terminals as well (de Oliveira et al., 2012)

The literature review timespan is from 2001 to 2019.

3.1 Containers terminal

To solve the BAP for containers terminals it is used three operational research methods: (1) Mathematical Optimization, (2) Heuristics and Meta-Heuristics and (3) Simulation and Simulation-Optimization.

In the first, Mixed Integer Linear Programming (MILP) is used by Raa et al. (2011), Agra & Oliveira (2018) and Correcher et al. (2019), with several objectives such as minimizing handling time of vessels, vessels delay in berths and fuel consumption.

Related with Heuristics and Meta-Heuristics, several methodologies were used. Among them, Greedy Randomized Adaptative Search Procedure (GRASP), Hybrid combination of Tabu Search and Path Relinking (PR) and Adaptative Large Neighbourhood Search (ALNS) was used by Lee et al. (2010), Lalla-Ruiz et al. (2012) and Mauri et al. (2016), respectively.

Finally, related with Simulation and Simulation-Optimization, Budipriyanto et al. (2017) explored the BAP for a container terminal. However, it is noted that most of the works in the literature are based on assuming a deterministic situation for arrival time of vessels and handling time. This work intends to use a Discrete Event Simulation Model to deal with uncertainty, formulating two alternatives: non-collaborative response and collaborative response. In the second, as in Venturini et al. (2017) and Dulebenets et al. (2018), it is admitted that 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.

Zeng & Yang, (2009) proposed a Simulation-Optimisation model for loading operations in container terminals. It generates sequences through a Genetic Algorithm 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.

3.2 Liquid bulk terminal

Related with Liquid Bulk Terminals, Robenek et al., (2014) solve the BAP as Umang et al. (2013) did in the previous year, extending the problem by considering yard locations to specific cargo types and by considering that each vessel only carry one type of cargo. The problem was formulated as a Mixed Integer Programming, with the objective of minimizing the total service of each vessel.

Although, this model could not solve the problem even for small size instances.
On 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 three different approaches to solve the problem, which latter on were compared based on computational results. The first one was a Mixed Integer Programming, aiming to determine the vessels' berthing assignment along the quay terminal. The second was a Generalized Set Partitioning Problem (GSPP), which was also used by Buhrkal et al. (2011) to solve a discrete and dynamic BAP for a container terminal. The last approach was a Meta-Heuristics based on Squeaky Wheel Optimization where, in each iteration, a solution is constructed and analysed, with this solution being used to a new priority order to obtain the next solution. The results of these 3 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.
Finally, there are no papers applying Simulation and Simulation-Optimization to Liquid Bulk Terminals.

3.3 State of art characterization

Papers related with the BAP show an the upwards, in the recent years.
It is also noticed 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.
There is also a difference between the methods used to solve the BAP. Heuristics, with 43 works, present a good tool to solve problems with several instances and relatively low computational time. 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 done, two papers that consider this factor: Shang et al., (2016) and Xiang et al., (2017).
Therefore, it is possible to identify the following gaps in the literature: (1) few studies on Liquid Bulk Terminals, (2) little exploration of Simulation and Simulation-Optimization and (3) 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 treated in the literature but also, among other advantages, it is adequate to treat parameter variability. 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 mitigate the effects of variability on system performance while allowing the evaluation of scenarios that minimize operational indicators.

4. Simulation model

4.1 Key Performance Indicators

In Sines' liquid bulk terminal system there are several objectives proposed, whether operational or financial, to access its performance. In this case, the Key Performance Indicators **Port Operational Time** and Demurrages were considered to assess the achievement of cost minimization and service level maximization.

4.2 Conceptual model

Sines' Liquid Bulk Terminal is characterized in activities and queues. Moreover, system entities are characterized as (1) Permanent, which, in terminal's system **Berths** and **Pipelines** are identified and (2) Temporary where **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 (1) Life Cycle Diagram and (2) Activity Cycle Diagram.
In both diagrams, activities are represented as rectangles and queues as ellipses.

Life cycle diagrams

Berth

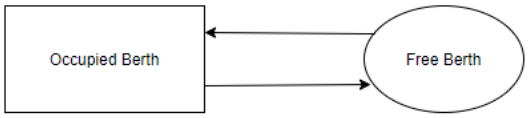

Figure 5: Life cycle diagram for entity "Berth"

Pipeline

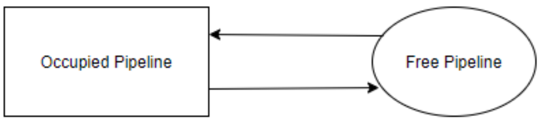

Figure 6: Life cycle diagram for entity "Pipeline"

Vessel

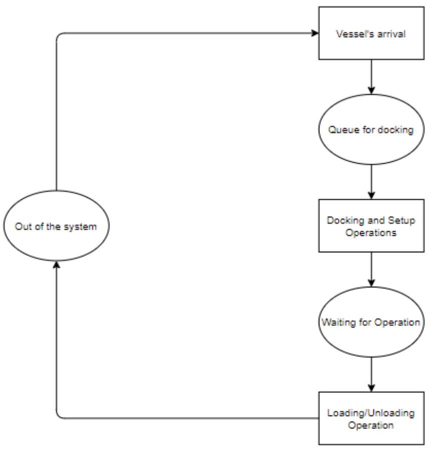

Figure 7: Life cycle diagram for entity "Vessel"

Activity cycle diagram

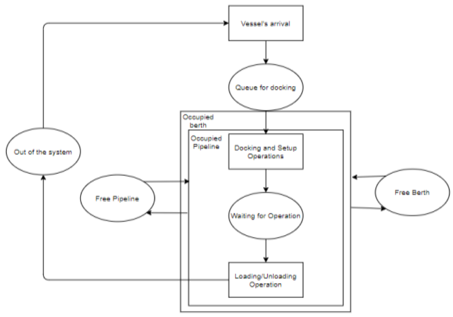

Figure 8: Activity cycle diagram of terminal system

This conceptual model was implemented in SIMUL8 software and validate against real terminal's data. The model proved capable of replacing the real system to test alternative scenarios.

5. Results analysis

5.1 Scenarios description

Now that the model is validated and allows to replace the terminal for testing new configurations, the following scenarios intend to test alterations in products allocation to pipelines, aiming to minimize the 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: (1) **Optimization 1, Optimization 2, and Optimization 3** denominated **O1, O2 and O3**; (2) **Simulation 1, Simulation 2, and Simulation 3** denominated **S1, S2 and S3**,; (2) **Optimization Simulation 1, Optimization-Simulation 2, Optimization-Simulation 3**, denominated **OS1, OS2 and OS3**; (3) **Steady State 1, Steady State 2, Steady State 3** denominated **SS1, SS2 and SS3**; (4) **Steady State – Queuing policy 1, Steady State – Queuing policy 2, Steady State – Queuing policy 1**, denominated **SS-QP1, SS-QP2 and SS-QP3**.

Each scenario is characterized based on five aspects: (1) Time horizon, (2) Pipeline allocation, (3) Berth allocation, (4) Queue policy and (5) Uncertainty. Figure 9 presents all characteristics for all scenarios.

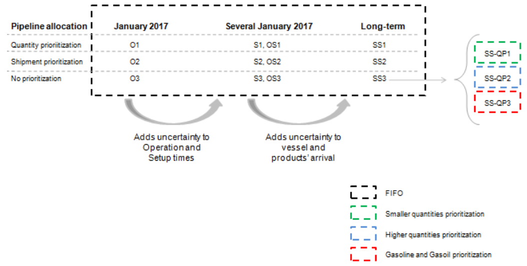

Figure 9: Scenarios' description according to its characteristics

5.2 Scenarios results

The results for all scenarios are divided by time horizon. First, terminating simulation, then steady state ones, ending in queueing policy scenarios.

5.2.1 Terminating simulations

General results

First, a sample of the mean POT and Demurrages of the 524 replications was introduced in the histograms of Figure 10 and Figure 11.

As Figure 10 for POT demonstrates, both Simulation and Optimization-Simulation for scenarios 1, 2 and 3 have its mode for the same classes. There is only one exception, scenario S3. This one has its mode in class on the right of the remaining, proving to output higher values for POT.

Figure 11 divided scenarios S3 and OS3 into two distinct histograms due to the pronounced difference in the value range of Simulation and Optimization-Simulation, allowing patterns to be distinguished more clearly.

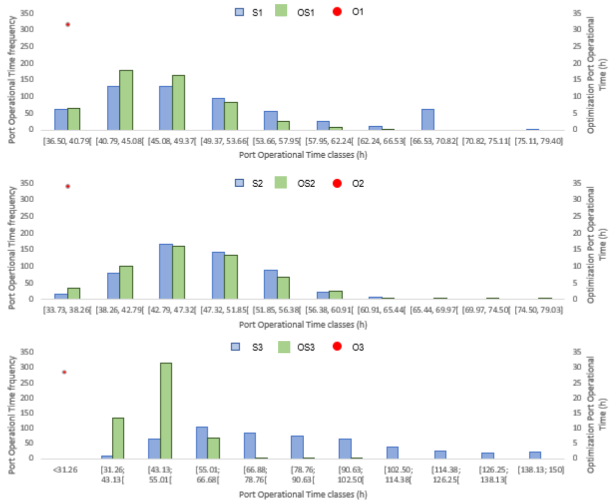

Figure 10: Port Operational Time data distribution histograms for terminating scenarios

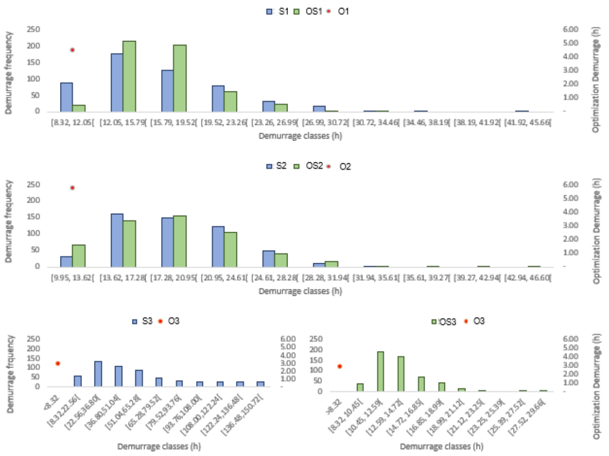

Figure 11: Demurrage time data distribution for terminating scenarios

Considering the 4 charts, the scenario with the leftmost peak is OS3. This is followed by S1 and OS1, moving to S2 and OS2. Finally, S3, as well as for POT, proves to be the scenario with the worst results, with the mode on the right of the remaining and a range of values higher than the others.
Comparing Simulation and Optimization-Simulation in its 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. This pattern changes to the higher values, for both POT and Demurrages.
Finally, all charts compare the 524 replicas POT with the optimization approach of Rato (2018) for each scenario. It is visible that Optimization provides better results on minimizing POT on each scenario, but the main conclusion is that these results have low probability to happen. This optimal value is very difficult to achieve because it does not consider delays or inefficiencies in operations.
Related with the Demurrages, as it was mentioned, its values must be equal to zero for the cost being zero. In this field, the best scenarios are the optimization ones. From the Simulation and Optimization-Simulation scenarios OS3 is the best with 27 vessels with vessels with demurrage zero among the 57 arriving vessels.
Although, sometimes they are not, but they should be as lower as possible. Figure 12 presents the percentages for best and worst scenario, OS3 and S3, respectively, of Demurrages equal to zero and higher than 12 hours.
On scenario OS3, among the 57 vessels, 49.12% had demurrage different from zero. From these vessels, 62.07% had demurrage values higher than 12 hours, increasing costs for the company. On the other hand, on scenario S3 87.72% of the vessels had Demurrages different from zero. From these vessels, 86.00% had demurrages higher than 12 hours.

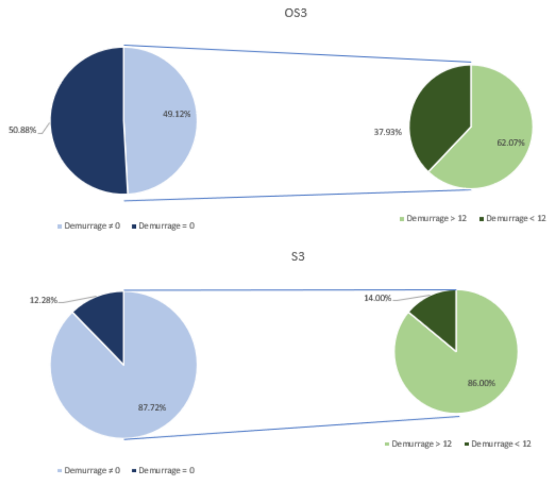

Figure 12: Comparison of vessels with Demurrage time equal to zero and higher than 12 hours, for scenarios S3 and OS3

Finally, based on the vessels that had not demurrage equal to zero, the variation of the costs compared to the real terminal ones are explicit in Figure 13, for all terminating scenarios.

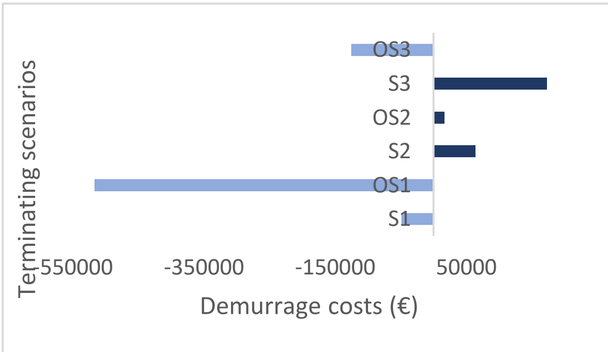

Figure 13: Comparison of Demurrage costs of terminating scenarios and real case study

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, a product that is very expensive per hour of demurrage. The S3 scenario shows poor results for almost all products, so it was expected to be the costliest scenario for the terminal.

Variability

The considerations of uncertainty in setup and operation times through Simulation and Optimisation-Simulation of terminating simulation represents a very useful tool for the evaluation of changes to the Liquid Bulk Terminal.
Boxplots on Figure 14 and Figure 15 present the data distribution for POT and Demurrage, respectively.
Optimization-Simulation scenarios demonstrate lower mean values when compared to Simulation approach, for almost all the six products transacted at the terminal. On the other hand, median values are approximately homogeneous for Simulation and

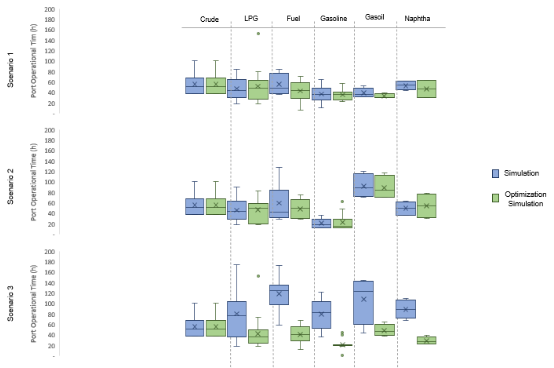

Figure 14: Port Operational Time boxplots of terminating scenarios, divided by product

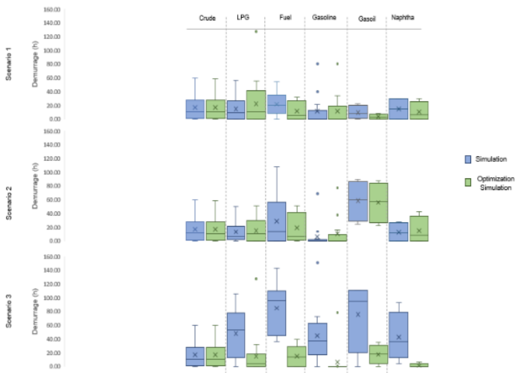

Figure 15: Demurrage boxplots of terminating scenarios, divided by product

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 compared to the other scenarios. Finally, 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. Fuel, LPG, and Naphtha have better results for scenario OS3 in all statistics, beneficiating from the **no pipeline allocation.** 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 for scenario OS1**, since it allocated to pipeline C instead of pipeline D in scenarios S2 and OS2. It also presents good results for scenario OS3.

5.2.2 Steady State simulations

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 the same conclusions. Based on that, for this section it will only be analysed the Port Operational Time results.

Firstly, to know the POT value that results from the steady state simulation of each scenario, it is necessary to introduce the averages and their trend, to determine the limit of the average series, corresponding to the POT value of each scenario.

Therefore, Figure 16 presents the trend of the average POT of all 20 replicas for all vessels that berthed, for the 3 scenarios.

Scenario SS3 converges to the lower POT values, with 35,064 hours.

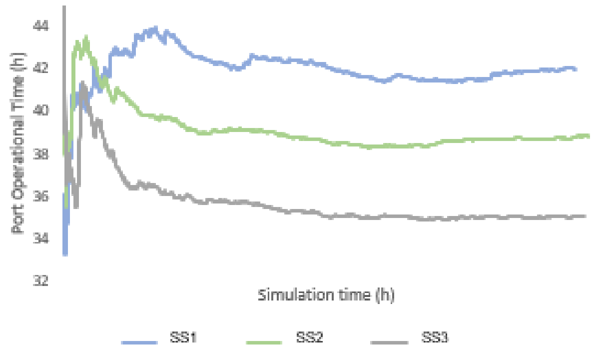

Figure 16: Mean Port Operational Time of steady state scenarios over time

However, this is an average value for all vessels and does not accommodate the inherent and important variability. Hence, the following boxplots in Figure 17 demonstrates the variability associated with scenarios' POT.

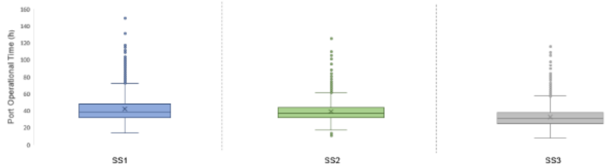

Figure 17: Port Operational Time boxplot of steady state scenarios

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, although SS3 has a slightly higher variability than SS2, it is noticeable that this is for lower values.

5.2.3 Queueing policy simulations

Based on the scenario SS3, the influence of queue policies on this indicator will now be tested. For this purpose, as mentioned, 3 scenarios derived from SS3 are developed: SS-QP1, SS-QP2 and SS-QP3. The results for these new scenarios are presented in Figure 18, comparing them with the SS3 scenario.

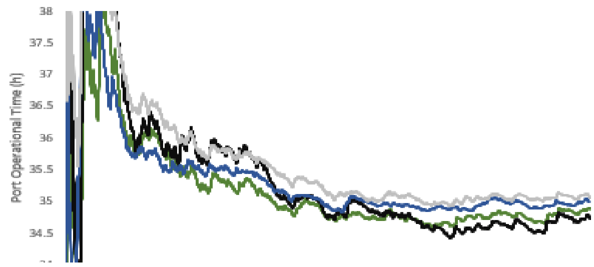

Figure 18: Mean Port Operational Time of Queueing policy scenarios over time

Based on the above values, there are 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 for the three scenarios.
Based on Figure 19, it can be observed that scenario SS-QP2, where the highest quantities are prioritized, presents the smallest average and median POT, but has the second highest interquartile variability. It also presents the highest number of outliers.
Among the four scenarios represented, SS-QP3, where Gasoline and Gasoil are prioritized in the queue for docking, presents a mean POT of 34.93 hours, with the lowest interquartile amplitude of 10.641 hours.

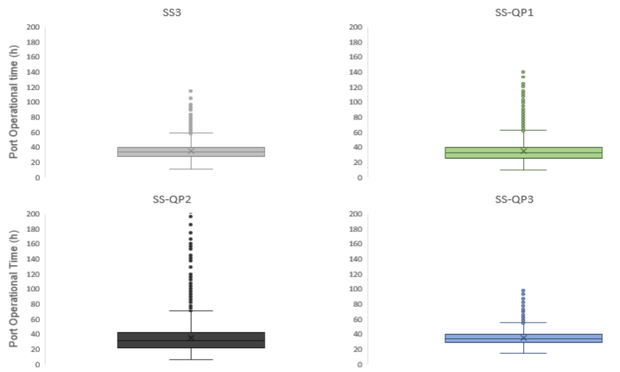

Figure 19: Port Operational Time boxplots of Queueing policy scenarios

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.

5.3 Selection of the best scenarios

Terminating simulations

For the selection of the best terminating scenario, that is, the scenario that minimizes the Port Operational Time and Demurrage, it is now made a comparison between all scenarios and real terminal outputs, for both KPI.
Based on a methodology of Carson & Nicol, (2014) the **best scenario is OS3**, where Optimization-Simulation is used with the flexibility of product allocation to pipelines.

Steady state simulations

The best steady state scenario is now calculated.
Based on the Bonferroni methodology present in Carson & Nicol, (2014), the confidence intervals are constructed.

$$CI_{95\%}(SS1 - SS2) = [0.7817;\ 5.6814]$$
$$CI_{95\%}(SS1 - SS3) = [5.3095;\ 9.3517]$$
$$CI_{95\%}(SS2 - SS3) = [3.1638;\ 5.0344]$$

The most important conclusion is the existence of statistical evidence that scenario SS3 has average POT values lower than the others. Therefore, this reveals itself as the best tested scenario for the Liquid Bulk Terminal in the long term. As in the terminating simulation scenarios, the scenario where there is no prioritization of pipelines to products is the one the results in the best scenario overall.

Queueing policy scenarios

The same methodology as for steady state scenarios was used. The confidence intervals are presented:

$$CI_{95\%}(SS3 - SS - QP1) = [-1.071;\ 1.239]$$
$$CI_{95\%}(SS3 - SS - QP2) = [-1.153;\ 1.153]$$
$$CI_{95\%}(SS3 - SS - QP3) = [-1.116;\ 1.890]$$
$$CI_{95\%}(SS - QP1 - SS - QP2) = [-1.988;\ 1.591]$$
$$CI_{95\%}(SS - QP1 - SS - QP3) = [-0.576;\ 1.183]$$
$$CI_{95\%}(SS - QP2 - SS - QP3) = [-1.170;\ 2.173]$$

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, nor that any of them overlap with the other, since all these confidence intervals contain zero. Therefore, this Confidence Intervals do not exclude the possibility that there are no differences between the queueing policy scenarios' POT averages.

6. Conclusion

Firstly, a theoretical introduction was made on the Global, European, and Portuguese context of energy and oil industry. It was obvious that a good terminal organization is crucial on this sector.
Then it was explicit the characteristics and operations of a Liquid Bulk Terminal in general and the Liquid Bulk Terminal of Sines in particular, ending in access its performance. It was observed a problem on the allocation of vessels to berths and pipelines. Variability on the data was not considered when scheduling the terminal's operation, another noteworthy aspect.
So, a literature review was performed based on the BAP. Several operational research methodologies were studied, concluding that there are few studies on Liquid Bulk Terminals, very little exploration of Simulation or Simulation-Optimization and nonexploitations of parameter variability. Therefore, a simulation approach is appropriate to solve the problem of the Liquid Bulk Terminal of Sines, and to propose alternative scenarios to its operations.

Hence, a conceptual model was performed to model the terminal's operations. This model was implemented in SIMUL8 software.

The model was validated, and 15 scenarios were proposed to address new terminal's allocations.

Scenarios were divided in three time horizon: one month of January 2017, terminating simulation of January 2017 and steady state simulations. For the terminating simulations horizon, general results and variability of output data was analysed. In the end, scenario OS3, where Optimization-Simulation was used with flexibilization of prioritization of pipeline allocation to products was considered the best.

For the steady state scenarios, flexibilization of pipeline allocation also proves itself as the best scenario. Finally, the results of queueing policy scenarios were analysed, and it was concluded that no queueing policy presents better results than another, and than the original FIFO.

Throughout this work, there were limitations that could be overcome and others that limited its performance. 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 time quite difficult. The lack of knowledge of the existence of operational restrictions was also an obstacle.

There is also future work on the problem addressed in this dissertation. 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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