Transportation Research Part E 115 (2018) 147–163

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

Optimal equipment deployment for biomass terminal operations

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ARTICLE INFO

Keywords:
Biomass equipment
Biomass terminals
Terminal operations
MILP
Equipment selection
Terminal logistics

ABSTRACT

This paper investigates the optimization of biomass terminal equipment deployment. A mixed integer linear programming model is developed and applied to minimize the terminal's investment and operational costs related to dedicated and partially used or shared equipment between a terminal's operational steps. The results minimize annual terminal costs through equipment and infrastructure selection and utilization. Tipping points where the technology and equipment type or size change in relation to the increasing throughput are highlighted. Analytical results emphasize the importance of storage costs in all biomass terminals, as well as the critical influence of operational costs in larger facilities.

List of acronyms

EU	European Union
MILP	mixed-integer linear programming
PPI	port performance indicator

Measurement units

Mt	million tons
tph	tons per hour
€	euros
h	hours
y	years
t	tons
kt	kilotons

1. Introduction

Biomass use in the European Union (EU) is expected to significantly grow in the co-firing and heating sectors by 2030 (European Biomass Association, 2016). At the moment, 4% of the total biomass used for energy purposes in the EU is imported (Dafnomilis et al., 2017). However by 2030, this amount (both in percentage of total biomass and in absolute amounts) could substantially increase,

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https://doi.org/10.1016/j.tre.2018.05.001
Received 9 November 2017; Received in revised form 4 April 2018; Accepted 10 May 2018
Available online 22 May 2018

taking into account potential supply gaps in electricity production or the closing down of coal power plants (Dafnomilis et al., 2017; Mai-Moulin and Junginger, 2016). The Netherlands has been relying on biomass (specifically wood pellet) imports in order to reach the renewable energy target for electricity production, and is expected to rely on them for the future as well. This corresponds to approximately 3.5 Mt of imports (Dafnomilis et al., 2017). The above throughput can substantially increase when biomass is imported to Belgium, Denmark and Germany. The Port of Rotterdam aims to handle up to 10 Mt of biomass by 2020, and as such assume a hub role for biomass imports to the whole of Northwestern Europe (Port of Rotterdam Authority, 2013) (du Mez, personal communication, May 2017).

Biomass is considered a bulk material, such as coal or iron ore. However, unlike these products, biomass requires specific equipment and techniques used during bulk handling, transport and storage (Hancock et al., 2016). Use of unsuitable equipment can lead to deterioration of the product or lead to health and safety hazards, such as dust production and explosions, self-heating and ignition or respiratory issues (Dafnomilis et al., 2015). The equipment at a port terminal handling biomass need to match biomass's specific properties. This includes specifically designed equipment (e.g. grabs) that minimize product deterioration; fully covered or enclosed transportation and storage facilities; spark detectors, fire detection and suppression systems and temperature monitoring through the whole handling chain. This is not entirely realized at the moment; traded volumes are low, so most terminal operators choose not to invest in specialized infrastructure (Dafnomilis et al., 2017). This can lead to a general degradation of the product and incur significant financial losses, as well as facility and personnel hazards (Dafnomilis et al., 2017). Increasing the service reliability, profit margins and reducing cargo damages are therefore essential to a biomass bulk terminal and are identified as some of the most important Port Performance Indicators (PPIs) (Ha and Yang, 2017; Talley et al., 2014).

Due to the above reasons, biomass terminal logistics are more demanding in terms of designing the terminal setup and selecting the suitable equipment to efficiently handle the product. The additional safety equipment and facilities increase the capital investments required, and, since only a handful of port terminals are dedicated biomass terminals, mostly in the US, Canada and the UK, terminal operators do not have a lot of information sources on which to base the required investment decisions. Despite the existence of dedicated biomass terminals and the expected biomass trade growth, there is currently no comprehensive method to assist terminal operators in optimizing equipment and facility selection when dealing with biomass. The scientific literature relating to equipment and facility deployment is minimal, and focuses on extremely particular cases or is applied on relatively small scale examples. The existing literature data, such as capital and operational costs of equipment and facilities are usually simplified approaches and do not reflect the actual situation within the industry. This is the scientific gap that this paper aims to address, by providing a model that can be used in the field of biomass terminal design, taking into account dedicated and shared equipment within the same terminal. The results can assist terminal operators and port authorities with strategic level planning decisions related to biomass terminal investments.

1.1. Literature review

A substantial amount of research has been performed on terminal design, both for dry bulk material and container terminals. Dry bulk terminals are usually characterized by the presence and size of the terminal jetty. Dry bulk vessels can have large draughts, because of the large cargo density and thus large tonnage, and as such, it can be more economical to realize a jetty/pier instead of a quay wall (Kox, 2017). Terminals located in deep waters however, such as the port of Rotterdam, can still make use of quay walls for bulk cargo handling without the need for a jetty (Port of Rotterdam Authority, 2018). The equipment used for each necessary function that a terminal performs, such as loading/unloading vessels, transport of material and storage is unique and more complex than the equivalent for container terminals (van Vianen, 2015). Most importantly however, the equipment selected and installed must take into account the numerous properties of the cargo, such as density, angle of repose, dust generation, hazardous and handling properties (Kox, 2017; Bradley, 2016). The selection of equipment differs per transport direction and depends on the type and quantity of the bulk material, space and environmental conditions and the intensity of operations. Dust generating materials like cement require enclosed transport and small terminals with low capacity requirements can make use of wheel mounted mobile installations (Kox, 2017). The type of storage selected is also completely dependent on the material handled, ranging from open storage, to covered storage (warehouses and sheds, to silos and domes) (Dafnomilis et al., 2015; Kox, 2017). Finally, the productivity of equipment used is measured in tons of material handled per hour of operation (Ligteringen, 2014; UNCTAD, 1985; PIANC, 2014).

A comprehensive design method that still serves as an important guideline on bulk terminal design was introduced by the United Nations Conference on Trade and Development (UNCTAD, 1985, 1991) in 1985 and again in 1991, focusing on the physical characteristics, management and operation of bulk terminals. At the same time, the Transportation Department of the World Bank (Frankel et al., 1985) published a comprehensive report on bulk terminal development, including information on terminal logistics and mathematical models used in evaluating preliminary design options. Memos (2004) provided planning parameters and other bases for estimating vessel queuing times, vessel service time and estimation of storage area needed for dry bulk cargo terminals. Discrete-event simulation for designing and improving the operations of dry bulk terminals was used by Ottjes et al. (2007). Lodewijks et al. (2007) discusses the application of discrete event simulation as a tool to determine the best operational control of the terminal and the required number of equipment and their capacity. Cimpeanu et al. (2017) introduced a discrete event simulation model as well to analyze bulk carrier unloading and material transport, storage and discharge. Taneja et al. (2011) suggested that Adaptive Port Planning methods, which value flexibility of design, are better suited in times of uncertainty than the traditional methods. van Vianen (2015) approached the issue suggesting an expansion of existing design methods, based on stochastic variations of the operational parameters, rather than developing a new design method. Bruglieri et al. (2015), Babu et al. (2015) and Robenek et al. (2014), among others, have investigated yard planning problems in bulk terminals. The berth allocation problem has also been

extensively examined by Robenek et al. (2014), Ernst et al. (2017), Umang et al. (2013) and Al-Hammadi and Diabat (2017).

Scientific research into specific types of equipment used in dry bulk terminals has also been performed. Schott and Lodewijks (2007) provides an overview and analysis of the terminal facilities provided for handling, storage and processing of bulk materials. General information on equipment needs of dry bulk terminals has been provided by Negenborn et al. (2017). Research on types of equipment has been performed by Strien (2010), on equipment used in stacking, reclaiming or the combination of these 2 functions. Wang et al. (2011) developed a model for the optimum allocation of loading and unloading equipment at a bulk terminal. The unloading capacity of a bulk cargo terminal was examined by Bugaric et al. (2011) using queuing theory. Pratap et al. (2017, 2016) looked into crane and unloader allocation respectively in two different works. Wu et al. (2007) and Wu (2012) researched dedicated biomass terminals in details and provided a database of suitable equipment for biomass terminal operations. Studies on the selection of equipment through different software or modelling approaches have been performed by Temiz and Calis (2017) and Prasad et al. (2015) regarding equipment selection in construction sites. Velury and Kennedy (1992) used a similar approach to the one discussed in this work, although the depth and detail of data used were more superficial.

Container terminal design differs from bulk terminal design in several major elements. Vertical quay walls directly connected to the land are used, instead of jetties in the case of bulk terminals (de Gijt, 2005, 2010). The storage yard in container terminals is preferably as close to the berth as possible (Quist and Wijdeven, 2014). The handling of containers from and to the storage yard is performed mostly via mobile equipment such as tractor trailer units, container stackers or carriers and automated guided vehicles (AGV) (PIANC, 2014). The storage yard is an uncovered open area, and in the design phase, the storage capacity of empty containers as well as the container freight station needs to be taken into account. The container yard has dedicated equipment for container handling as well (Mohseni, 2011). Finally, the productivity of the equipment used is measured in terms of moves performed per hour for the transportation equipment (PIANC, 2014; Agerschou et al., 2004), or average container stacking height and density for the storage yard equipment (Ligteringen, 2014; PIANC, 2014; Bose, 2011).

Despite the differences in terminal design approach, the research into container terminal design focuses on similar approaches as the bulk terminal design field. Iris et al. (2015), Tao and Lee (2015) and Liu et al. (2016) investigated the berth allocation and, to a smaller extend, the quay crane and yard allocation problem in container terminals. Imai et al. (2014), Lau and Zhao (2008) and Liu and Ge (2017) used heuristic approaches and queuing theory to study a strategic berth scheduling problem, to integrate the scheduling of handling equipment and to model the assignment of quay cranes in a container terminal respectively. Martin Alcalde et al. (2015) presented a method for determining the optimal storage space utilization in a container storage yard based on a stochastic approach. Sun et al. (2013) developed a general simulation framework to facilitate the design and evaluation of mega-sized container terminals which require multiple berths and yards. Most relevant to this work, Chang et al. (2015) used a centralized data envelopment analysis to optimize resource allocation in a container terminal based on a single company's perspective. Similarly, Mbiydzenyuy (2007) realized a linear programming model for a container terminal's equipment configuration, based on a case study of a small port in Sweden.

Apart from significant research on container and bulk terminals, the field of biomass and biofuel supply chains has also been investigated by numerous researchers. Poudel et al. (2016a,b), Marufuzzaman and Ekşioğlu (2017), Ghaderi et al. (2016) and Quddus et al. (2018) all examined different approaches in designing and managing biomass supply networks and transportation chains. de Jong et al. (2017), Lee et al. (2017), Yue et al. (2014) and Ahmad et al. (2016) developed approaches for optimizing biomass to biofuel production under different conditions and scenarios. Stevens and Vis (2016) conceptualized port integration with biofuel supply chains on a qualitative level. Some of the only scientific literature that specifically deals with biomass terminals originates mostly from Scandinavian researchers such as Sikanen et al. (2016), Kons et al. (2014), Virkkunen et al. (2015) and Gautam (2016). However, the above works only look into land terminals located next to forested source areas and do not go into a detailed examination of the terminals beyond an assessment of scenarios with different biomass throughputs, truck capacities and transport distances.

1.2. Objective and contribution

While most of the studies presented in Section 1.1 had a goal of providing information, improving or optimizing terminal design, the focus was asymmetrically put on the simulation field of research. Terminal simulation tries to measure the performance of the terminal under different scenarios, and does not necessarily consider achieving the optimum solution as its end goal. On the other hand, research on equipment selection usually focuses on optimizing the (un)loading operational steps only, which are deemed as the most important parts of the terminal handling chain. Total equipment allocation and utilization in these approaches have a second role, even though they can be equally (or more) important costs of a terminal. Most importantly, all the above works are lacking either in depth of data used (equipment database, parameters etc.) or in scale of application – only performed for a pre-existing site of a specific company or for a unique small scale port terminal. The precise equipment configuration, and the utilization of such equipment are some of the most critical decisions that dry bulk terminals must take, and affect almost every aspect of a terminal's operation. The goal of an efficient equipment configuration and utilization planning is twofold: firstly, to minimize the total investment costs incurred while determining a terminal's design; secondly, to minimize the operational costs while handling a product. An approach through this scope however is distinctly lacking in the present scientific literature.

To this end, we propose an optimization model to determine the total equipment allocation and utilization in a solid bulk biomass terminal. The scope of the model includes the complete activities within a terminal, from the unloading of the biomass from an arriving vessel, to the loading at a vessel at the end of the handling chain. Our research goal is to provide a model that can be used in the field of biomass terminal design, assisting terminal operators and port authorities with biomass terminal investment decisions.

The results can support tactical level decision planning when applied to existing bulk terminals, which may need to retrofit equipment or parts of their handling chain, but are mostly geared towards assisting in strategic level planning – investing in new terminal setups, infrastructure and equipment decisions. For this purpose, the equipment configuration is presented on a detailed level within the terminal bounds, and, most importantly, the utilization of this equipment is taken into account and is linked directly to the material throughput, as is the case in reality. The equipment allocation and utilization are optimized in order to provide a better estimation of a dedicated biomass terminal's logistics. In summary, our work contributes to the above in that we take a holistic approach, unbound by pre-existing conditions, and at the same time using an extensive database with data depth that is unique for the occasion. Consequently, to the best of the authors' knowledge, this paper provides the following novel contributions:

1. A defined mathematical model for optimizing biomass terminal equipment configuration, not only for dedicated equipment, but also for equipment that is partially used and shared between different operational steps
2. An approach for minimizing total (investment and operational) costs in biomass bulk terminals from a strategic planning point of view, taking into account all the discrete operations of a terminal, as well as the respective equipment needed
3. Results that are based on real world data instead of assumptions or relevant experience only, thus providing increased credibility and validity of the outcomes of the proposed model

The authors were able to collaborate with numerous industrial experts, including the biggest and most experienced solid bulk terminal operators in the port of Rotterdam, the Port of Rotterdam Authority, equipment manufacturers, power plant and energy industry stakeholders. Their input was used in ascertaining the accuracy of operational assumptions, as well as confirming the validity and usefulness of the results and their approximation of real-life terminal design.

The article is organized as follows. The outline and context of the terminal design and setup selected for this paper is explained in Section 2. The mathematical model is presented in Section 3. The computational results are presented in Section 4, showing that our model is capable of providing significant information regarding terminal equipment configuration and utilization decisions in a reasonable amount of time. We conclude in Section 5 and discuss future work.

2. Biomass bulk terminal design

For the purposes of this paper, the focus in terminal design is on the equipment configuration, i.e. what type of equipment to use and in what amount for each selected task. A proportionate amount of attention is given to equipment utilization, i.e. how much is the selected equipment used to perform its task. The terminal operations are assigned into 6 discrete steps: receiving and transshipment of material, first transportation, storage of material, reclaiming, second transportation and finally, loading of material onto a vessel, truck or train for further transportation outside the terminal boundaries (see Fig. 1 for an illustration of the proposed biomass bulk handling terminal setup). The operational steps are defined based on the specific function that is performed within their bounds, as described above. In order to perform said function, unique equipment associated with it needs to be present in each operational step, chosen based on their capacity, capital and operational costs, as well as potential synergy with equipment in adjacent operational steps.

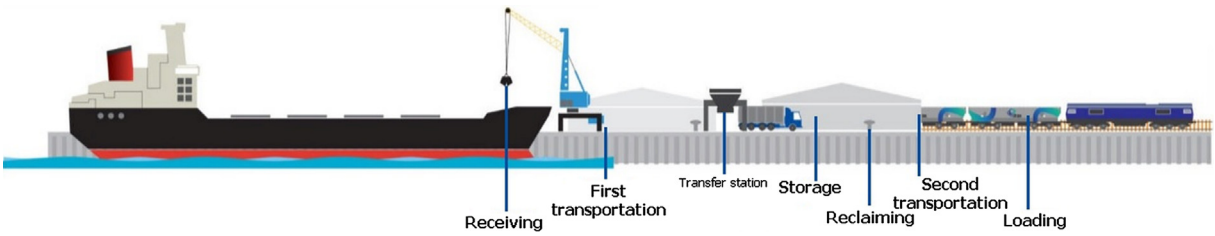

Fig. 1. Illustration of the proposed solid biomass bulk handling chain (Rivers, 2013; Lanphen, 2015).

We consider a wide range of types of equipment that can be used in each discrete operational step, depending on their function. In total, 15 different types of equipment of 82 different sizes and capacities are in the database used for this paper at the moment, with plans to be significantly expanded (see Section 5). The most common equipment used in each specific bulk terminal function, i.e. operational step is included in this research. Grabs and grab cranes are used for the receiving step, with pneumatic unloaders as an additional option for increased capacity. Belt and pipe conveyors, as well as trucks are used for the two transportation steps. Pneumatic conveyors are present in the transportation step when a pneumatic conveyor is used as the selected receiving equipment, since they constitute a continuous closed system, expanding into both operational steps. Warehouses, domes, silos, bunkers and floating barges are the options under consideration for the storage of bulk material. Only enclosed storage options are taken into account since wood pellets require it (Hancock et al., 2016; Dafnomilis et al., 2015, 2017) (Ruijgrok, Pothoven and Lokker, personal communication, May 2017). Underground hoppers are used in the reclaiming step when dealing with domes or silos, since gravity reclaiming is easier performed that way. Respectively, front loaders are used when the storage option selected is a bunker or a warehouse. Finally, loaders generally consist of a feed conveyor and a chute emptying into a vessel, or, less often, a gran and grab crane that perform the same function. Where data was available, all additional equipment or systems related to biomass bulk terminals were included in the equipment capital and operational costs. A full list of the types and sizes of equipment used can be seen in Table 1 at the end of this section.

The information presented in this section originated from an extensive literature review and industrial field investigation. The most detailed and relevant information came from the authors' personal visits to several of the biggest and most experienced bulk (and biomass) terminals in the Port of Rotterdam in the Netherlands. This provided a unique opportunity to gain a detailed account of first hand industrial conditions of biomass handling. Personal interviews were conducted with representatives from terminal operators that handle biomass in the Port of Rotterdam, the Port of Rotterdam Authority, and other fields closely related to biomass production and handling. During these interviews and visits to the facilities, equipment of the industrial stakeholders engaged in biomass handling and storage were investigated and they are presented in this section. A general overview of the types of equipment used in each discrete operational step can be found in Fig. 2.

Fig. 2. Example of solid biomass handling equipment (Dafnomilis et al., 2017).

Each type of equipment in each operational step is linked to its respective capital and operational costs, relating also to its capacity and its lifetime. For example for the operational step 'transportation' there are 9 different belt conveyor capacities, ranging from 300 tph to 2500 tph capacity, and of different lengths, depending on their position and function in the terminal handling chain (see Table 1). Both the capacity and the length are important parameters of the model, as they directly affect the capital and operational costs of each equipment. In this particular case, as the capacity increases a wider belt with a more powerful drive and support structure is needed. Likewise, as length increases, we need additional structural elements and more powerful drives.

Utilization of equipment is directly linked to and affects the operational expenses of a terminal. According to industrial experts, operational costs can actually be the biggest factor in a terminal's annual expenses, especially as the throughput and the size and capacity of the related equipment is increased; bigger and heavier equipment means larger drives, more fuel or electricity consumed while in operation and more personnel to maintain or operate them (Corbeau and Pothoven, personal communication, May 2017).

All the additional measures needed to be taken into account for dedicated biomass handling equipment, i.e. temperature sensors, dust extraction systems, fire detection and suppression systems, covered or enclosed conveyors, incur extra costs relative to simple bulk handling equipment. These costs are incorporated in the capital and operational costs of the equipment used for this work, after extensive literature study and close collaboration with numerous industrial experts as stated in Section 1.2.

Table 1
Equipment database.

Operational step	Equipment type	Capacity	Lifetime [y]
Receiving	Mobile crane 25 t & grab 23 m^3	500 [tph]	20
	Mobile crane 50 t & grab 42 m^3	880 [tph]	20
	Gantry crane 25 t & grab 23 m^3	1000 [tph]	40
	Gantry crane 50 t & grab 42 m^3	1750 [tph]	40
	Pneumatic unloader	500:500:2500 [tph]	7
Transport1	Belt conveyor	300, 600, 1000, 1200, 1500, 1800, 2000, 2200, 2500 [tph]	10
	Pipe conveyor	300, 600, 1000, 1200, 1500, 1800, 2000, 2200, 2500 [tph]	10
	Pneumatic conveyor	500:500:2500 [tph]	7
	Truck	25.5 [t]	10
Storage	Warehouse	15,000 [t]	30
	Dome	15,000 [t]	30
	Silo	20,000 & 110,000 [t]	30
	Bunker	20,000 & 130,000 [t]	30
	Floating barge	2500 [t]	15
Reclaiming	Underground hopper & belt conveyor, 200 m length	300, 600, 1000, 1200, 1500, 1800, 2000, 2200, 2500 [tph]	10
	Underground hopper & pipe conveyor, 200 m length	300, 600, 1000, 1200, 1500, 1800, 2000, 2200, 2500 [tph]	10
	Front loader	9 [t]	10
Transport2	Belt conveyor, 500 m length	300, 600, 1000, 1200, 1500, 1800, 2000, 2200, 2500 [tph]	10
	Pipe conveyor, 500 m length	300, 600, 1000, 1200, 1500, 1800, 2000, 2200, 2500 [tph]	10
	Truck	25.5 [t]	10
Loading	Loader	500:500:2500 [tph]	15

3. Mathematical model

The optimization approach presented in this paper is formulated as a mixed-integer linear programming (MILP) problem that minimizes terminal infrastructure and operational costs on a normalized annual basis. Our MILP model differs from simulation based approaches in the way that it optimizes a detailed equipment configuration solution. It is also, to the best of the authors' knowledge, the first terminal model to take into account shared equipment (equipment used in more than one operational step) into account, and provide information on the utilization of equipment. Costs related to utilization of equipment is normally calculated as a percentage of the equipment's capital costs. In this work, we link it to the actual throughput of the terminal in order to demonstrate its importance and effect on total costs, especially at larger terminal sizes. The overall goal is to minimize the total annual costs of a biomass terminal by optimizing the amount of fully utilized and shared or partially used equipment within the terminal.

One of the most important decisions, following a functional analysis is the breakdown of terminal operations in 6 steps, as mentioned in Section 2. However, no matter the level of detail that can be achieved with a specific terminal design approach, certain assumptions about terminal operations had to be taken. Each operational step in the terminal handling chain is assumed to be independent of the others (unless specifically stated otherwise, see constraint (6) in Section 2.2), with deterministic characteristics. In reality, the assignment of such discrete steps within a terminal is not so straightforward. This is more evident when using continuous equipment such as conveyor belts, where there may be transfer stations or towers present connecting multiple equipment. In our model, we incorporate the transfer stations and their associated costs in the transportation steps of the terminal.

As input for the model, equipment and terminal data need to be specified beforehand, as well as relevant assumptions. Based on these data, the cost function is minimized respecting certain system constraints. The output of the model is the optimal terminal configuration with specific installed capacities for the chosen equipment in terms of overall costs. The optimization performed by the model is an overall terminal logistics optimization and not a step-specific one. In certain cases it might seem that the results in individual operational steps are contrary to common sense or relevant experience, but that proposed solution will be the cost optimal from a terminal perspective.

3.1. Notations

The following notations are used for developing the MILP model

Indices:		
I	Set of equipment types indexed by i	
J	Set of operational steps indexed by j	
System parameters:		
CC_i	Capital costs of equipment i	[€]
CAP_i	Capital costs of equipment i on an annual basis	[€]
OP_i	Operational costs of equipment i	[€/ton]
C_i	Nominal capacity of equipment i	[tph]
η_i	Effective utilization of equipment i	[%]
EqC_i	Average annual capacity of equipment i	[t]
EPC_i	Peak capacity of equipment i	[t]
CRF_i	Capital recovery factor of equipment i	[-]
LT_i	Lifetime of equipment i	[y]
AT	Annual throughput of the terminal	[Mt]
TW	Time window to complete vessel unloading	[h]
OPH	Annual operational hours of the terminal	[h/y]
sf	Storage factor	[-]
VS	Vessel size	[t]
IR	Interest rate	[%]
M	Sufficiently large number to control binary variables	[−]
B_{ijkl}	Parameter to control interdependency of equipment	[−]

$$B_{ijkl} = \begin{cases} 1, & \textit{when equipment } k \textit{ in step } l \textit{ requires the presence of equipment } i \textit{ in step } j \\ 0, & \textit{otherwise} \end{cases}$$

Decision variables:	
n_{ij}	Number of dedicated (or fully used) equipment i in step j
m_i	Number of shared or partially used equipment i
x_{ij}	Utilization of equipment i in step j

The investment in equipment is split into two parts: dedicated equipment and shared or partially used equipment. Dedicated equipment is used for a single operational step only and operated for 100% of the time. The number of dedicated equipment of type i in step j is indicated by n_{ij}. n_{ij} signifies the amount of equipment present in the terminal, as well as the utilization of the particular equipment, since it is used 100% of the time.

Partially used or shared equipment is used by one or more operational steps and are operated at a single step for less than 100% of

the time. The number of partially used or shared equipment of type i is indicated by m_i. The fraction of time that the partially used or shared equipment m_i is used for step j is indicated by x_{ij}.

3.2. Objective function formulation and constraints

The objective function Z represents the total annual costs of a biomass terminal and depends on the design variables corresponding to the amount of fully utilized and shared or partially used equipment within the terminal. The mathematical representation of the optimization problem can therefore be formulated in the following way:

$$\min Z = \sum_{i\in I} [\sum_{j\in J} n_{ij} + m_i]*CAP_i + [\sum_{i\in I}\sum_{j\in J} [n_{ij} + x_{ij}]*OP_i]*AT \tag{1}$$

s.t.

$$\sum_{i\in I} (n_{ij} + x_{ij})*EqC_i \geqslant AT \quad \forall\, j \in J \tag{2}$$

$$\sum_{i\in I} (n_{ij} + x_{ij})*EPC_i \geqslant \mathbf{max}(VS) \quad \forall\, j \in J \tag{3}$$

$$\sum_{i\in I} (n_{ij} + x_{ij})*EqC_i \geqslant sf*AT \quad \text{when } j = 3 \tag{4}$$

$$\sum_{i\in I} (n_{ij} + m_{ij}) = 1 \quad \text{when } j = 2,4 \tag{5}$$

$$B_{ijkl}*(n_{ij} + x_{ij}) \leqslant B_{ijkl}*M*(n_{kl} + x_{kl}) \quad \forall\, i,k \in I\ ,\forall\, j,l \in J \tag{6}$$

$$\sum_{j\in J} x_{ij} \leqslant m_i \quad \forall\, i \in I \tag{7}$$

$$n_{ij}, m_i \in \mathbb{N}^{0} \quad \forall\, i \in \mathbb{I}\ ,\forall\, j \in \mathbb{J} \tag{8}$$

$$0 \leqslant x_{ij} \leqslant 1 \quad \forall\, i \in I\ ,\forall\, j \in J \tag{9}$$

Relations between parameters present in the model are as follows:

$$CAP_i = CC_i*CRF_i \quad \forall\, i \in I \tag{10}$$

$$CRF_i = \frac{IR*(1 + IR)^{LT_i}}{(1 + IR)^{LT_i} - 1} \quad \forall\, i \in I \tag{11}$$

$$EqC_i = C_i*\eta_i*OPH \quad \forall\, i \in I \tag{12}$$

$$EPC_i = TW*C_i \quad \forall\, i \in I \tag{13}$$

The objective (1) is to minimize the annual capital and operational costs incurred by the selected equipment. As mentioned in Section 2.1, dedicated equipment is used for a single operational step only and operated for 100% of the time. The number of dedicated equipment of type i in step j is indicated by n_{ij}. Therefore, n_{ij} contributes to both capital and operational costs in the objective function. Similarly, the number of partially used or shared equipment of type i is indicated by m_i and the fraction of time that equipment m_i is used for step j is indicated by x_{ij}. Therefore, m_i contributes to the capital costs and x_{ij} to the operational costs in the objective function respectively. For example, in the result where a silo would be used as the optimal storage option as dedicated (fully used) equipment, $n_{silo,3} = 1$. $n_{silo,3}$ is used in the calculations of the capital costs since we have 1 unit of infrastructure incurring full capital costs, but it is also used in the calculations of the operational costs with a utilization of 1, since it is used 100% of the time. If the silo was only partially used at 50% utilization, then $m_{silo} = 1$ and $x_{silo,3} = 0.5$. m_{silo} is used in the calculations of the capital costs since we have 1 unit of infrastructure incurring full capital costs, regardless of utilization. $x_{silo,3}$ is used in the calculations of the operational costs with a utilization of 0.5 since it is only used for 50% of the time. Similarly, if a truck was used in transport steps 2 and 4 for 25% and 50% of the time respectively, then $m_{truck} = 1$ and $x_{truck,2} = 0.25$, $x_{truck,4} = 0.5$.

The capital costs are calculated by Eq. (10). CRF_i represents the capital recovery factor (the annual equivalent of the capital cost) of equipment i and is given by Eq. (11), where IR is the interest rate and LT_i is the technical and economic lifetime of equipment i. The operational costs

OP_i, as indicated in Section 2.1, are directly related to equipment i on a euro per ton basis, based on relevant literature and personal communication of the authors with industrial experts (UNCTAD, 1985, 1991; Frankel et al., 1985) (Pothoven, Corbeau, Ruijgrok and Lokker, personal communication, May 2017).

The capacity of the sum of the equipment used in each operational step j on an annual basis is ensured in (2) to be able to handle the average annual throughput of the terminal. The average annual capacity of the selected equipment EqC_i is calculated in Eq. (12), where C_i is the nominal capacity of the selected equipment, η_i the effective utilization of the selected equipment and OPH the operational hours of the terminal on an annual basis.

Constraint (3) is a peak capacity constraint that ensures that the selected equipment will be able to unload the maximum size vessel VS that is serviced by the terminal, at the minimum required service time TW. The minimum required service time is dependent on the size of the vessel which is, in turn, dependent on the amount of throughput of the terminal. These inter-relations can be seen in Table 2. The

equipment peak capacity is then given by Eq. (13). The peak capacity design is not always in effect, rather the user chooses whether he wants to focus on this approach, or a design based on the average annual capacity approach. In the latter case, constraint (3) is deactivated.

Table 2
Vessel size and service time based on terminal throughput (UNCTAD, 1985, 1991; van den Brand, 2017).

Annual throughput [Mt]	Vessel type	Max vessel size [t]	Service time window [h]
AT ≤ 3.5	Handymax/Panamax	65,000	48
3.5 ≤ AT ≤ 7	Capesize A	100,000	72
7 ≤ AT ≤ 10	Capesize B	140,000	96
AT ≥ 10	Capesize C	180,000	144

Storage constraint (4) guarantees that all the possible equipment used for storage is able to hold a percentage of the total annual throughput. The storage factor is defined as the ratio of storage capacity over the annual throughput between the required stockyard size and the terminal's annual throughput (van Vianen, 2015).

When deciding on continuous equipment, the general rule in terminal design is that there should be only one present for each discrete operational step. Unless looking into the far end of large scale terminals, single conveyor belts of varying capacity can handle the incoming material. Even when talking about redundancy of equipment in conveyor belts, it is taken into account in the form of individual components; idlers, belt fabric rolls, drive motors etc. Otherwise, logistics increase disproportionately and issues with available land, support structures etc. become overcomplicated. Constraint (5) signifies that whenever a continuous equipment is used in the 2 inter-terminal transportation steps, the amount is limited to a single type and capacity only.

Terminal planning may also require certain types of equipment to be interdependent, or mutually exclusive. For example, when unloading a flat warehouse, it is only possible to accomplish through front loader use. This interdependency is established by constraint (6). Due to the nature of the input, it has to be 100% controlled by the user via the use of the binary parameter B_{ijkl}.

Constraint (7) guarantees that the utilization of each shared or partially used equipment can never exceed the actual amount of used equipment. Summing the utilization over all operational steps where shared or partial equipment may be used and denoting it to be equal or less to the units of equipment ensures that.

Constraints (8) and (9) guarantee that the units of dedicated or shared equipment are positive integers only (including 0), and that the utilization of equipment is a real number between 0 and 1 respectively.

3.3. Relevant data

Other assumptions used to calculate the values for the model constraints appear in this section. A considerable effort has been made for the assumptions to depict as close as possible the industrial setting reality, rather than educated guesses or literature data. The overall projects industrial partners were a great asset in this endeavor, proving first hand field experience and input.

We assume a 1 km transportation distance between the arriving vessel and the storage facilities, as well as a 200 m transportation length after reclaiming and a 500 m transportation distance to the loading point, at the end of the terminal chain.

In the context of this paper, the term equipment utilization refers to the percentage of the terminal's total operating hours that an equipment is being used. That means that a result of e.g. 0.5 utilization for a 7000 operating hours per year terminal, indicates that that particular piece of equipment is functioning for 3500 h throughout the year. The operating hours of the terminal is one of the varied parameters of the model developed in this work.

Dry bulk terminals usually have a storage factor of 0.1 (10%) (Pothoven and Lokker, personal communication, May 2017). However, this is the rule of thumb for terminals handling coal or iron ore, which can be stored outside in piles, for long periods of time and do not require special safety measures. In the case of biomass, there is a need for enclosed storage which significantly increases costs. Additionally, biomass requires shorter storage times in order to avoid problems like self-heating and ignition or chemical and biological deterioration, which in turns leads to lower storage needs (Dafnomilis et al., 2017) (Pothoven and Ruijgrok, personal communication, May 2017). For the aforementioned reasons, in this work, we assume a storage factor sf of 0.02 or 2% of the annual throughput of the terminal. In this way, the logistics of storage become more manageable and the storage time is kept low.

The annual operational hours of the terminal OPH are assumed to be 7000. Port terminals usually operate 24/7 year round. However, taking scheduled and unscheduled maintenance and downtime and important holidays into account gives a more realistic number of 7000 h per year (Bouwmeester, Pothoven, Lokker and Theunissen, personal communication, May 2017).

A uniform interest rate IR of 0.06 (or 6%) is used throughout the model due to lack of more detailed data at the current stage. The effective utilization rate η_i is assumed to be 0.9 (or 90%) for all equipment types. Each specific equipment has a specific utilization rate, related to numerous factors – individual characteristics, material handled, speed of transportation etc. Moreover, the technical and economic lifetime LT_i of the equipment are assumed to be the same. Economic lifetime is the expected period of time during which a unit of equipment is useful to the average owner. The economic life of an asset could be different than its actual technical life. The values related to the lifetime of equipment are based on relevant literature and personal communication of the authors with industrial experts (UNCTAD, 1985, 1991; Frankel et al., 1985; Memos, 2004) (Pothoven, Corbeau, Ruijgrok and Lokker, personal communication, May 2017).

A detailed database of the equipment types and their respective capacities used in each operational step can be found in Table 1. The detailed cost data for each equipment type cannot be included in this work as they are considered confidential information between the authors and industrial partners.

4. Computational results

Based on the input data presented in Section 3 the MILP model was solved using the inherent MATLAB MILP solver ('intlinprog', MATLAB R2015b, v8.6.0.267246) using a dual simplex algorithm. In terms of solve time, a single application of the problem is solved to optimality within 4.7 s on an Intel Core i5-4670 CPU @ 3.4 GHz processor, and 8 GB of RAM. The above formulation of the problem was constructed for the maximum amount of biomass equipment we could find accurate reliable data for and approximates a realistic case– 6 operational steps within a port terminal's boundaries, and 83 different types of equipment to be used for the terminal's operations. In order to analyze the complexity of the model, we used a randomly generated database of 10 operational steps and 1000 different types of equipment, leading to 11,000 decision variables. The model can solve approaches of this size to optimality within approximately 17 s, making it appropriate for larger scale problems as well.

By applying the model to a wide range of throughputs, results for the costs per ton of throughput are obtained Fig. 3). Minimization of total terminal costs per ton is achieved around 5 Mt of throughput and remains relatively stable thereafter. As can be discerned from Fig. 3, certain differences between discrete terminal sizes do not follow the economies of scale 'doctrine'. For example, Table 3 shows the results in costs per ton, and equipment selection between two terminals of 5 and 6 Mt respectively, for which an observable difference in costs (8%) per ton of throughput is present. The tipping points where technology and equipment selection can most evidently be observed here. The larger terminal while using the same equipment for transport and reclaiming (with a higher utilization), needs to use larger equipment and infrastructure for receiving, storage and loading, which drives up costs per ton. After that point, costs continue to decrease until the 10 Mt milestone is reached, where another major switch to larger equipment is present once more. The general trend however supports the industry's experience of aggregating handling and storage facilities in order to take advantage of economies of scale (Corbeau, Bouwmeester and Pothoven, personal communication, May 2017).

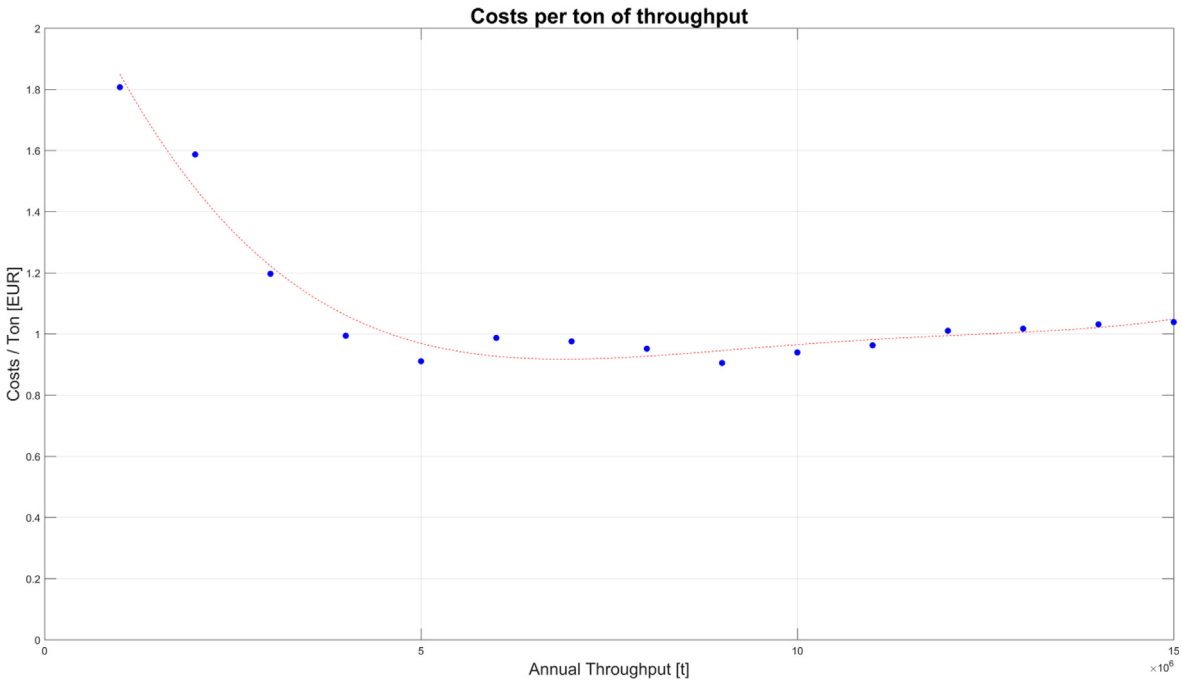

Fig. 3. Cost per ton of throughput for terminals of 1–15 Mt of throughput.

Table 3
Equipment selection for two consecutive terminal sizes.

Annual throughput [Mt]	$5 * 10^6$	$6 * 10^6$
Costs per ton of throughput [€/ton]	0.911	0.987
Receiving	Mobile crane 50 t & grab 42 m^3 880 [tph]	Gantry crane 25 t & grab 23 m^3 1000 [tph]
Transport 1	Belt conveyor 1200 [tph]	Belt conveyor 1200 [tph]
Storage	Silo 100 [kt]	Bunker 130 [kt]
	Floating barge 2250 [t]	Bunker 20 [kt]
Reclaiming	Underground hopper & belt conveyor 1200 [tph]	Underground hopper & belt conveyor 1200 [tph]
Transport 2	Belt conveyor 1200 [tph]	Belt conveyor 1200 [tph]
Loading	Loader 1000 [tph]	Loader 1500 [tph]

Results like this showcase the importance of economies of scale in terminal setups and suggest that the model can be an important asset in aiding stakeholders with terminal design and investment decisions. In the context of dedicated biomass terminals design this means that equipment selection and utilization on its own becomes less significant as the size of the terminal increases. Wider implications of the results suggest that a smaller number of medium to larger size terminals are probably the best solution to increasing biomass throughputs instead of multiple smaller terminals. For the case of Northwest Europe, as briefly discussed in Section 1, it seems that there is no considerable difference in terms of costs per ton on whether to situate biomass terminals in a central location, thus creating a central biomass hub for the whole region, or split them between the limited number of respective importing countries – as long as all respective terminals are above the 5–6 Mt throughput threshold in order to take advantage of economies of scale. Other important cascading factors need to be considered at the same time, such as geographical location of the terminal, further transportation connections to the hinterland, client demand and location relative to the terminals, and low port charges or environmental regulations (Tongzon, 2009). In any case, relevant decisions are directly related to expected throughput. In the case of biomass, the high uncertainty of future developments, owning to lack of long term political commitments also affects industry investments. Dedicated (biomass) terminals require significant investments upfront. If terminal operators are unable to take advantage of economies of scale over a long period of time, there is little point in proceeding with such a task. Easier access and encouragement of investments usually leads to reduction in logistics costs and increases in port efficiency (Chang and Tovar, 2014).

Table 4 presents in detail the results of the optimization for the equipment selection and utilization for terminals with a throughput of 1, 5 and 10 Mt respectively. The equipment selection and utilization depicted here are the optimum result for each specific terminal in terms of average annual costs. Smaller terminals use equipment with lower capacities at a lower utilization rate, switching to heavier equipment with higher capacity that is used more as the throughput increases. In the storage step, combination of a bigger and a smaller type of storage offers the best results, enabled by the choice of small, floating barges to be used as extra storage facilities. With most types of equipment, this form of small, additional equipment types is usually unavailable. One exception is trucks, which are used as complimentary transport methods for small size terminals (approximately 500 kt per year throughput) as it makes no financial sense to invest in a heavy equipment like a conveyor belt yet. Despite their significantly higher operational costs compared to the other transportation methods, trucks also appear in larger terminals, where investing in another major transporting equipment would incur much larger investments.

Table 4
Optimal equipment allocation and utilization for a terminal with a throughput of 1, 5 & 10 Mt.

Annual throughput [Mt]	$1 * 10^6$		$5 * 10^6$		$10 * 10^6$	
	Equipment	Utilization	Equipment	Utilization	Equipment	Utilization
Receiving	25 t mobile crane & 25 m^3 grab	0.32	50 t mobile crane & 42 m^3 grab	0.90	50 t gantry crane & 42 m^3 grab	0.91
Transport1	300 tph belt conveyor (1 km)	0.53	1200 tph belt conveyor (1 km)	0.66	1800 tph belt conveyor (1 km)	0.88
Storage	20 kt bunker 2250 t floating barge	1.00 0.89	110 kt silo 2250 t floating barge	1.00 0.44	2 * 110 kt silo 20 kt bunker	1.00 0.11
Reclaiming	300 tph underground hopper & belt conveyor (200 m)	0.53	1200tph underground hopper & belt conveyor (200 m)	0.66	2000 tph underground hopper & belt conveyor (200 m)	0.79
Transport2	300 tph belt conveyor (500 m)	0.53	1200 tph belt conveyor (500 m)	0.66	1800 tph belt conveyor (500 m)	0.88
Loading	500 tph loader	0.32	1000 tph loader	0.79	2000 tph loader	1.00

Focusing on major equipment and technology tipping points, 25 ton mobile cranes are used up to a 3 Mt terminal, 50 ton mobile cranes from 3 to 5 Mt, 25 ton gantry cranes for 6 Mt terminals, and above that size, all terminals use 50 ton gantry crane with different degrees of utilization. Small terminals (1 and 2 Mt throughput) use 20 kt bunkers for storage. 100 kt silos appear at 3 Mt up to 5 Mt terminals. Bigger terminals, 6 Mt and above, switch to 130 kt bunkers and add extra storage infrastructures as their size increases – 15 Mt terminals need a 130 kt bunker and two 110 kt silos as storage capacity.

From an optimization perspective, belt conveyors are always preferable to pipe conveyors for transportation of biomass. Due to higher investment and operational costs, pipe conveyors are usually used when specific reasons arise, such as more strict environmental regulations concerning dust emissions, proximity to populated areas etc. It should be noted also, that at this point the additional costs regarding covered belt conveyors are not taking into account miscellaneous equipment that should be used when dealing with biomass, such as temperature and spark monitoring throughout the belt, dust extraction or explosion prevention and suppression systems.

Figs. 4 and 5 offer a detailed overview of the total costs for 3 individual terminal throughputs, broken down per operational step and the individual costs as a percentage of the total. For each operational step, the annual equivalent of the capital cost of the selected equipment along with the annual operational cost can be seen. In smaller terminals, the infrastructure costs dominate the total costs in every operational area of the terminal. This is expected, as even smaller terminal equipment have significant investment costs; since the throughput is limited the operational costs incurred are kept low.

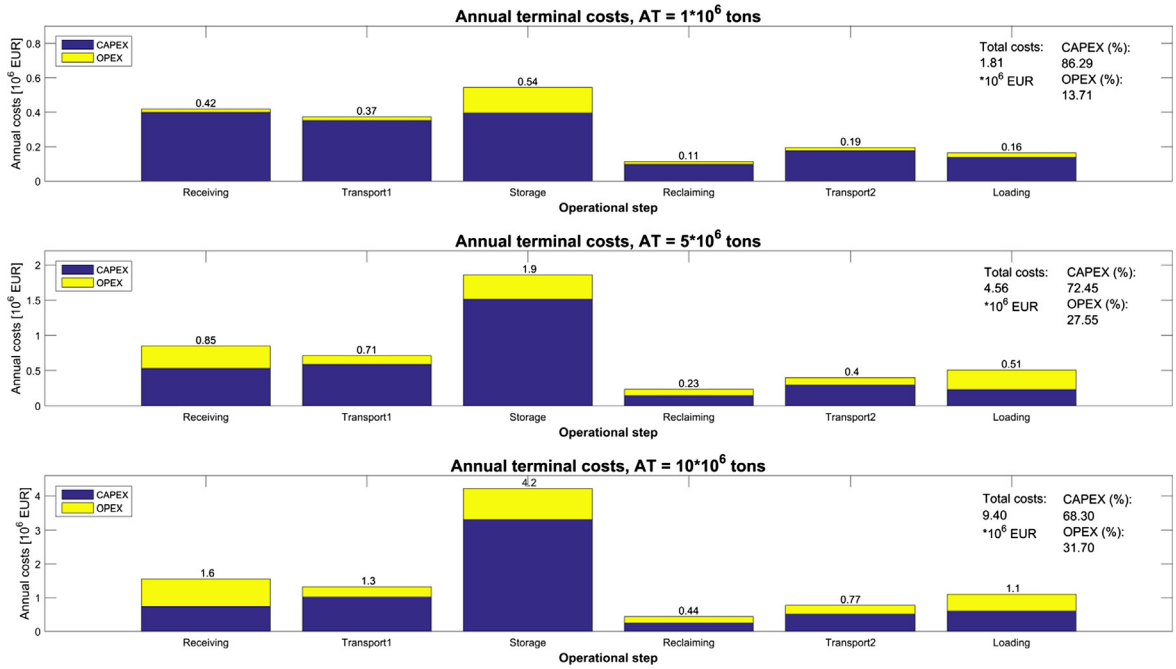

Fig. 4. Total annual costs (1, 5 & 10 Mt throughput terminals).

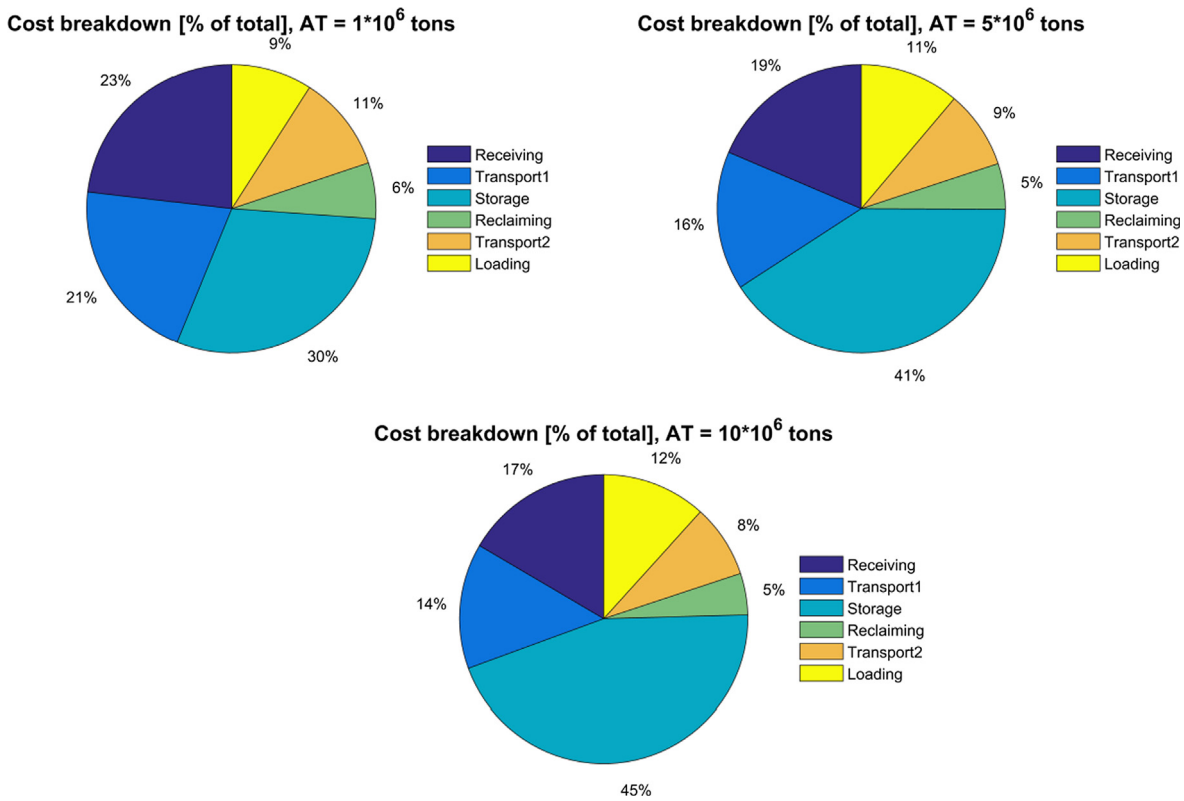

Fig. 5. Total cost breakdown (1, 5 & 10 Mt throughput terminals).

The importance of operational costs as the throughput (and therefore the size) of the terminals increases is obvious in Fig. 4. Operational costs of equipment are directly linked to throughput and directly affect the operational expenses of a terminal. While the amounts may seem insignificant at first for smaller size terminals, as the size and throughput of a terminal increases, so will the

utilization of increasingly larger types of equipment. Using bigger, heavier equipment, operating longer hours or moving more material incurs much higher costs on an annual basis that the annual equivalent of each equipment's capital cost. Operational costs can reach up to 32% of the total terminal costs and 55% of the individual costs in certain operational steps. These numbers are confirmed by industry expert group the author are collaborating with on this work (Pothoven, Lokker and Theunissen, personal communication, May 2017).

Storage costs are by far the biggest contributors to the total costs in all terminal sizes. This is because biomass as a bulk material requires enclosed storage, continuous temperature monitoring and safety equipment, which increases the storage infrastructure costs exponentially, especially the infrastructure costs. Storage costs represent already 30% of the costs in smaller terminals, increasing gradually and representing almost half the total costs at bigger size terminals Fig. 5. This is contrary to the expected economies of scale effect, which would suggest all costs to decrease as terminal size increases. The reality is that enclosed storage can only go up to a certain size before running into problems with available land use, need for support structures or material stress against the inner walls of the facility. A single bulk material storage facility is generally limited to a maximum size of around 130 kt (Ruijrok and Geijs, personal communication, May 2017). This in turn leads to multiple storage facilities of the maximum available size as terminal throughput increases, causing disproportionately high storage costs for larger terminal sizes. However, as seen in Fig. 3, the economies of scale in the other operational areas of a terminal are sufficient to bring about a leveling out of the costs per ton as terminals increase in size.

Fig. 6 presents the results of optimizing for a peak capacity approach (details can be found in Section 2.2), for two specific terminals of 3.5 and 10 Mt throughput respectively. Smaller size terminals tend to be impacted a lot more in terms of size and utilization of equipment when designing for peak capacity. Bigger and heavier equipment is required to handle a specific size of vessel in a specific allotted time, leading to a significant difference in total costs. On the other hand, moving to bigger size terminals eliminates this difference, since the selected equipment for the non-peak approach is of sufficient capacity to handle bigger size vessel during peak approaches as well. The non-peak and peak cost graphs in this case are completely identical.

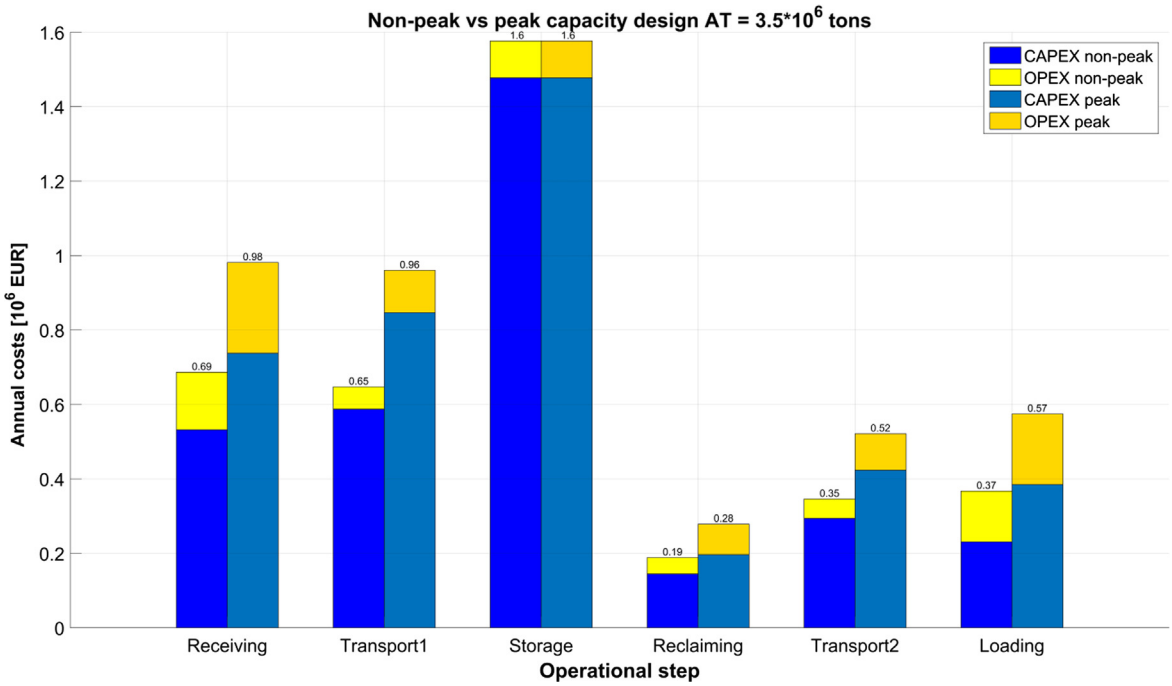

Fig. 6. Non-peak vs peak capacity design (3.5 Mt throughput terminal).

Storage costs remain the same during both approaches as they are unrelated to service times of vessels, but only to total throughput of a terminal in our model. Additionally, the percentage breakdown of each operational step in both approaches for a terminal of 3.5 Mt of throughput can be seen in Fig. 7. The 'spread' between the individual step costs is more balanced, since the equipment in all other steps except storage either switch to bigger types, or are utilized more during the peak approach. The storage costs still remaining dominant, even in peak approach though.

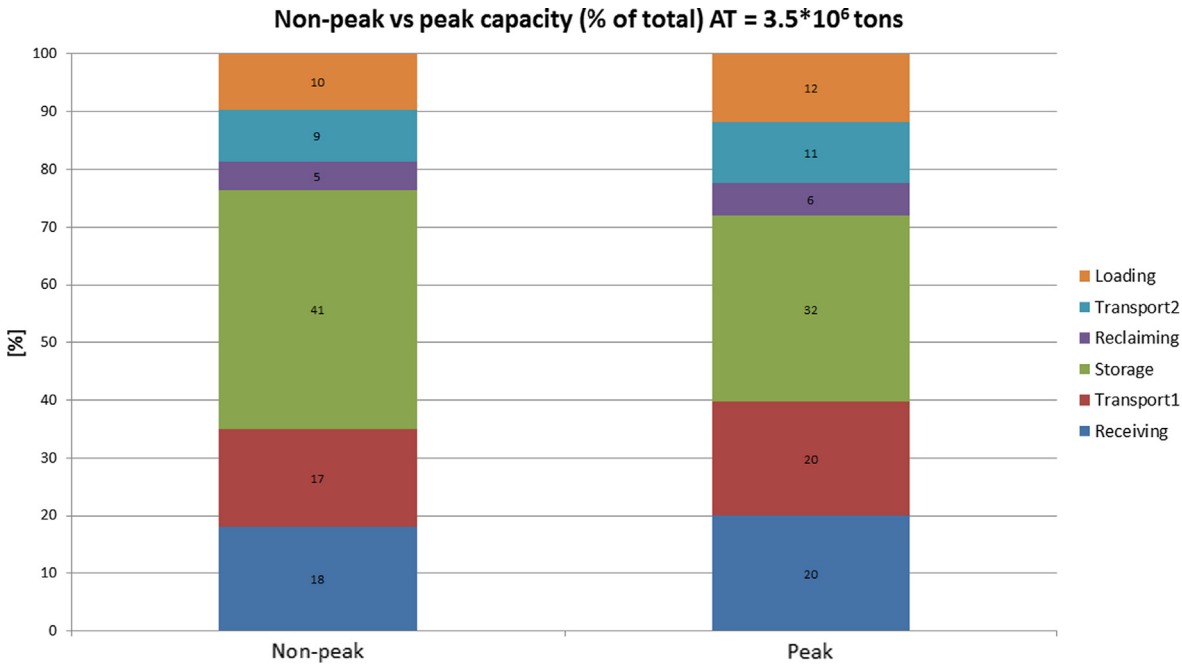

Fig. 7. Non-peak vs peak capacity cost breakdown (3.5 Mt throughput terminal).

In Fig. 8, the effects of the annual operational hours on the decrease of costs is depicted. For small terminals which have already invested in small equipment with low utilization, the effect of increasing the operational hours is extremely low in terms of costs decrease (less than 2% from 6000 to 8000 operational hours). The terminal is able to handle all throughput even at lower available operational hours, as the minimum required equipment is sufficient. As terminal size increases, an increase in operational hours is significantly more impactful, leading up to 13% reduction in total annual costs in some cases. As the operational hours increase, the optimum terminal setup moves to bigger heavier equipment with lower utilization. In contrast, for lower operating hours, smaller equipment is used at a near full utilization. This means that while terminals will incur higher capital expenses for the heavier equipment, they will be using it much less to handle the same throughput, as their capacity also increases. As explained before, utilization costs have a higher impact for larger size terminals than capital costs, which leads to a total decrease of costs with an increase in operational hours.

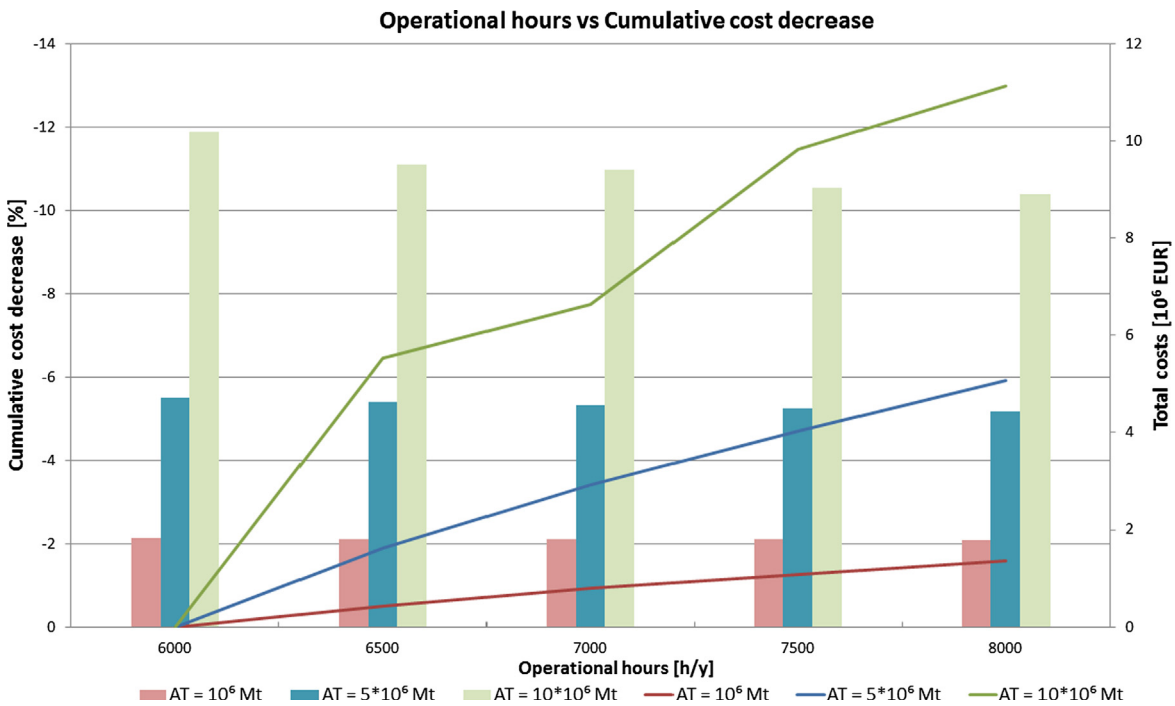

Fig. 8. Operational hours vs Cumulative cost decrease (1, 5 & 10 Mt throughput terminals).

Table 5 provides an overview of the calibration process of the model. For the initial data (collected in May 2017), only values obtained from scientific literature or freely available in online or printed sources were used. As mentioned in Sections 1.1 and 1.2, the scientific literature directly relating to the subject is either dated (UNCTAD, 1985, 1991; Frankel et al., 1985), or contains intentionally vague data due to confidentiality or other reasons. However, we were able to get access to more detailed data over the course of this work (with the final data collected in October 2017). As a result, through this calibration process the deviation of the final results significantly decreased. Initially, total annual costs for a 3.5 Mt terminals amounted to 13.56 million euros, a considerable +256% difference with the final, rational value of 3.81 million euros per annum.

Table 5
Model calibration (total annual costs of a 3.5 Mt terminal).

	Initial results	Interim results	Interim results	Final results
Total annual costs [10^6 €]	13.56	4.16	3.61	3.81
Deviation [%]	+256	+9.2	−5.2	0

Fig. 9 highlights the improvements made in calculating the costs per ton of throughput for a wide range of terminal sizes. When using literature data and educated assumptions, the initial absolute values are in stark contrast with the final results. Costs per ton handled in port terminals decrease significantly as data accuracy increased; from 3.6 €/ton for a 10 Mt terminal to 0.94 €/ton. Additionally, the trends of development did not resemble the economies of scale effect that was expected until late in the data collection period. As an additional frame of reference, the wood pellet handling prices for a small terminal (500 kt) in the Port of Rotterdam in 2014 where around 3.5–4 €/ton when intermediate storage was used. Our model achieves an optimal price of 2.1 €/ton, effectively decreasing costs by 39–47%. The final results illustrate that access to real-life detailed data relating to capital and operational costs of the equipment and infrastructure database is of paramount importance to verifying and validating such a model.

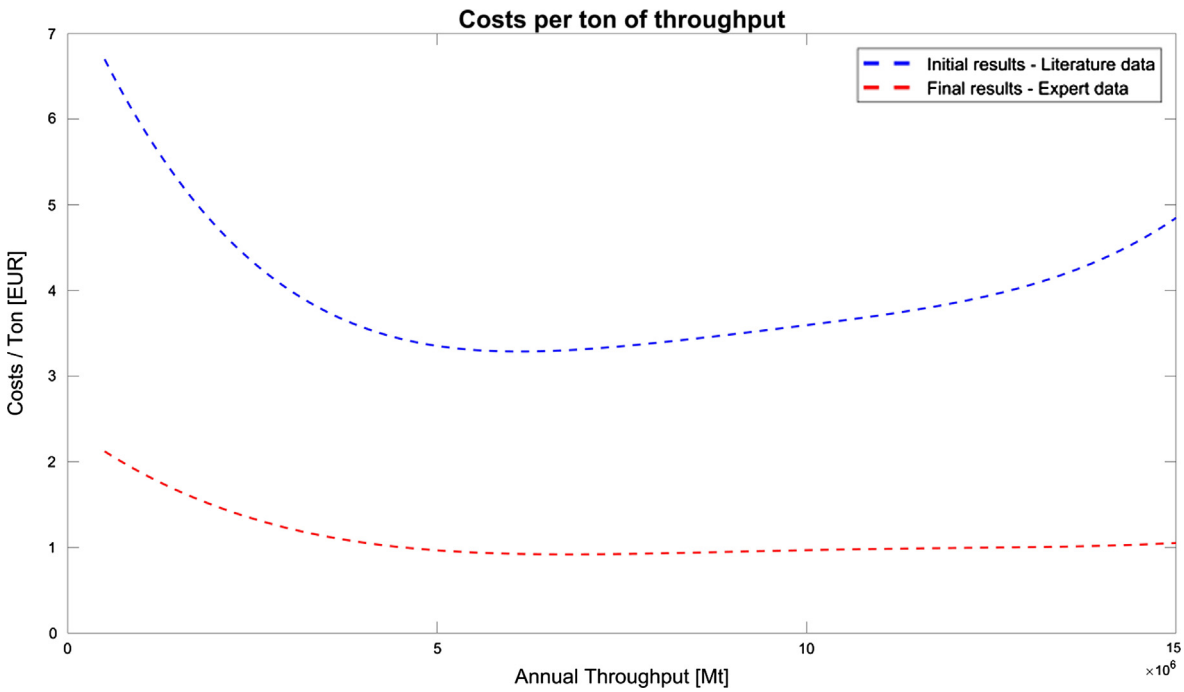

Fig. 9. Costs per ton of throughput calculation progress.

The relevance and validity of the assumptions and results presented in this chapter were discussed with a wide range of industrial experts that the authors collaborate on for the purposes of the broader project this paper is a part of. They have been verified to be as close to reality as possible at this stage. Partners include the biggest and most experienced solid bulk terminal operators in the Port of Rotterdam, the Port of Rotterdam Authority, equipment manufacturers, power plant and energy industry stakeholders. Their comments and feedback were useful in figuring out the accuracy of operational assumptions, as well as confirming the validity and usefulness of the results and their approximation of real-life terminal design.

5. Conclusions and further work

It has been shown that the model presented and developed in this paper is fit for its intended purpose: identifying the optimal selection and utilization of equipment of a dedicated biomass terminal in terms of total annual costs. This manuscript is, to the best of the authors' knowledge, the first attempt to investigate terminal equipment selection and utilization to such an extensive manner and detail.

- Computational results based on real-life input data for biomass bulk terminals indicate that the optimum size of terminals in order to achieve the minimum cost per ton of throughput is achieved at 5 Mt of throughput and beyond.
- The total optimal equipment allocation and utilization is presented alongside each specific terminal size. We are able to observe when a switch to a different type of technology or equipment is needed as throughput increases.
- Partially used equipment in specific steps or shared equipment between different operational steps is also taken into account with the same level of detail as dedicated equipment.
- Most relevant work in literature focused on simulation of different scenarios rather than optimization of operations; attempts at optimization of equipment and operations logistics had been limited in scope and application.

The results also demonstrate the relevance of biomass storage needs over the total terminal logistics. Necessary enclosed storage can contribute to as much as 45% of the total terminal logistics, since enclosed facilities can only reach a certain size before requiring multiple units to accommodate the throughput. The importance of the effect of the utilization of equipment on bigger size terminals is also presented. Decoupled from a percentage of capital costs, operational costs have a significant role in terminal logistics, amounting to 32% of the total terminal costs in larger terminals and 55% of individual operational steps. The model can be used as a decision tool for practitioners and regulators in order to rationalize tactical level decision planning (when there is a chance of retrofitting or adjusting existing terminal equipment) or strategic level planning when designing a dedicated biomass port terminal. Its framework allows the model to potentially be used for optimization of a biomass terminal in terms of energy consumption or CO_2 emissions, as long as the relevant equipment operation data are known to a similar detail.

Further improvement of the model will include an expansion of the database with more equipment types per operational step. As mentioned throughout the body of the text, an effort is made to stick to data as close to real-life industrial conditions as possible, made feasible by the close cooperation of numerous industrial partners. This, however, means that in this 'quest' for detailed foundations, the usefulness of our model's output depends directly on the quality of the input. For this reason, a constant effort is made to update all relevant equipment data in order to stay relevant to current circumstances. The detailed cost components of support and safety systems – such as dust extraction, continuous temperature monitoring etc. – in certain types of equipment will also be implemented in the optimization routine.

Different approaches to biomass storage will also be investigated in further work. Instead of a fixed percentage of the annual throughput, terminal storage facilities could be designed based on: a) The demand rate and related safety stock levels. This however means knowing when and how much biomass each terminal client demands and planning accordingly. b) The bulk carrier size and arrival intervals. The bulk vessel size is based on the total throughput (see Section 2.3), so the storage facilities could be designed to accommodate, e.g. one full maximum size vessel. This, however, means that the arrival rate must be known in detail and plan appropriately beforehand.

Redundancy of equipment is another important cost factor that has not yet been taken into account. Most terminals usually plan ahead and have extra units of equipment on stand-by, in case of failure or emergency. Of course this is most common for smaller types of equipment, like the grabs of the grab crane, or related miscellaneous components (generators, inverters, idlers for conveyor belts etc.). These do not necessarily constitute terminal 'equipment', but can however have a substantial impact on terminal logistics. At a later stage, linking the interest rates and effective utilization to each specific equipment type will improve the accuracy and realism of the results as well.

Further work on the subject will tackle the limitations of this current model, transitioning to a dynamic, multi-stage planning approach to biomass terminal investments. This approach is necessary as the yearly forecasted throughputs of biomass are subject to great variations, to which a static model cannot adequately adapt. The results will be a total optimization approach across the whole investigated time period, where investments on equipment and infrastructure will be made in anticipation of future throughputs, i.e. overdesigned or over capacity equipment may be purchased ahead of time, as future developments will make their acquirement the optimal case. Salvage of equipment will also be integrated as an integral decision variable in the model, adding complexity and realism to our approach. The input for this work will be biomass throughput scenarios, defined over a specific time horizon, over which investments in equipment and infrastructure will need to be carried out. This will enable us to have an overview of the investments needed in infrastructure and the expected operational costs throughout the whole time period for which we have data related to terminal throughput.

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- Ton Theunissen, Senior Project Developer, ENGIE BV

Acknowledgements

This work is part of the BioLogiKNL project, which aims to develop knowledge of the logistics chains of biomass from abroad to the Netherlands (Netherlands Enterprise Agency, 2013; Social and Economic Council of the Netherlands, 2013). It was made possible by the financial support from the 'Subsidieregeling Energie en Innovatie Biobased Economy: Kostprijsreductie Elektriciteit- en Warmteproductie.' (Grant No. TEBE213008).

The authors are also grateful to the representatives of the respective terminals and facilities for their helpful cooperation in providing relevant information and useful feedback.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.tre.2018.05.001.

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