Development and Analysis of a Port Terminal Loader Model at RUSAL Aughinish

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Abstract

The present study addresses the analysis of bulk carrier loading and discharge at the RUSAL Aughinish Alumina refinery, located on the west coast of the Republic of Ireland. We design a realistic simulation model taking into account not only deterministic features, but also elements of uncertainty. Following a statistical analysis of the results, we are able to indicate how the most important variables affect large scale performance descriptors such as berth occupancy, queueing hours and costs. The model is thoroughly validated against historical data and is subsequently applied to determine the impact of changes in key parameters on overall port operation and to suggest possible improvements of the modelled system.

Keywords: marine terminal operation, berth activity, discrete event simulation model

1. Introduction

RUSAL Aughinish is the largest alumina (aluminium oxide) refinery in Europe, located in the south-west of Ireland within the Shannon estuary, highlighted in Figure 1. The company produces alumina from bauxite using the Bayer process. The bauxite is imported from Brazil and Guinea in West Africa and processed into alumina. The product is then exported via a port terminal which is utilised for alumina shipment loading and raw material cargo discharge (with the exception of bauxite discharge, which has a dedicated port terminal). Relevant details about the geographical, logistical and operational aspects of the company are discussed in the following subsections.

An increasing demand has determined the need for a careful analysis of the factors contributing to the increased berth occupancy and of the potential methods to alleviate the existing pressure. Furthermore, future investment decisions may be considered based on a comprehensive, realistic model. Analytical (statistical) tools are initially designed to model several building blocks describing aspects

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of the activity at the jetty. However due to the complexity of the undertaking, a discrete event simulation model is used in this study. The large number of variables and the degree of uncertainty would generate an analytically intractable system. Well-studied and designed computational tools are therefore employed.

1.1. Literature Review

The approach of numerical simulations based on models with statistical features is well studied in the literature. We note in particular the review of Angeloudis and Bell [1], where it is underlined that large scale dynamic behaviour of multiple-component systems is very challenging to address. Furthermore, the applied nature and required performance level of these models indicate that computational tools are necessary in order to design and correctly test novel performance-enhancing strategies. As in the work of Bielli et al. [2], we underline that there are often two possible scenarios to strengthen and expand berth activity. Increasing the efficiency of current operations must be weighed against the economics of equipment upgrades.

An increasingly high number of successful models have been designed for terminals throughout the world. We expand on some of the most relevant ones for the present study in the following paragraphs. Cortes et al. [3] consider the Seville inland port and its entire logistic chain, where movement through the estuary, as well as the actual activity at the port itself are taken into account in order to conclude how current resources are able to mitigate present and future challenges. A similar exploration has been performed at Gioia Tauro in Italy by Legato and Mazza [4]. The model described in their work illustrates good agreement with realistic terminal activity and is subsequently used to target the most sensitive aspects of the process. Several policies and resource handling upgrades are considered and tested. Lin et al. [5] describe a model used to understand and optimise investment planning in the Humen Port in China. The system is highly complex, with various types of ships and cranes to be considered alongside scheduling aspects. The purpose was to minimise costs while maintaining a desired service level. The results show how costs can be reduced with an updated investment plan as given by the investigation. A model has also been constructed for the Trabzon Port in Turkey by Demirci [6], where alternative investment strategies have been produced based on the proposed simulation tool. Kia et al. [7] underline how such a model has lead to significant improvements and reduction of costs after having appropriately identified the bottlenecks in their system.

Several general simulation platforms have been proposed; for example the work of Sun et al. [8] in the form of MicroPort, which considers programming layers in order to allow for a large number of elements in a flexible modelling system. Very often however, models require highly specialised features and many elements that may be difficult to incorporate. Intricate examples can be provided within the studies of Yun and Choi [9], Canonaco et al. [10] and Rangel et al. [11], where specific characteristics within the specialised industries must be taken into account. Qu and Meng [12] describe a cellular automata-based approached for modelling ship movement in the Singapore Straits, also embedding expert judgement elements in the automatic decision making-process. Working with experienced personnel and conducting relevant interviews, a system with many possible alternatives becomes significantly more manageable.

Ship arrival scheduling is often the most important factor in improving port activity. Even under conditions of uncertainty, as underlined by Zhen et al. [13], understanding this aspect is shown to be crucial. Wanke [14] considers diverse berth allocation policies for a port in Brazil. The closely linked impact of processing times and costs is clearly indicated. Dragovic et al. [15] introduce a very well-designed and analytically rich tool within a similar framework.

The work of Shabayek and Yeung [16] illustrates the importance of high accuracy in such simulation models by conducting a case study on the Kwai Chung terminals in Hong Kong. The differences observed when comparing to actual data have been encouraging. Here the authors stress the idea of modelling various quantities from empirical distributions, which will be an important feature in this investigation as well.

The present study shares similarities with some of the above noted entries. However, our work is distinct, as it models the uniqueness of the RUSAL Aughinish shipping operations (local geographical elements such as tidal windows and various port restrictions, flexible maintenance), while also differing in the combination of parameters (several cargo types, on- and off-shore delays, as well as maintenance service times). Furthermore, the analysis is performed for a number of port characteristics such as demurrage costs, berth occupancy, queueing hours and cargo (alumina) output. By contrast, previous explorations concentrate on a single target, usually cost-related.

The paper is organised as follows. In subsection 1.2 we summarise the main properties of the berth activity. In section 2 we introduce the mathematical model and underline its most relevant characteristics. Section 3 is reserved for the description of the results of the designed simulations. We start by validating against historical data in subsection 3.1, followed by the testing of several proposed scenarios in subsection 3.2. We then present our conclusions in section 4.

1.2. Berth Activity Description

As part of a complex operational structure and in order to satisfy its large shipping needs, RUSAL Aughinish maintains and operates its own port terminal (see Figure 2) for the import of bauxite and export of alumina. While bauxite is the principal raw material imported (via a dedicated terminal, which is not the subject of the present study), there are three other raw materials imported via the port terminal being modelled. In the present work, we construct a model for the port terminal of the jetty, highlighted in the subimages of Figure 2. This is the area used in order to load alumina into ships (called Type A ships or Type A bulk carriers), as well as to unload three types of bulk carriers, which will be referred to as Type B, C and D in the following sections. We underline that Type A bulk carriers are the most significant of the four in the company activity by an extensive margin, in terms of both number of vessels and overall cargo transport.

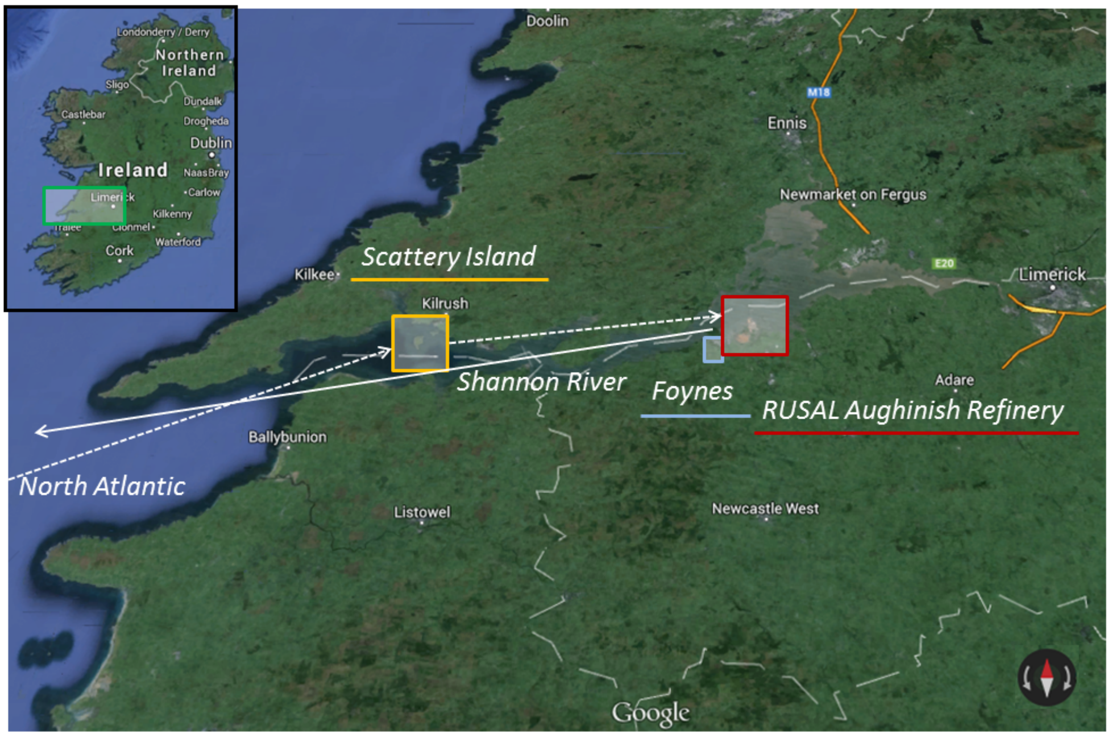


Figure 1: Geographical description of the RUSAL Aughinish operation area.

Each year RUSAL Aughinish operate to a shipping schedule. There are several aspects that may modify this schedule, from shipping company requirements to costs. Furthermore, the exact arrival times of ships is naturally subject to a certain degree of uncertainty, which must be accounted for. The ships firstly arrive at Scattery Island, an island at the mouth of the Shannon Estuary approximately 40 km west of Aughinish. The island is highlighted in yellow in Figure 1. At this point, a shipping pilot boards the bulk carrier to guide the shipment to the Aughinish port terminal. Note that multiple ships (which may also be of different types - A, B, C or D) can arrive at Scattery Island within a short time interval, generating ship queues that must be negotiated in a sensible manner. Once a ship has arrived and declared it is available for loading, i.e. served a "Notice of readiness", the allocated lay time (the time in which the company is responsible for operation activities) begins to reduce. The bulk carrier does not leave Scattery Island unless the tides are suitable and the port terminal is free.

Due to operational reasons, RUSAL Aughinish need to ensure that there is no strong downstream tide (i.e. going from east to west in Figure 1) when a bulk carrier is berthing. As a result, ships coming into and out of the jetty can only do so in the time between one hour after low tide and one hour before high tide. The correct tidal window is one of the most stringent conditions that needs to be imposed on the system and is represented by a constant period of time spanning several hours due to the very small variations in the window between low and high tides occurring in the area. Cycles of favourable/unfavourable tidal movements are hence embedded into the operational schedule.

Once the pilot boards at Scattery Island, the journey time to the Aughinish port terminal is approximately three hours. Upon arrival, a pre-loading inspection is carried out by an independent surveyor. Should the ship fail inspection (for example due to mechanical failure), this falls under the responsibility of the shipping company; so do the associated costs for the repair itself and the delays caused by the actions undertaken. The level of the damage dictates whether the issue can be handled on-site in Aughinish or whether the bulk carrier may have to leave the berth to complete repairs at the nearby port of Foynes (highlighted in blue in Figure 1).

Loading commences once a bulk carrier has been passed fit for purpose by the independent surveyor. A consistently high loading rate is targeted. However, in certain instances loading rates reduce to below this target or loading may be suspended entirely due to either shore- or weather-related issues. Shore-related delays include events such as shore equipment breakdown, while weather-related delays often include issues such as high winds or heavy rain.

Upon completion of loading and following a post-load inspection, the ship departs from the Aughinish port terminal within the tidal window. At this point the lay time is halted and the next bulk carrier can be brought in from Scattery Island. The procedure repeats itself for each ship in the schedule.

The event-based nature of the activity, as well as the natural formation of queues at Scattery Island are strong arguments in favour of constructing a comprehensive simulation model, capable of describing the underlined steps in full detail and allowing for the analysis of the effects of certain parameters in the system. The model we consider is presented in Section 2.

2. Simulation Model

In this section we describe the theoretical framework used to analyse and further investigate the shipping process at RUSAL Aughinish. The model replicates the arrivals and departures of ships, as described in Section 1.2, into the port terminal. A few relevant simplifications have been considered as part of the modelling exercise.

i. Ships arrive at Scattery Island based on a known schedule at the beginning of the year;
ii. A bulk carrier can only arrive at the Aughinish port terminal from Scattery Island at certain tidal times;

Figure 2: Aerial view and detail of the jetty and port terminal.

iii. Pilot availability is always assumed;
iv. Once the pre-load inspection is over, loading can begin immediately;
v. The loading rate is a pre-determined quantity, based on the ideal loading rate of the present equipment and the inclusion of any potential shore- or weather-related delays, which would ultimately lead to a reduced effective loading rate for the respective ship;
vi. In the case of alumina bulk carrier loading, the existence of sufficient material to be loaded onto ships is assumed;
vii. The possibility of designing and setting up of a queue sorting mechanism based on cost reduction is considered.

All of the above items represent realistic features, required for a rigorous description of the company activity. In order to best illustrate the queueing theory model, we make use of algorithm 1, which provides the pseudocode for the simulation model. Tables 1 and 2 explain the notation used in the algorithm. Table 1 gives the event times associated with bulk carrier i while Table 2 gives the different activities of bulk carrier i. In both tables, $*$ is used to represent events/activities that are of probabilistic nature.

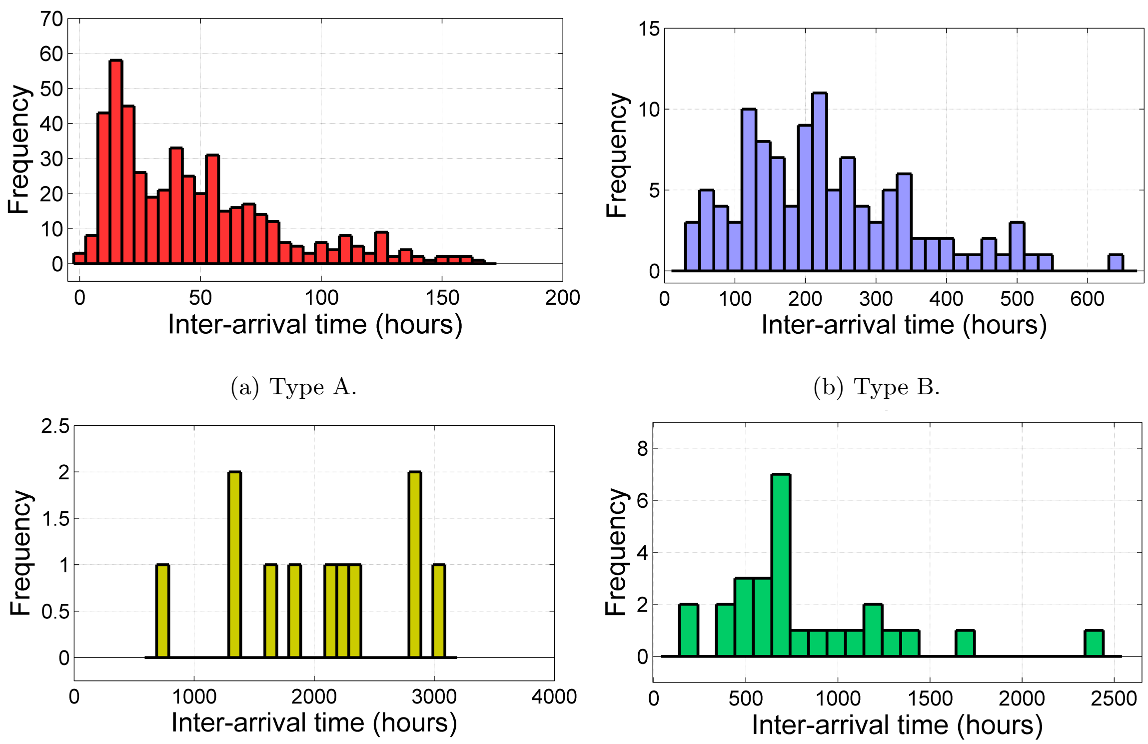
Table 1: Event times for bulk carrier i.

a_i^*	Arrive at Scattery Island
b_i	Depart Scattery Island
c_i	Arrive at Aughinish port terminal
d_i	Start unloading
e_i	Finish unloading
f_i	Finish inspection
g_i	Depart Aughinish port terminal

We assume a fixed number of bulk carriers of Type A (alumina), B, C and D as inputs to the system. The inter-arrival times between ships of the same cargo are then generated by sampling from a distribution derived from historical data. For all validation tests, the model parameters were derived from the data provided by the company. Inter-arrival times are then sampled from this prior information (carried out using the inverse cumulative probability distribution function) and a schedule of ships can then be formed by merging the existing four schedules (for each cargo type) and accounting for start and end effects. Figure 3 presents the distributions in detail and illustrates a strong variability in the system. This is the key source of uncertainty, with expected consequences in the final results. A reduction of the variation of arrival times, acting as a regularisation in the model, would directly lead to enhanced port performance, however this is difficult to achieve in reality.

Table 2: Bulk carrier activities.

Waiting time at Scattery	$b_i - a_i^*$
Voyage up river (in hours)	$T \equiv c_i - b_i = 3$ (constant)
Tie up/survey etc.	$(d_i - c_i)^*$
Loading bulk carrier	$(e_i - d_i)^*$
Inspection duration	$(f_i - e_i)^*$
Start of next tidal window	w_t
Tidal Window Open (TidalWindow)	$w_{t-1} \leq g_i \leq w_{t-1} + TidalWindow$
Depart Aughinish	$g_i = f_i$ if $TidalWindow$, $g_i = w_t$ otherwise
Time to clear berth	S (constant)



(a) Type A.

(b) Type B.

(c) Type C.

(d) Type D.

Figure 3: Inter-arrival time distributions for (a) Type A, (b) Type B, (c) Type C and (d) Type D ships.

Similar sampling procedures are used when designing bulk carrier capacities and various types of delays (ship-, shore- and weather-related). Other variables, such as ideal loading rates or demurrage rates, are considered to be constant (differing only due to bulk carrier cargo type). Finally, simple dependencies exist in the system. For example the lay time allowed is a linear function of the ship type and ship capacity, matching the real-life policy in the system.

The parameter space is first populated by the known constants; it then incorporates the data constructed from empirical probability distributions, followed by the determination of the dependent variables. Once all these elements have been set, ships undergo the steps illustrated in algorithm 1 and quantities such as costs and queueing hours can be computed on a ship-by-ship basis, adding to yearly quantities. The model incorporates additional features, such as known periods of maintenance at the port terminal and their duration throughout the year. A maintenance schedule is known at the beginning of the modelled activity, with operations taking place at regular intervals over a predetermined number of days. Hence bulk carrier movement and servicing is modified accordingly to accommodate for this interval of time in which no active loading or discharge can take place. At the end of the modelled activity, we compute berth occupancy, alumina output and several other quantities of interest.

Multiple bulk carriers present on Scattery Island waiting to be serviced is a common occurrence in the modelled system. A queue sorting policy is required to handle several types of ships (with additional intrinsic characteristics in each category). Material availability at the refinery is not a bottleneck in the process and relevant materials for the production process are assumed to be present in the storage facilities at all times. We therefore shift our goal towards cost minimisation and impose a demurrage rate based policy. This strategy gives priority to the bulk carriers which would produce the highest costs if forced to remain in the queue for longer periods. Upon inspection of the availability of the port terminal, we analyse the known fixed demurrage rates and the ship capacities of all bulk carriers in the queue and authorise the most cost-demanding bulk carrier to arrive at the port terminal first. More concretely, when ship i leaves berth, we determine the next ship $i + 1$ to arrive from the queue at Scattery Island by analysing the fixed demurrage rates and allowing the ship with the highest demurrage rate to proceed, so as to avoid it generating larger costs by remaining in the queue for a longer time. Occasionally, for operational reasons, the plant may urgently need a ship of certain type and thus the respective ship will be berthed first regardless of potential demurrage costs. As a result, the queue based policy implemented in this model is a simplification. Further policy improvement is possible, however with this simple method we account for one the most significant factors we wish to mitigate, namely demurrage-related expenses.

Within the algorithm structure we also consider the possibility of a ship failing inspection and departing the terminal. The rate of occurrence of this event is extracted from the historical dataset and proves to be infrequent. The number of hours (sampled again from the reference empirical distributions) during which the bulk carrier undergoes repair work is then added to ship-related delays.

The sampling mechanism will dictate the pattern of the data, but not a specific ordering structure. For example, consider the situation in which a notable weather-related event took place in the middle of the historical activity year and it was hence followed by a large queue of ships accumulating at Scattery Island waiting to be serviced. It is likely that our initial data construction will include such an event, but it may take place at any point in the activity year, not at a specific time. This does not affect the computations of large scale quantities such as yearly costs or berth occupancy and is an inherent feature of the system.

In the following section we first illustrate the validation procedure via an event-based simulation platform, followed by the testing of several performance-enhancing options within the same computational structure.

3. Results and Analysis

Having discussed the model and algorithm in previous sections, we are now interested in its reliability and potential in identifying and studying large scale strategic features. We first validate the model against existing historical data in subsection 3.1, followed by a comprehensive set of explorations of the impact of relevant scenarios in subsection 3.2. The latter are meant to serve as basis for future investment decisions, as they investigate the impact of key variables that could be improved by equipment changes or general logistical modifications.

3.1. Model Validation

We start, as suggested in algorithm 1, by generating initial data from existing historical distributions. The dataset in question spans a 365 day period, representing the most recent full activity year for which complete data was available and provided by RUSAL Aughinish. This dataset will be referred to as the historical data or the reference year in the following sections of this document. The discrete sampling procedure is based on sampling from empirical inverse cumulative probability distributions and its effectiveness will be discussed within this subsection. At this point we also specify additional parameters that do not require an original distribution to sample from, as they are simple numerical values. Examples include demurrage rates, bulk carrier numbers or number of repetitions of the simulations. At first, the data is meant to reproduce the parameter space of the activity of the reference year. Probabilistic data generation will account for a wide range of scenarios, however on average we expect to reproduce the same quantitative values as achieved in real life. All data presented in this section is sampled from a set of 7500 simulations. The level of computational effort has been chosen after numerical experiments indicated that a number of $\mathcal{O}(10^3)$ or more simulations are sufficient to produce statistically reliable results. We underline that values reported in the present

```
Data:  Historical data to generate bulk carrier characteristics
Result:  Dynamics of activity at berth and Scattery Island
SpecifyParameters(); InputDataFiles();
for i = 1 → TotalQueueSize do
    if a_{i+1} + T > g_i then
        if TidalWindow then
            b_{i+1} = a_{i+1}; c_{i+1} = a_{i+1} + T;
        end
        else
            b_{i+1} = max(a_{i+1}, w_t − T); c_{i+1} = a_{i+1} + w_t;
        end
    end
    else
        if TidalWindow then
            c_{i+1} = max(a_{i+1} + T, e_i + S); b_{i+1} = c_{i+1} − T;
        end
        else
            c_{i+1} = w_t − T + S; b_{i+1} = c_{i+1} − T;
        end
    end
    InspectShipPreload(); LoadShipWithDelays(); InspectShipPostload();
    if TidalWindow then
        g_i = f_i;
    end
    else
        g_i = w_t;
    end
end
OutputData();
VisualizeResults();
```

Algorithm 1: Queueing Model - Simulation Pseudocode

document are scaled with respect to the reference year, i.e. in Figures 4-13, value 1 corresponds to the actual value observed in the reference dataset for the variable in question.

We start by presenting the physical duration of the simulation, in years, as shown in the form of a histogram in Figure 4. We aim to reproduce the activity over the duration of one year. The uncertainty factor is provided by the fact that inter-arrival times between bulk carriers are probabilistically generated, while queue prioritisation policies at Scattery Island might also affect the dynamics of the system.

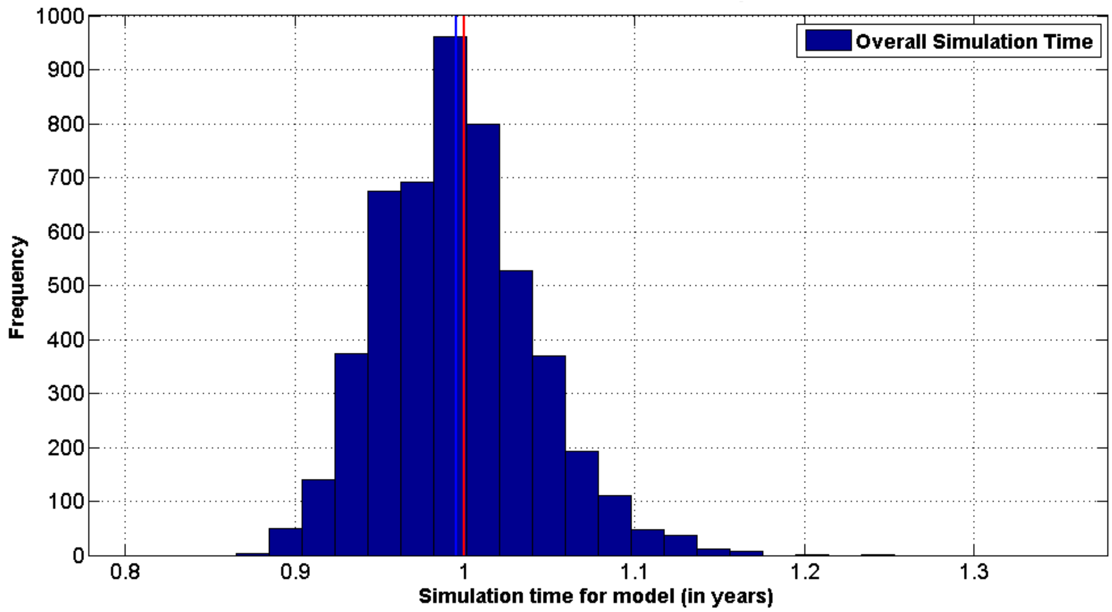
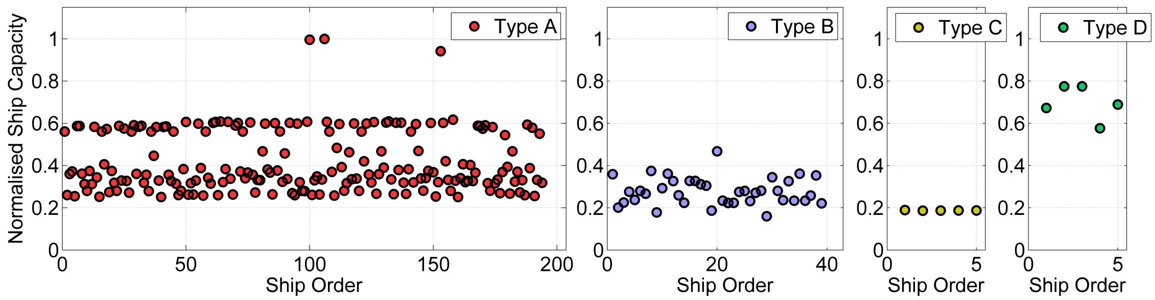


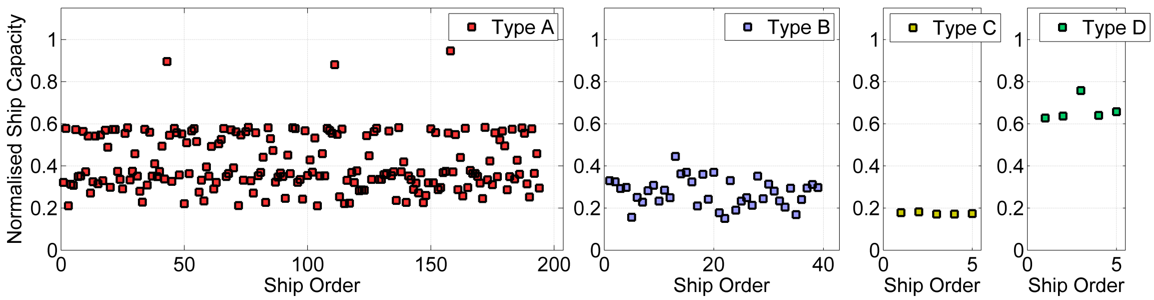
Figure 4: Histogram of the duration in physical time (years) of simulated port terminal activity. The blue vertical line indicates the average of the simulations, while the red vertical line denotes the reference value of 1 year (the target of the model).

We obtain a negligible error between actual (historical) and simulated time windows. The one year mark is shown in a red vertical line, while the simulation average is plotted as a blue line. The generated simulation time histogram shows a realistic pattern around mean 1, with more than 95% of the data within a 5% interval of variation. We can then conclude that assessing further indicators is performed correctly and will represent a viable estimate for yearly data.

We examine individual simulations and visualise how a set of bulk carriers and their characteristics match the expected pattern (a quantitative discussion based on the results in Table 3 is presented later in this subsection). Figure 5, describing the ship capacity distribution for a typical simulation, is analysed as follows. In the top panel we show the real ship capacity distribution. There are three large Type A (alumina) bulk carriers visible, a wide range of mid-capacity bulk carriers of roughly 60% of the maximum capacity, while the majority of the bulk carriers are small capacity ships of 25% – 40% of the maximum value. Type B, C and D bulk carriers are also presented. The ordering is of course immaterial, we aim however to reproduce a similar type of distribution of ships, which is clearly noticeable in the bottom panel of the same figure. The plots have been separated into ship types in order to facilitate visual comparison. Their arrival schedule within each ship type category spans throughout the entire tested period and the final arrival schedule is obtained by a merging procedure of the four different schedules.



(a) Historical data.



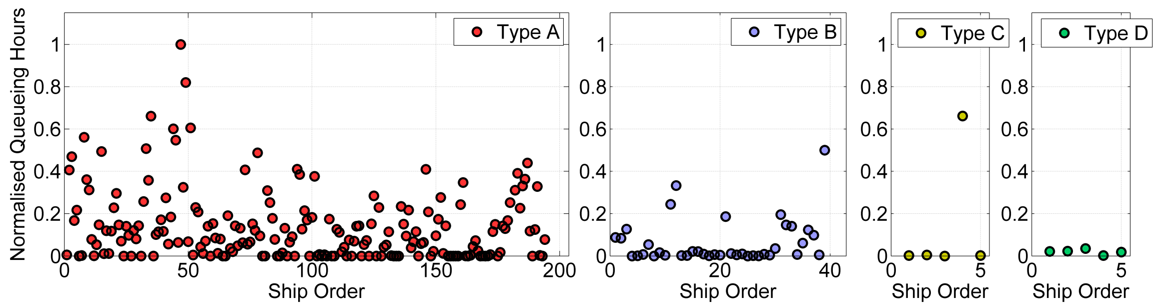
(b) Simulation data.

Figure 5: Example ship capacity distribution from a sample simulation. The real data (a) is compared to the simulation data (b) produced from distribution sampling.

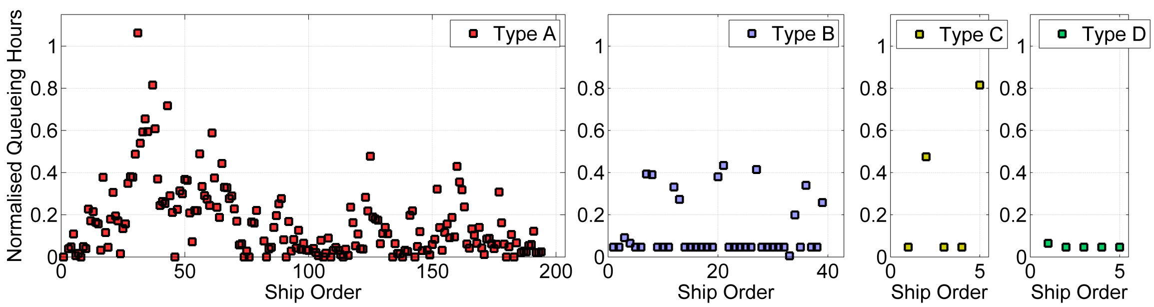
Monitoring bulk carrier capacities represents a visualisation of initial data. A similar type of plot can be generated at the end of the simulation with the dynamic data obtained, for example for queueing hours at Scattery Island.

In Figure 6 real data is again presented on top, while the data from a given simulation is shown in the bottom panel. The similarity is again noticeable. When consulting the queueing hours of ships of type B, C and D, the queue handling mechanism of giving priority to high demurrage rate ships is again visible. These three categories of infrequent ships carry high demurrage rates and are sent to the port terminal as soon as the previous bulk carrier is loaded, thus providing a visible common upper limit (linked to the tidal window). Sometimes, due to shore-related delays or equipment malfunction this is not possible (due to a previous ship remaining at berth for a long time), which explains the occasional outliers to the previously mentioned mechanism.

Returning to the analysis of information over a large number of simulations, similar bulk carrier capacities should automatically translate to an alumina output which is very close to the target historical value. This is clear from Figure 7, where 95% of the results lie within 3% of the expected



(a) Historical data.



(b) Simulation data.

Figure 6: Example queueing hour distribution from a sample simulation. The real data (a) is compared to the simulation data (b), with the visualisation separated into ship types.

average. The dashed vertical lines indicate these limits, while the red vertical line is the target mark of 1 (matching real data exactly) and the blue vertical line is the average of the simulations.

All performance indicators are related and hence obtaining accurate results for the individual components is paramount to validating the model. Alongside qualitative agreement, we also use objective quantitative measures in the form of L^1 norms (Eq. 2, a standard choice equivalent to the mean absolute percentage error) in order to assess the performance of the numerical simulations. A relative factor is defined for each quantity of interest as

$$N(i, Q_S, Q_R) = \frac{|Q_S(i) - Q_R|}{Q_R}, \tag{1}$$

where Q_R represents the real (historical) data value of the respective quantity and $Q_S(i)$ is the obtained value of the same quantity at simulation i.

By averaging the above set we obtain the desired L^1 norm, expressed as

$$\bar{L}^1(Q) = \frac{1}{n} \sum_{i=1}^{n} N(i, Q_S, Q_R). \tag{2}$$

The resulting L^1 norms, standard deviations, coefficients of variation and errors between simulation means and reference values are indicated in Table 3, where costs, berth occupancy, queueing hours

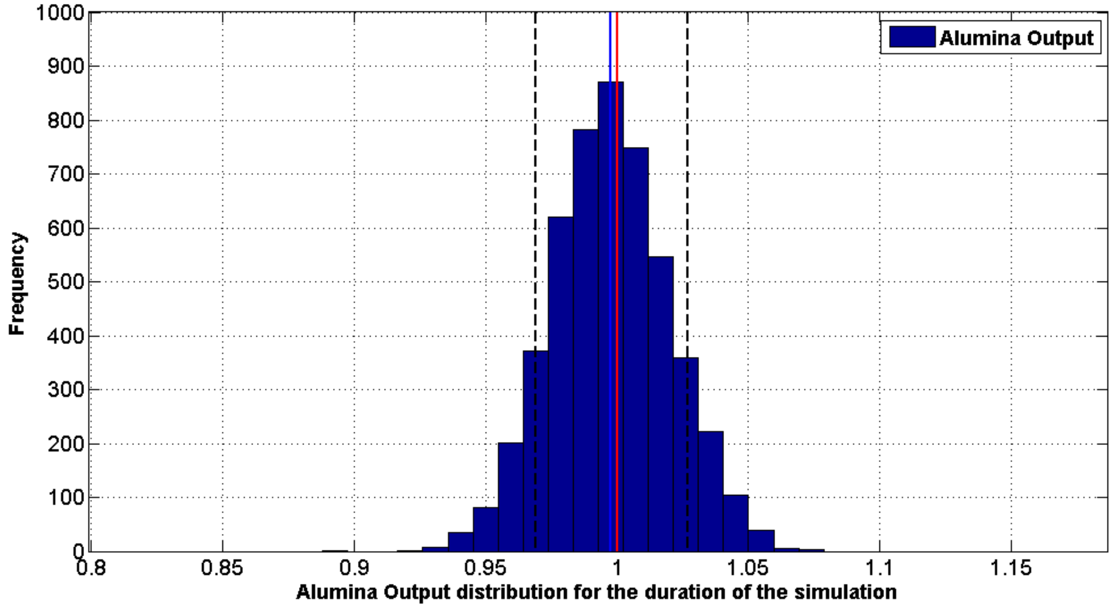


Figure 7: Alumina output histogram. The blue vertical line indicates the average of the simulations, while the red vertical line denotes the reference value for 1 year (the target of the model). Dashed vertical lines highlight the middle 95% interval.

and alumina output are the target indicators. Bulk carrier capacities can be described in a similar fashion, however instead of iterating only over the total amount of simulations, we additionally iterate internally over the amount of ships for a given simulation, procedure which can be straightforwardly extended from the above equations. In the case of ship capacity and queueing hour comparisons, we have also resorted to the well-known two-sample Kolmogorov-Smirnov test as means of verification. We are especially interested in ships of Type A and Type B, where sufficient information is available for conclusive tests(ships of type C and D only have five samples in each simulation). In the case of ship capacities the $p-$values obtained are 0.223 and 0.708, respectively, while in the case of queueing hours we obtain 0.174 and 0.0931, also presented in Table 4. In both cases, the relevant values are higher than 0.05, suggesting there is no statistically significant difference between the real and simulated distributions of ship capacities and queueing hours for the target ship types.

An additional measure employed and reported in the third column of Table 3 is the percentage error between the mean of the simulations and the reference value for all quantities of interest Q, defined as

$$E(Q) = \left| 1 - \left(\frac{1}{n} \sum_{i=1}^{n} Q_S(i) \right) \Big/ Q_R \right| \cdot 100, \tag{3}$$

which serves as a strong indicator of the success of the validation.

We notice very little variation in alumina output, since this is the least sensitive variable in the

Table 3: Model validation summary: model results compared to actual data from the reference dataset

Indicator	Mean L^1 error norm across simulations (St. dev.)	Coefficient of variation	Error (%) between simulation mean and reference value
Bulk carrier capacity	0.074735 (0.011993)	0.160481	1.568708
Costs	0.21918 (0.147965)	0.675082	1.675322
Berth occupancy	0.091954 (0.047996)	0.521955	7.619873
Queueing hours	0.275992 (0.192276)	0.696674	5.326139
Alumina output	0.014895 (0.009898)	0.664555	0.621312

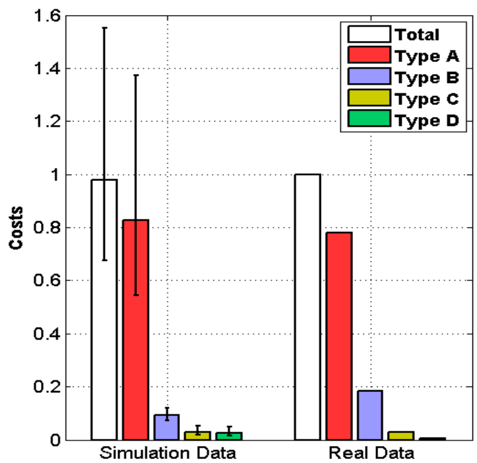
Table 4: Distribution validation via the two-sample Kolmogorov-Smirnov test: model results compared to actual data from the reference dataset, revealing p-values larger than 0.05

Distribution	Type A ships p-value	Type B ships p-value
Bulk carrier capacity	0.223	0.708
Queueing hours	0.174	0.093

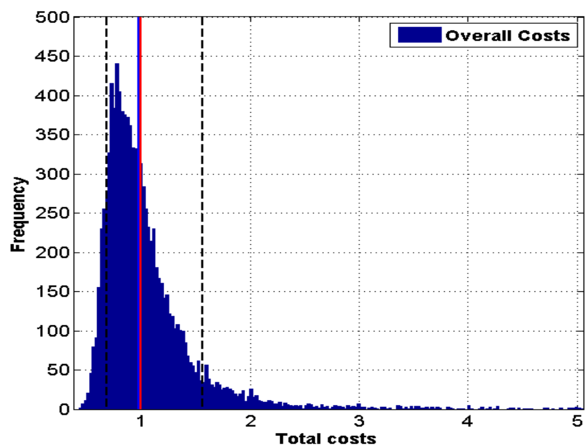
system, while other indicators show minor discrepancies when compared to the historical data. With reasonable coefficients of variation (smaller than 1) in the context of a multi-variable highly probabilistic setup, we conclude that the validation study has been successful.

Figure 8a illustrates the cost study summary for this set of simulations. Figure 8b shows a histogram plot, similar to the illustrations constructed for previously discussed variables. As the vertical red line (historical value) and vertical blue line (mean simulation value) are indistinguishable (the mean of the simulations is 98.3% of the expected result), we conclude that the model is a viable tool for predicting demurrage-related costs. The vertical dashed lines again indicate that 95% of the simulated data lies between approximately 80% and 155% of the real life value. We observe a positively skewed distribution with a peak which slightly underestimates the historical data (by $8-9\%$), which can be explained as follows. Since we simulate circumstances very close to reality, we expect proximity to the real data. Additional modelling features such as a queue prioritisation system that allows high demurrage rate ships to advance in the queue (when possible) should yield slightly improved results. However we do not regulate or restrict the occurrence of rare events, such as long-term unfavourable weather conditions or shore equipment breakdown. These lead to an accumulation of ships at Scattery Island (as seen in Figure 6 as well) that persists for most of the duration of the simulation and negatively affects the computed cost. Human intervention in the scheduling may be used to resolve the conflict, however the procedure is sensitive. This is the main reason why excluding outliers is a viable way of accounting for rare events and considering 95% of the simulated data for further decision-making processes is a sensible approach.

In Figure 8a we show bar plots of the mean costs and the upper and lower levels of the 95% confidence interval. This is illustrated for both total costs (which are expanded in detail in Figure 8b), as well as for each category of bulk carriers in particular. We notice that Type A ships are indeed the most important factor in the determination of costs. Good agreement is visible in all these plots, with the additional note that the queue prioritisation feature results in reduced costs for bulk carriers of Type B, C and D, while slightly increasing the costs for bulk carriers of Type A. This is precisely the type of behaviour we expect from this change and it results in realistic marginally decreased overall costs.



(a) Costs - results summary.

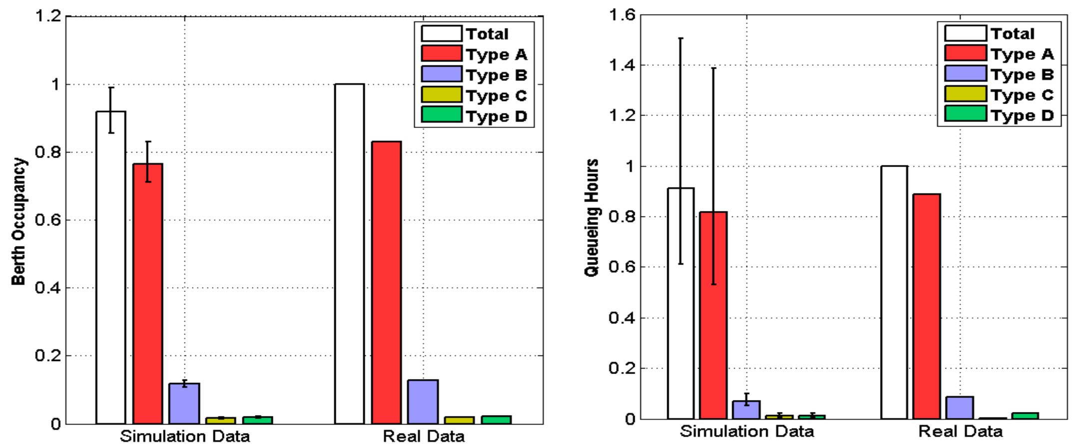


(b) Costs - histogram.

Figure 8: Mean demurrage costs produced by each type of bulk carrier and overall, compared to real data for the reference year. (a) The bars indicate the minimum and maximum of the 95% confidence interval. (b) In the histogram, the blue vertical line indicates the average of the simulations, while the red vertical line denotes the value for reference year. Dashed vertical lines highlight the limits of the 95% confidence interval.

Figure 9 is used to visualise berth occupancy and queueing hours. Results are well aligned with previous findings, in which the historical data is reproduced accurately, with minor improvements given the queue priority mechanism and with a variation explained by the wide range of probabilistically generated variables accounting for many of the real life occurring situations.

We conclude the validation by underlining that the results are clearly comparable in value to their equivalents from the reference year, while the data distribution analysis illustrates a well behaved simulation platform capable of delivering realistic results. We therefore proceed with a set of test scenarios



(a) Berth occupancy - results summary.

(b) Queueing hours - results summary.

Figure 9: (a) Mean berth occupancy and (b) mean queueing hours produced by each type of bulk carrier and overall, compared to real data for the reference year. The bars indicate the minimum and maximum of the 95% confidence interval.

that allow us to investigate potential improvements of the port terminal activity in subsection 3.2.

3.2. Test Scenarios

Having established the convincing performance of the model via several validation studies, we now aim to use the platform as a predictive tool and formulate a set of studies and scenarios of relevance for the activity at the berth.

In subsection 3.2.1 we describe the impact of loading rate variation on the key variables in the problem. We then pursue to investigate the effects of two additional factors, namely pre-load inspection times (3.2.2) and shore-related delays (3.2.3). Finally, in 3.2.4 we consider the case in which the capacity of the vessels can be modified and conduct an additional study of loading rate variation on the newly designed ship fleet.

The selected variables represent all the quantities that could be modified at the port level. Given a very large set of parameters, we aim to isolate the most relevant ones and illustrate their impact on the performance indicators (costs, queueing hours, berth occupancy and alumina output). With this knowledge, future investments and strategies can be considered in an efficient manner.

3.2.1. Loading Rates

One of the most important characteristics of the port terminal activity is the loading procedure of material from and onto bulk carriers. The process is very sensitive and damages or issues that arise in this sector have an instant impact on all relevant aspects of the workflow in the company.

Table 5: Fleet modification: model results compared to actual data from the reference dataset at loading rates varying from 0.9 to 2.0 of the reference value.

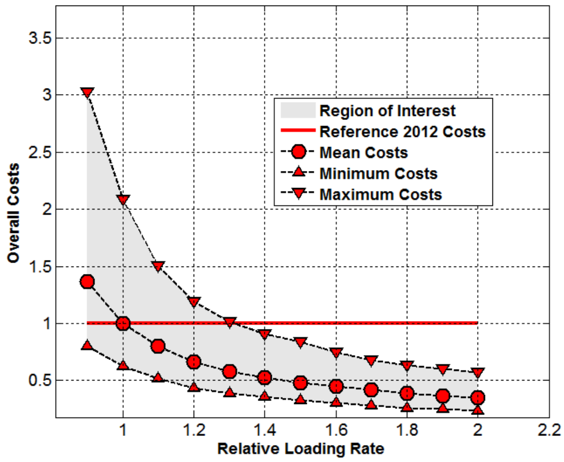
Loading rate	Berth occupancy (min/max)	Queueing hours (min/max)	Costs (min/max)
0.9	0.97 (0.88/1.08)	1.26 (0.69/2.98)	1.36 (0.80/3.02)
1.0	0.92 (0.84/1.03)	0.94 (0.56/2.05)	1.01 (0.63/2.08)
1.1	0.88 (0.80/0.99)	0.76 (0.48/1.49)	0.80 (0.52/1.51)
1.2	0.84 (0.76/0.95)	0.64 (0.43/1.18)	0.66 (0.44/1.19)
1.3	0.82 (0.74/0.92)	0.58 (0.40/1.03)	0.58 (0.39/1.02)
1.4	0.80 (0.72/0.90)	0.54 (0.37/0.93)	0.53 (0.36/0.91)
1.5	0.77 (0.70/0.88)	0.50 (0.35/0.86)	0.48 (0.33/0.84)
1.6	0.75 (0.69/0.86)	0.48 (0.34/0.79)	0.45 (0.30/0.75)
1.7	0.74 (0.67/0.84)	0.46 (0.33/0.72)	0.42 (0.28/0.68)
1.8	0.72 (0.65/0.82)	0.44 (0.32/0.68)	0.39 (0.26/0.63)
1.9	0.70 (0.63/0.80)	0.42 (0.31/0.66)	0.37 (0.25/0.61)
2.0	0.69 (0.62/0.79)	0.41 (0.30/0.64)	0.35 (0.24/0.58)

Furthermore, potential upgrades to the system may prove valuable and can be considered as means to increase berth operation efficiency. We construct a series of tests that allow us to study the exact influence of modifying the loading rates, taking into account realistic limitations of the machinery. From the physical standpoint, the current design would not allow for an increase to more than twice the current loading rate. However, we can also take into account equipment degradation and impose smaller loading rates in order to visualise the effects of the change on performance indicators.

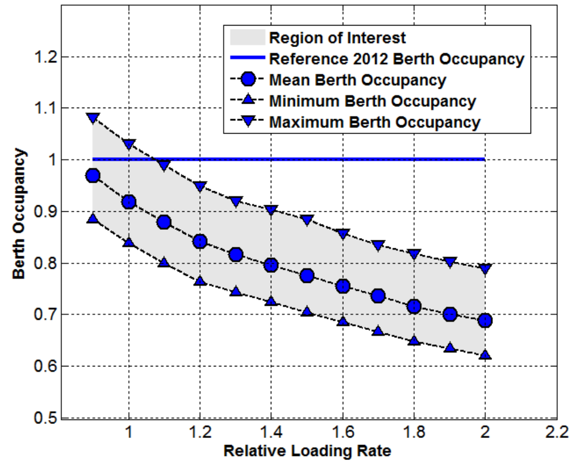
Table 5 summarises the results of the investigation, with further visualisations of the findings presented in Figure 10. We impose loading rates varying from 90% of the average reference dataset loading rate up to 200% of the respective value (the physical limitation to the system). We consider increments of 10%, leading to a total of 12 studies, each designed to collect statistics from 15000 simulations for a sufficiently large statistical sample. We report on the relevant means and lower and upper values of the 95% confidence interval for berth occupancy, queueing hours and costs.

With the exception of the loading rate variation, all other parameters are generated in the same manner as in the validation study. This is because we aim to isolate the impact of certain independent variables (in this case loading rates) on the system, which is the natural way to proceed in a complex multi-variable queueing model.

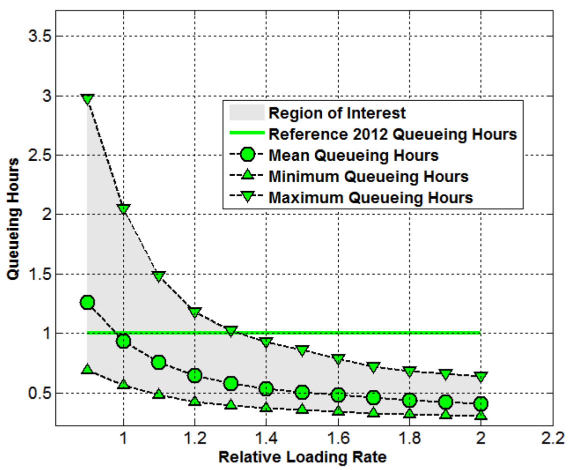
The general trends are clear from both quantitative data and by analysing individual plots in Figure 10. Increasing the loading rate leads to a decrease in queueing hours, berth occupancy and costs. We are however keen on studying the sensitivity of the system as well.



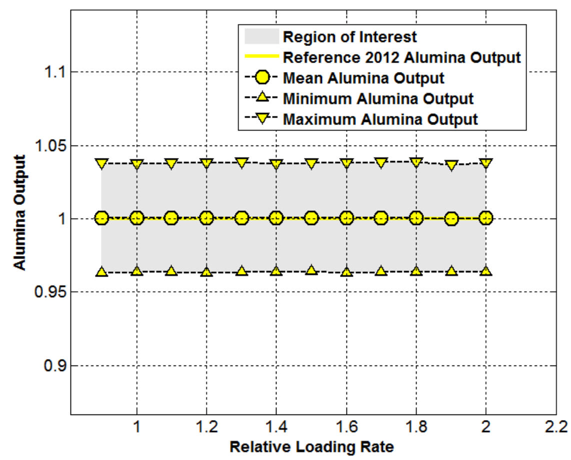
(a) Costs.



(b) Berth occupancy.



(c) Queueing hours.



(d) Alumina output.

Figure 10: Loading rate variation from 90% to 200% of the historical reference value and its effects on (a) costs, (b) berth occupancy, (c) queueing hours and (d) alumina output.

We notice a very strong link between the cost and queueing hour dynamics. Since costs are directly proportional to hours outside the allowed lay time, this is not surprising. By first considering the case of reducing the loading rate by 10%, we notice a striking impact on the performance of the simulated system. An average 36% cost increase illustrates the importance of maintaining and potentially increasing the loading rates. Very large variation indicates the likelihood of rare events affecting the system, such as large delays initially produced by weather or ship queue accumulation at Scattery Island being propagated for the entire duration of the study. With a low loading rate, the service times of ships is increased for each individual bulk carrier, while queues continue to grow.

Hence maintaining an efficient servicing is vital to the system.

As the loading rate increases, both means and variations in costs and queueing hours decrease, leading to a behaviour which is less prone to be affected by delays or external phenomena. We also note that the decrease in berth occupancy is almost linear, while the variation remains approximately the same for the parameter set considered.

Finally, even at very high loading rates, some costs will always be present due to the probabilistic nature of the system. Queues of ships at Scattery Island may often occur, leading to minor (and quantifiable) expenses. We postulate that after increasing the loading rate to more than 150% of its historical value, queueing hours and costs reach a plateau behaviour and further upgrades up to 200% of the reference loading rate would only lead to negligible improvements as compared to the potential costs of achieving the respective loading rate levels.

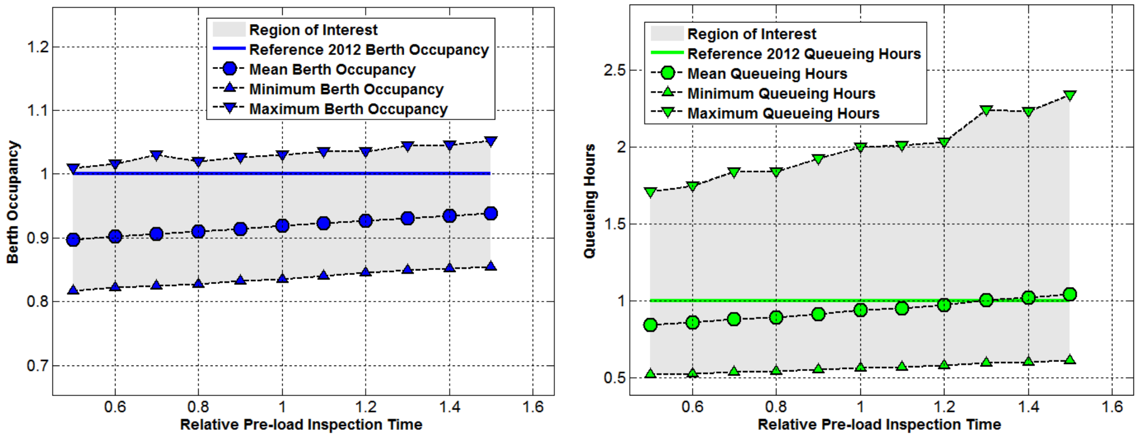
Since the bulk carrier capacities are generated from the same distributions as the real data, we unsurprisingly obtain a fleet of ships transporting the same amount of alumina as in the reference dataset (Figure 10d), with very small variance.

3.2.2. Pre-load Inspection Times

A second set of studies is conducted in order to observe the impact of varying pre-load inspection times on the large scale performance indicators. Prior to starting the loading or unloading procedure, bulk carriers are inspected, as previously outlined. On rare occasions, bulk carriers leave the port terminal for repair, which produces further dynamics in the system.

We are interested in investigating what happens when the pre-load inspection times are varied from 50% to 150% of the historical reference value. The results are shown in Figure 11, where we illustrate the computed berth occupancy (Figure 11a) and queueing hours (Figure 11b). Alumina output will not change, since ship capacities are generated from the historical distributions again, while we have noticed that cost and queueing hour behaviours align well and hence studying a single variable will automatically provide information about the other. The average pre-load inspection times are varied in increments of 10%, leading to 11 tests of 15000 simulations each.

We notice a very small variation in this study, with berth occupancy increasing from 90% to 94% of the historical reference value when advancing from reduced inspection times to increased inspection times. In the same regime, queueing hours vary from 89% to 103% of the reference value. Therefore we conclude that investing resources in more efficient inspection routines will indeed generate some benefits, however the effect on the berth performance will be small, especially when compared to alternative investment options.



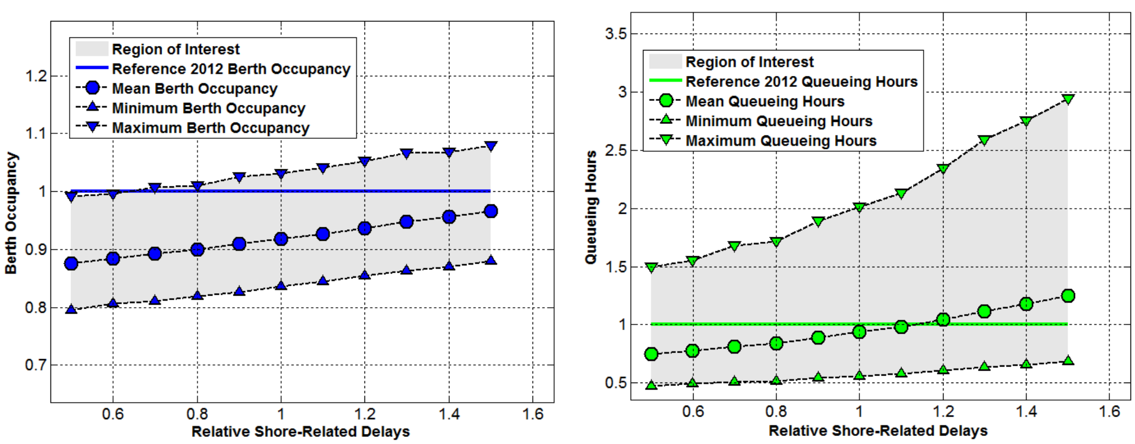
(a) Berth occupancy.

(b) Queueing hours.

Figure 11: Pre-load inspection time variation from 50% to 150% of the historical reference value and its effects on (a) berth occupancy and (b) queueing hours.

3.2.3. Shore-related Delays

The third scenario studied illustrates the impact of various shore-related delays, such as berth equipment malfunction. As in the previous subsection, we aim to construct these delays from the same historical distributions, however modify the magnitudes from 50% to 150% of the reference value, in increments of 10% and observe how berth occupancy and queueing hours are affected after sampling data from 15000 simulations for each study (see Fig. 12).



(a) Berth occupancy.

(b) Queueing hours.

Figure 12: Shore-related delay variation from 50% to 150% of the historical reference value and its effects on (a) berth occupancy and (b) queueing hours.

With queueing hours reaching approximately 75% when such delays are reduced to a half, we consider this variable of significant importance. Furthermore, an augmentation of the delays to 150% of the historical value is shown to lead to almost a 27% increase in queueing hours. Berth occupancy again increases monotonically in the expected way, with additional delays leading to high berth occupancy. Improvements and upgrades in this sector could lead to significant benefits. On the other hand, we also show how equipment degradation could potentially affect port terminal performance, which can then be taken into account when suggesting future economic strategies.

3.2.4. Bulk Carrier Capacity Modification

Up to this subsection, all test scenarios presented have been built as a modification of data constructed from historical distributions. This is a viable testing methodology, since it offers the possibility to investigate studies in similar conditions to the historically observed behaviour. However, in order to expand our search space for system performance description, we also consider a different type of study. Given that the capacities of the ships arriving at berth can be influenced within a long-term planning framework, we would like to observe what would happen in the case of arrival of bulk carriers of a certain desired capacity instead of using capacities constructed from the same distribution as in the historical data.

The most important elements to consider are

1. preserving (or increasing, if desired) the alumina output;
2. taking advantage of the tidal window, which currently represents the most important geographical limitation to the system and which cannot be altered;
3. incorporating a certain degree of uncertainty in order to account for various types of delays.

Optimally using the tidal window relates to decreasing the amount of time a ship remains at berth unnecessarily. We can estimate the capacity of the bulk carriers that would allow pre-load inspection, loading and post-load inspection (accounting for variation and a small amount of delays) and subsequently departure before the tidal window closes[17]. The current capacities of bulk carriers is quite varied and would allow for a range of possible choices. For simplicity, we propose a set of medium-sized ships, which are routinely processed by the company and would represent a realistic possibility. We then construct a fleet of ships with the capacity of 0.55 of the maximum capacity in the historical dataset, which would fit the framework described in the previous paragraphs. The specific value of the bulk carrier capacity was chosen due its property of being in the optimal range for tidal window usage, as well as being part of one of the common families of vessels presently serviced at the port terminal (see Figure 5). Such a set of bulk carriers would allow for an improved berth dynamics and we can take into account a certain imposed alumina output in order to generate the correct number of respective ships. Several validation studies should be performed in order to assess the

Table 6: Fleet modification: model results compared to actual data from the reference year at loading rates varying from 0.9 to 2.0 of the average historical dataset value.

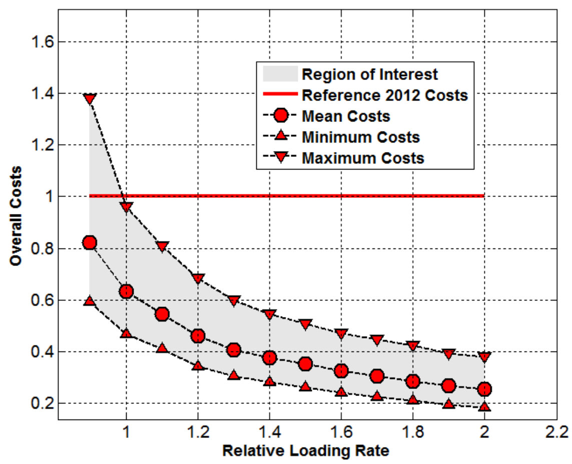
Loading rate	Berth occupancy (min/max)	Queueing hours (min/max)	Costs (min/max)
0.9	0.93 (0.85/1.03)	0.58 (0.38/1.09)	0.82 (0.59/1.38)
1.0	0.87 (0.79/0.96)	0.46 (0.33/0.75)	0.63 (0.47/0.96)
1.1	0.84 (0.77/0.93)	0.40 (0.29/0.64)	0.54 (0.41/0.81)
1.2	0.80 (0.73/0.89)	0.36 (0.27/0.55)	0.46 (0.34/0.69)
1.3	0.78 (0.71/0.86)	0.33 (0.25/0.49)	0.41 (0.31/0.60)
1.4	0.76 (0.70/0.84)	0.32 (0.24/0.46)	0.38 (0.28/0.54)
1.5	0.75 (0.68/0.82)	0.31 (0.24/0.44)	0.35 (0.26/0.51)
1.6	0.72 (0.66/0.80)	0.30 (0.23/0.42)	0.32 (0.24/0.47)
1.7	0.70 (0.63/0.78)	0.29 (0.22/0.41)	0.30 (0.22/0.45)
1.8	0.67 (0.61/0.76)	0.28 (0.22/0.40)	0.29 (0.21/0.42)
1.9	0.65 (0.59/0.75)	0.28 (0.22/0.38)	0.27 (0.19/0.39)
2.0	0.63 (0.57/0.73)	0.27 (0.21/0.37)	0.26 (0.18/0.38)

feasibility of the new queue of ships, including the verification of the total duration of the simulation. This change only affects alumina bulk carriers, since they form the core of the port terminal activity (highest volume of material by a large margin) and offer the greatest flexibility in a realistic context.

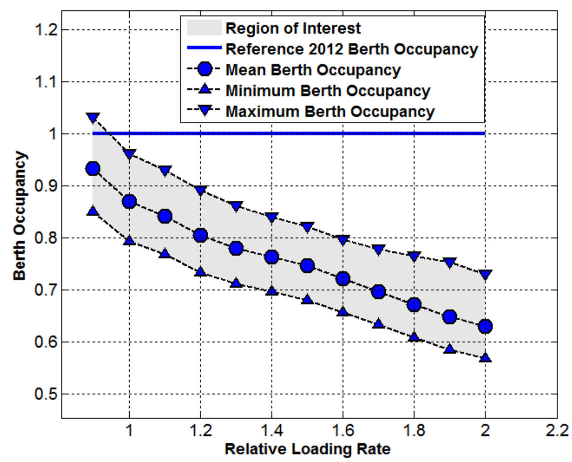
The study considers not only the modification of the bulk carrier capacities itself, but also a loading rate variation similar to that of subsection 3.2.1. With loading rates varying again from 90% to 200% of the reference loading rate in increments of 10%, we summarise results in Table 6 and provide the accompanying plots in Figure 13.

We first note the findings at the level where loading rates remain the same as in the reference dataset, which is the case when the only modification is the number and capacities of alumina bulk carriers arriving at the port terminal, under the condition that the total alumina output stays the same. We notice a reduction in costs of 37% and a reduction in the number of queueing hours by 54%, both illustrating that such a choice would produce tangible performance changes in the system.

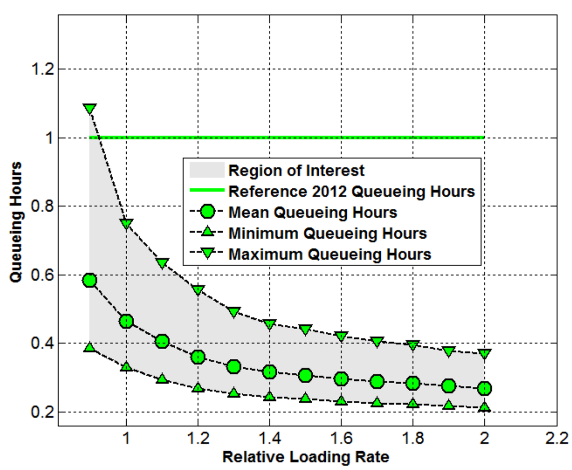
If we now turn our attention to the variation of costs (Figure 13a) and queueing hours (Figure 13c) as the loading rate increases, we observe a strikingly improved mean performance when comparing to the exploration with the fleet of bulk carriers created from the historical dataset (Figure 10a and Figure 10c). We also notice that the spread of the 95% confidence interval is significantly reduced, showing less variance in the results and an activity less prone to be disrupted by rare events. Furthermore, we observe a similar phenomenon as in the previous case in subsection 3.2.1, where after an increase to



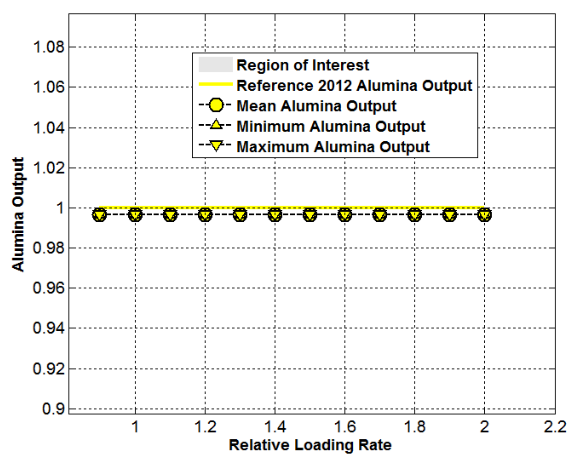
(a) Costs.



(b) Berth occupancy.



(c) Queueing hours.



(d) Alumina output.

Figure 13: Fleet modification to a fixed number of mid-capacity bulk carriers (0.55 of maximum value of the reference fleet) of Type A and its effects on (a) costs, (b) berth occupancy, (c) queueing hours and (d) alumina output.

150% of the historical loading rate, little improvement is obtained by additional investments.

Berth occupancy decreases in a natural manner with the loading rate increase, down to 63% of the reference value for the best case scenario. Finally, since we fix bulk carrier capacities and numbers, there is a constant alumina output for each subcase of this particular study.

3.3. Sources of Error

In this subsection we present some of the simplification procedures of the modelling process and possible sources for errors. All the aspects noted here can be considered as suggested improvements to the model and simulation platform in itself.

Firstly, we note that the basic queue policy at Scattery Island is tailored towards cost minimisation, however it may be improved. Since demurrage rates for delays are constant in time, priority is given to high demurrage rate ships as a simple mechanism. This could however be updated by taking into account tidal windows and various port conditions in order to enable for a more advanced queue filtering system.

The model does not consider any correlation of some of the initial data prescribed. The distributions are considered to be independent random variables. Whereas for example demurrage rates are prescribed as a function of capacity, delays (ship-related, shore-related, others) produced are sampled without taking other bulk carrier characteristics into account. In most situations this is a suitable assumption, since a large number of events, such as for example weather delays, are independent of the ship type. However a rigorous correlation study might indicate possible improvements in this direction.

Rare events such as weather-related incidents or severe shore equipment breakdown have significant effects on the results, leading to formation of queues at Scattery Island, which affect all subsequent bulk carriers. In some cases in real life, an intervention is possible in order to modify incoming ship schedules to limit the long-term effects in such circumstances. There is no current policy in place to handle a specific situation of this nature, which then ultimately translates into higher costs and more queueing hours.

Finally, we do not account for the presence of limited storage facilities, such as silos for incoming alumina. The model assumes that a bulk carrier arriving at the port terminal can always be loaded, hence material is always considered available. This is however not an unrealistic assumption, since the number of occurrences where this assumption was breached in real life during the last several years has been negligible.

4. Conclusions

The model proposed in this paper describes the logistic activity of the port terminal at the RUSAL Aughinish refinery in Ireland. We have presented a detailed description of the port dynamics, including ship-related, shore-related and external components.

The constructed numerical simulation platform has been thoroughly validated using a number of port metrics. After showing promising results, the model has been used as a predictive tool in order to assess the impact of key parameters on several performance indicators such as berth occupancy and costs. We have determined that increasing loading rates and servicing vessels of specific capacities are the primary factors that could drive economic growth. Alleviating shore-related delays also showed significant improvements. All tested scenarios are feasible points in the investment planning process of the port.

The framework discussed was built by taking into account existing knowledge in the field of queueing theory and adapting it to the uniqueness of the port terminal dynamics. It however retains very general qualities and can serve as modelling and testing framework for further applications. Additionally, with new elements to improve the reliability of the system and successfully account for a wide range of probabilistic events, we consider the developed methodology to be a promising tool in the area of port dynamics modelling and examination.

Acknowledgements

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