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A Hybrid Dynamical Approach for Allocating Materials in a Dry Bulk Terminal

Jianbin Xin, Rudy R. Negenborn, and Teus van Vianen

***Abstract*— This paper proposes a new modeling and control methodology for allocating materials in a dry bulk terminal with a finite storage capacity. The dynamical process of material storage allocation in the terminal is modeled using a hybrid system perspective that combines both discrete-event and continuous-time dynamics. The stockyard space is partitioned into a number of slots for exchanging incoming and outgoing material flows in the terminal, leading to a so-called mixed logical dynamical (MLD) model with the maximal storage capacity. Based on the MLD model, a model predictive controller is then proposed for maximizing the economic profit in a rolling horizon manner. A number of Monte Carlo simulations have been performed involving a real case study for analyzing the effects of different slot volumes on the economic performance and the computational performance of the controller. Simulations also demonstrate the potential of the proposed methodology.**

***Note to Practitioners*—This paper is motivated by the problem of allocating dry bulk materials in the stockyard of a small import terminal. In current approaches for allocating materials, the storage capacity cannot be considered, and this could lower the terminal profit resulting from delaying the vessel in the terminal when a finite storage capacity is considered. This paper suggests a new approach from a hybrid system perspective that captures the dry bulk terminal operation dynamics. In this paper, we mathematically describe the process of allocating materials into different slots in the stockyard using a hybrid dynamical model and propose a model predictive controller to maximize the terminal operation profit. We then show how the slot size influences the economic performance and analyze its associated computations by conducting simulation experiments involving a case study. Simulation experiments also suggest that this approach achieves significantly more economic benefits compared with current approaches. In future research, a large intermodal terminal will be investigated whereby incoming and outgoing materials of different transport modalities need to be coordinated properly.**

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***Index Terms*—Dry bulk terminals, hybrid systems, material allocation, model predictive control.**

I. Introduction

Dry bulk terminals are transport hubs for transporting dry bulk materials. Typical dry bulk materials, such as coal and iron ore, are essential for producing electric energy and steel [1]. Facing the increased global demand for dry bulk materials [2], there has been significant growth in dry bulk transport over the last few decades. In 2014, major dry bulk materials accounted for more than 30% of the international seaborne trade by volume [3]. To meet the increased demand for transporting dry bulk materials, the performance of dry bulk material transport needs to be improved.

Decision problems facing maritime terminals typically can be divided into three categories, strategic, tactical, and operational [4]–[6], and this also applies to dry bulk terminals. For a dry bulk terminal, strategic problems are closely associated with the (re)design of new terminals, wherein the optimal terminal layout and the selection of equipment used in the dry bulk terminal [1], [2] are considered. For instance, van Vianen *et al.* [1], [7], [8] have investigated the stockyard size determination problem, the equipment selection problem, and the belt conveyor network design problem. Tactical problems in dry bulk terminals typically focus on the capacity level of equipment and determine the necessary number of a piece of equipment, e.g., quay cranes [9], for efficiently completing operations. At the operational level, the operation of equipment for transporting dry bulk materials is detailed, therein deciding which piece of equipment processes which material and which space of the stockyard is chosen for the storage of a particular material.

Research into operational decision problems facing dry bulk terminals primarily emphasizes quayside and stockyard operations (see Fig. 1 for a terminal overview). For a single area, the berth allocation problem [10] and the stacker/reclaimer scheduling problem [11]–[13] have been investigated. Terminal operations are highly interdependent [14], [15], and this motivates advancing research on integrated operations of different areas, e.g., the integration of the berth allocation into yard assignment [16] and the integration of scheduling arrival ships into storage space allocation [17]. Furthermore, related operations out of the terminal are incorporated into operations inside the terminal from a supply chain perspective [18], [19].

In these areas, the stockyard plays a crucial role in overall terminal operations. The stockyard is the location for temporary material storage, unloading incoming material flows, and loading outgoing material flows in the terminal. Therefore, the operational efficiency of the stockyard greatly influences the overall terminal performance. For the stockyard, the stacker/reclaimer scheduling problem and storage space allocation have been investigated. The stacker/reclaimer scheduling problem aims at minimizing the total time of all operations [11]–[13], whereas the storage allocation problem is studied for allocating materials properly toward cost minimization.

Traditionally, when materials are to be allocated in the stockyard, sufficient storage space is considered for storing newly arriving materials using static space allocation (SSA) [17], [19], and therefore, no actions are taken in the stockyard. The terminal, however, does not always have sufficient space prior to the arrival of new materials, as all materials may not have been removed from the stockyard. In this case, the vessel with newly arriving material has to wait in the terminal; as a result, the terminal has to pay a high demurrage—a penalty cost paid by terminal operators to the shipowner if ship (un)loading requires more time than predefined. To avoid unnecessary economic losses for terminal operators, new measures must be taken when a finite storage capacity is considered.

This paper proposes a new methodology for allocating materials in the stockyard at the operational level when a finite storage capacity is considered. The material storage process in the stockyard relates to hybrid system dynamics combining both discrete-event and continuous-time dynamics. Current allocation methods [17], [19] are based on discrete-event dynamics only, and therefore, the storage capacity cannot be considered in the modeling framework. In this paper, the system model is built using a dynamical hybrid approach for exchanging incoming and outgoing material flows. This approach partitions a row of the stockyard into a number of slots, leading to a so-called mixed logical dynamical (MLD) model with the maximal storage capacity. The MLD model can be further extended using exogenous inputs for describing the arrival of new materials. Based on the MLD model, a model predictive controller (MPC) is then proposed for real-time decisions aiming at the maximal profit, and a number of Monte Carlo simulations are conducted involving a real case study. Using the MPC framework, different slot volumes are compared in terms of both economic and computational performance. The simulations demonstrate the potential of the MPC controller in comparison with the static allocation method and the advantage of the extended MLD model. The last part of simulations gives an example of temporary storage to demonstrate the ability to achieve flexible material storage using the proposed MPC controller.

The remainder of this paper is organized as follows. Section II provides a new dynamic model for allocating materials in a stockyard using the hybrid system representation. Based on the dynamical model, an MPC is proposed in Section III. In Section IV, case studies and sensitivity analysis of the model parameters are conducted. Section V concludes this paper and provides future research directions.

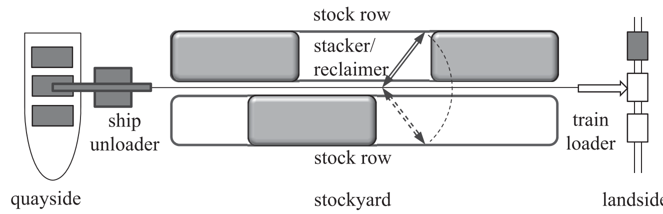

Fig. 1. Schematic of a small import dry bulk terminal.

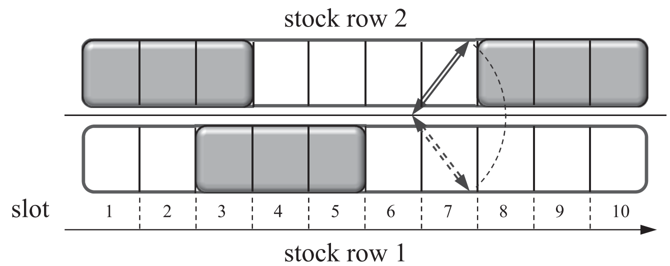

Fig. 2. Illustration of partitioning space of a stack row in the stockyard.

II. MODELING OF STOCKYARD MATERIAL FLOWS

This section provides a new model for material allocation in a stockyard of a dry bulk terminal using a flow perspective. In this paper, we investigate an import dry bulk terminal, which is typically located in Europe and China [7], [11]. An import dry bulk terminal in general includes a number of ship unloaders in the quayside, a stockyard for material storage, and a number of train loaders in the landside. The stockyard has a number of stock rows. Here, we consider a small dry bulk terminal that contains one ship unloader, one stacker/reclaimer, and one train loader. The setting of this small terminal is a basic unit of a dry bulk terminal, similarly as considered for container terminals [20], and this small terminal could possibly exist in the hinterland. The schematic layout of a small import dry bulk terminal is given in Fig. 1.

To model the process of allocating materials in the stockyard, a preliminary step is to locate different piles of materials in the space such that the occupation of these piles in the stockyard can be modeled mathematically for allocating new materials. For this, we partition one stock row into a number of slots equally, similarly as considered in [17], and the associated spacing arrangement is illustrated in Fig. 2.

The process of allocating materials in the stockyard is modeled using a flow perspective as a given dry bulk material being transported continuously by belt conveyors, similar to a flow, when the material is unloaded and then stored in a number of slots in the stockyard. Indeed, this flow perspective can be found frequently in freight resource allocation for a container terminal, e.g., in [21]–[25].

In this paper, we consider allocating N materials in two symmetric stock rows that have N_{s} slots in total. Between these two rows, one stacker/reclaimer is operated for stacking materials or reclaiming the materials in the space of these rows.

We define two sets $P \triangleq \{1, 2, ..., N\}$ and $Q \triangleq \{1, 2, ..., N_\mathrm{s}\}$ for numbering different materials and the stockyard location.

Regarding this process, the following important assumptions are made.

1) Only one type of material (coal or iron ore) is considered for the whole terminal.
2) A vessel only carries a single material.
3) Each vessel has a particular due time for unloading the associated material out of the vessel.
4) The train is always available when the material needs to be loaded.
5) There is only one stacker/reclaimer in the system.
6) The handling rate (stacking or reclaiming) of the stacker/reclaimer is a constant value.

Using a flow perspective, the dry bulk terminal dynamics is given in a state-space form as follows:

$$x_p^{\mathrm{quay}}(k+1) = x_p^{\mathrm{quay}}(k) - \sum_{q \in Q} \delta_{pq}^{\mathrm{in}}(k) u_{\mathrm{in}} \Delta T, \quad \forall p \in P \tag{1}$$

$$x_{pq}^{\mathrm{yard}}(k+1) = x_{pq}^{\mathrm{yard}}(k) + \delta_{pq}^{\mathrm{in}}(k) u_{\mathrm{in}} \Delta T - \delta_{pq}^{\mathrm{out}}(k) u_{\mathrm{out}} \Delta T, \quad \forall p \in P \quad \forall q \in Q \tag{2}$$

$$x_p^{\mathrm{land}}(k+1) = x_p^{\mathrm{land}}(k) + \sum_{q \in Q} \delta_{pq}^{\mathrm{out}}(k) u_{\mathrm{out}} \Delta T, \quad \forall p \in P \tag{3}$$

where, for $\forall p \in P$ and $\forall q \in Q$, we define the following parameters.

- p is the material index.
- q is the stockyard slot index.
- u_{in} [kt/h] is the stacking rate of the stacker/reclaimer.
- u_{out} [kt/h] is the reclaiming rate of the stacker/reclaimer.
- ΔT is the time step.

State Variables:

- $x_p^{\mathrm{quay}}(k)$ [kt] is the quantity of material p remaining to be unloaded at the quayside at time instant k.
- $x_{pq}^{\mathrm{yard}}(k)$ [kt] is the quantity of material p stored in the stockyard at slot q at time instant k.
- $x_p^{\mathrm{land}}(k)$ [kt] is the quantity of accumulated material p to be loaded at the landside at time instant k.

Binary Control Variables:

- $\delta_{pq}^{\mathrm{in}}(k) \in \{0, 1\}$ is the operating option of the stacker/reclaimer for stacking material p at slot q from time instant k to $k+1$.
- $\delta_{pq}^{\mathrm{out}}(k) \in \{0, 1\}$ is the operating option of the stacker/reclaimer for reclaiming material p at slot q from time instant k to $k+1$.

The waiting status of the vessel is essential for material handling. If the vessel stays beyond its planned departure time, a demurrage fee will be charged. This status, however, is not represented using the above-mentioned available variables but will influence the terminal's profit (additional details are given later). Therefore, here, we introduce $\delta_p^{\mathrm{quay}}(k)$ for describing this waiting status as follows:

$$\delta_p^{\mathrm{quay}}(k) \triangleq \begin{cases} 1, & x_p^{\mathrm{quay}}(k) > 0 \\ 0, & x_p^{\mathrm{quay}}(k) = 0. \end{cases} \tag{4}$$

If we define m_{quay} and M_{quay} as the minimal and maximal volumes of $x_p^{\mathrm{quay}}(k)$, based on [26] and [27], (4) is equivalent to

$$x_p^{\mathrm{quay}}(k) \leq M_{\mathrm{quay}} \delta_p^{\mathrm{quay}}(k) \tag{5}$$

$$x_p^{\mathrm{quay}}(k) \geq m_{\mathrm{quay}} \delta_p^{\mathrm{quay}}(k). \tag{6}$$

Similarly, allocating materials requires us to define whether a particular slot q is occupied for storing a particular material p, and therefore, we define $\delta_{pq}^{\mathrm{yard}}(k)$ $(p \in P, q \in Q)$ as follows:

$$\delta_{pq}^{\mathrm{yard}}(k) \triangleq \begin{cases} 1, & x_{pq}^{\mathrm{yard}}(k) > 0 \\ 0, & x_{pq}^{\mathrm{yard}}(k) = 0. \end{cases} \tag{7}$$

If m_{yard} and M_{yard} are defined as the minimal and maximal volumes of $x_{pq}^{\mathrm{yard}}(k)$, i.e., $m_{\mathrm{yard}} \leq x_{pq}^{\mathrm{yard}}(k) \leq M_{\mathrm{yard}}$, (7) is equivalent to

$$x_{pq}^{\mathrm{yard}}(k) \leq M_{\mathrm{yard}} \delta_{pq}^{\mathrm{yard}}(k) \tag{8}$$

$$x_{pq}^{\mathrm{yard}}(k) \geq m_{\mathrm{yard}} \delta_{pq}^{\mathrm{yard}}(k). \tag{9}$$

Because each slot q $(q \in Q)$ can be occupied by at most one material, using the defined $\delta_{pq}^{\mathrm{yard}}(k)$, this constraint can be described as follows:

$$\sum_{p \in P} \delta_{pq}^{\mathrm{yard}}(k) \leq 1, \quad \forall q \in Q. \tag{10}$$

Furthermore, the total occupation of material p $\sum_{q \in Q} \delta_{pq}^{\mathrm{yard}}(k)$ is limited by its total storage in the stockyard. As the total storage of material p may change over time due to its importing or exporting, this limitation is given as follows:

$$\sum_{q \in Q} \delta_{pq}^{\mathrm{yard}}(k) x_{pq}^{\mathrm{yard}}(k) \leq \sum_{q \in Q} x_{pq}^{\mathrm{yard}}(k), \quad \forall p \in P \tag{11}$$

where the term $\delta_{pq}^{\mathrm{yard}}(k) x_{pq}^{\mathrm{yard}}(k)$ is a nonlinear term and can be replaced by $z_{pq}(k) \triangleq \delta_{pq}^{\mathrm{yard}}(k) x_{pq}^{\mathrm{yard}}(k)$. The replacement $z_{pq}(k) = \delta_{pq}^{\mathrm{yard}}(k) x_{pq}^{\mathrm{yard}}(k)$ can be expressed by a number of linear inequalities [27] as follows:

$$z_{pq}(k) \leq M_{\mathrm{yard}} \delta_{pq}^{\mathrm{yard}}(k) \tag{12}$$

$$z_{pq}(k) \geq m_{\mathrm{yard}} \delta_{pq}^{\mathrm{yard}}(k) \tag{13}$$

$$z_{pq}(k) \leq x_{pq}^{\mathrm{yard}}(k) - m_{\mathrm{yard}} \left(1 - \delta_{pq}^{\mathrm{yard}}(k)\right) \tag{14}$$

$$z_{pq}(k) \geq x_{pq}^{\mathrm{yard}}(k) - M_{\mathrm{yard}} \left(1 - \delta_{pq}^{\mathrm{yard}}(k)\right). \tag{15}$$

For the case of one stacker/reclaimer, the machine is operated by either stacking material p at slot q, reclaiming material p at slot q, or being idle. This operational constraint is described as follows:

$$\sum_{p \in P, q \in Q} \delta_{pq}^{\mathrm{in}}(k) + \sum_{p \in P, q \in Q} \delta_{pq}^{\mathrm{out}}(k) + \delta_{\mathrm{stop}}(k) = 1 \tag{16}$$

where $\delta_{\mathrm{stop}}(k) \in \{0, 1\}$ is the idle option of the stacker/reclaimer for not handling any material from time instant k to $k+1$.

We let

$$\mathbf{x}^{\mathrm{T}}(k) = \big[x_1^{\mathrm{quay}}(k), \ldots, x_N^{\mathrm{quay}}(k), x_{11}^{\mathrm{yard}}(k), \ldots, x_{1N\mathrm{s}}^{\mathrm{yard}}(k), \ldots, x_{N1}^{\mathrm{yard}}(k), \ldots, x_{NN\mathrm{s}}^{\mathrm{yard}}(k), x_1^{\mathrm{land}}(k), \ldots, x_N^{\mathrm{land}}(k)\big]$$

$$\delta_{\mathrm{c}}^{\mathrm{T}}(k) = \big[\delta_{11}^{\mathrm{in}}(k), \delta_{11}^{\mathrm{out}}(k), \ldots, \delta_{1N\mathrm{s}}^{\mathrm{in}}(k), \delta_{1N\mathrm{s}}^{\mathrm{out}}(k), \ldots, \delta_{N1}^{\mathrm{in}}(k), \delta_{N1}^{\mathrm{out}}(k), \ldots, \delta_{NN\mathrm{s}}^{\mathrm{in}}(k), \delta_{NN\mathrm{s}}^{\mathrm{out}}(k), \delta_{\mathrm{stop}}(k)\big]$$

$$\delta_{\mathrm{a}}^{\mathrm{T}}(k) = \big[\delta_{11}^{\mathrm{yard}}(k), \ldots, \delta_{1N\mathrm{s}}^{\mathrm{yard}}(k), \ldots, \delta_{N1}^{\mathrm{yard}}(k), \ldots, \delta_{NN\mathrm{s}}^{\mathrm{yard}}(k), \delta_1^{\mathrm{quay}}(k), \ldots, \delta_N^{\mathrm{quay}}(k)\big]$$

$$\delta^{\mathrm{T}}(k) = [\delta_{\mathrm{c}}^{\mathrm{T}}(k), \delta_{\mathrm{a}}^{\mathrm{T}}(k)]$$

$$\mathbf{z}^{\mathrm{T}}(k) = \big[z_{11}(k), \ldots, z_{1N\mathrm{s}}(k), \ldots, z_{N1}(k), \ldots, z_{NN\mathrm{s}}(k)\big]$$

where $\mathbf{x}^{\mathrm{T}}(k)$ is the system state vector, $\delta_{\mathrm{c}}^{\mathrm{T}}(k)$ is the control logic variable vector, $\delta_{\mathrm{a}}^{\mathrm{T}}(k)$ is the auxiliary logic variable vector, and $\mathbf{z}^{\mathrm{T}}(k)$ is a real auxiliary variable vector. Based on the above-mentioned variable vectors, the dry bulk terminal dynamics including (1)–(3), (5), (6), (8)–(10), and (12)–(16) can be rewritten into a compact MLD model representation derived from [27] as follows:

$$\mathbf{x}(k+1) = \mathrm{A}\mathbf{x}(k) + \mathrm{B}_1\delta(k) + \mathrm{B}_2\mathbf{z}(k) \tag{17}$$

$$\mathrm{E}_1\delta(k) + \mathrm{E}_2\mathbf{z}(k) \leq \mathrm{E}_3\mathbf{x}(k) + \mathrm{E}_4 \tag{18}$$

where A, B_1, B_2, E_1, E_2, E_3, and E_4 are obtained when the storage process described by (1)–(16) is transformed into the compact form (17) and (18). This MLD model can describe the terminal dynamics in a computationally friendly manner that is well suited for the formulation of the system and control design [28].

Equations (17) and (18) focus on allocating materials that have already arrived at the terminal. However, new materials could arrive in the near future. For allocating these new materials together, the original MLD model can be further extended using exogenous inputs for representing the new material quantities and their exact arrival times, resulting in the following extended model:

$$\mathbf{x}(k+1) = \mathrm{A}\mathbf{x}(k) + \mathrm{B}_1\delta(k) + \mathrm{B}_2\mathbf{z}(k) + \mathrm{B}_3\mathbf{d}(k) \tag{19}$$

$$\mathrm{E}_1\delta(k) + \mathrm{E}_2\mathbf{z}(k) \leq \mathrm{E}_3\mathbf{x}(k) + \mathrm{E}_4 \tag{20}$$

where $\mathbf{d}(k) = [a_1(k), \ldots, a_N(k)]^{\mathrm{T}}$ is the exogenous input matrix, and $a_p(k)$ $(p \in P)$ represents the exogenous input of material p at time instant k. Since this extended model can be used as a predictive model, at time instant k, for a material p that arrives at $k+i$ $(i \in \mathbb{N})$, the amount of material p is represented by $a_p(k+i)$.

The newly extended model can take the future arrival time of the new materials into account. The uncertainties characterizing these new materials motivate the use of the predictive control, which will be proposed in a later section.

III. Hybrid Model Predictive Control

The MLD model obtained in Section II is indeed a hybrid model and based on the hybrid model, this section further proposes an MPC controller for allocating materials in the stockyard of the dry bulk terminal. The first part introduces a generic description of the MPC formulation, and the second part defines the objective function needed for a complete MPC control problem formulation in detail.

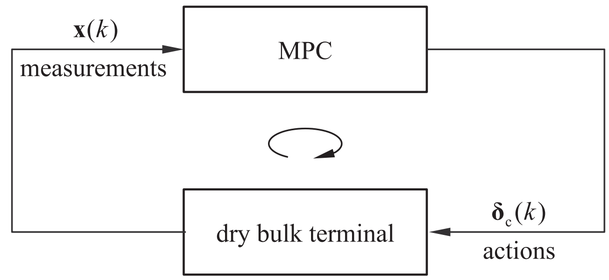

Fig. 3. Control loop of the dry bulk terminal.

A. MPC Formulation

MPC in general is a control methodology that explicitly utilizes a dynamical model to obtain control actions by minimizing an objective over a finite receding horizon. This control methodology has been successfully used in the domain of transportation and logistics [20]–[22], [29]–[31]. In MPC, the dynamical model is used to predict the future state of the system based on the current state and the proposed future actions. These control actions are calculated by minimizing the cost function, considering the constraints on the states, outputs, and inputs. MPC provides an online control framework for controlling systems with interacting variables, complex dynamics, and constraints. We consider one centralized MPC controller for the components, as shown in Fig. 3, to optimally allocate different dry bulk materials in the stockyard using the available equipment at the proper location and timing. The objective of the controller is to maximize the profit of the associated operations for unloading, loading, and storing materials all together.

In practice, for material storage in a stockyard, it is noted that the reclaiming of material should start after the completion of its unloading from the vessel. To include this in the MPC controller, supposing N_{p} as the prediction horizon, we add a conditional constraint to the MLD model

$$\forall p \in P, \quad \text{if} \sum_{i=1}^{N_{\mathrm{p}}} x_p^{\mathrm{quay}}(k+i) > 0,$$

then

$$\sum_{q \in Q} \delta_{pq}^{\mathrm{out}}(k+i) = 0 \quad \text{for } i = 1, 2 \ldots, N_{\mathrm{p}}. \tag{21}$$

The above-mentioned constraint indicates that for a particular material, the reclaiming operation cannot be performed if the unloading from the vessel is not finished. Because this constraint is not an inequality, we rewrite (22) into an inequality using a large positive integer number R as follows $(\forall p \in P)$:

$$\sum_{i=1}^{N_{\mathrm{p}}} x_p^{\mathrm{quay}}(k+i) \leq R\left(1 - \sum_{q \in Q} \delta_{pq}^{\mathrm{out}}(k+i)\right), \quad \text{for } i = 1, 2 \ldots, N_{\mathrm{p}}. \tag{22}$$

With (22), a complete MPC formulation is then given as follows:

$$\max_{\delta(k+i),\mathbf{z}(k+i)} J(\mathbf{x}(k+i+1), \delta(k+i), \mathbf{z}(k+i)) \tag{23}$$

subject to (19), (20), (22), and

$$\begin{aligned} \mathbf{x}_{\min} &\le \mathbf{x}(k+i+1) \le \mathbf{x}_{\max}, \\ \delta_{pq}^{\text{in}}(k+i) &\in \{0,1\}, \delta_{pq}^{\text{out}}(k+i) \in \{0,1\}, \delta_{\text{stop}}(k+i) \in \{0,1\}, \\ i &\in \{0, 1.., N_{\text{p}} - 1\} \end{aligned} \tag{24}$$

where the both the constraints $\delta(k+N_{\text{c}}-1) = \delta(k+i)$ and $\mathbf{z}(k+N_{\text{c}}-1) = \mathbf{z}(k+i)$ for $N_{\text{c}} \le i \le N_{\text{p}}-1$ can be included additionally if a control horizon N_{c} ($N_{\text{c}} \le N_{\text{p}}$) is considered. The use of the control horizon leads to a reduction of decision variables, resulting in a decrease of the computation burden and a smoother control signal [32], [33].

B. Objective Function

The objective function J is used to maximize the profit of the associated terminal operations. This profit function includes three parts

$$J = J_1 - J_2 + J_3 \tag{25}$$

where J_1, J_2, and J_3 represent the net handling revenue, the demurrage cost, and the stock revenue, respectively. In the following part, we discuss the composition of each part in detail.

J_1 is the net revenue obtained from handling materials in dry bulk terminals. The revenue includes unloading materials from dry bulk ships and loading materials onto railcars. A mathematical description of J_1 is given as follows:

$$\begin{aligned} J_1 = c_p^{\text{in}} \sum_{i=0}^{N_{\text{p}}-1} \sum_{p\in P, q\in Q} \delta_{pq}^{\text{in}}(k+i) u_{\text{in}} \Delta T \\ + c_p^{\text{out}} \sum_{i=0}^{N_{\text{p}}-1} \sum_{p\in P, q\in Q} \delta_{pq}^{\text{out}}(k+i) u_{\text{out}} \Delta T \end{aligned} \tag{26}$$

where the parameters c_p^{in} ([euro/kt]) and c_p^{out} ([euro/kt]) represent the net unitary unloading revenue and the net unitary loading revenue, respectively, for which the handling costs are excluded from the total handling revenue.

J_2 describes the demurrage fee resulting from delaying the departure of dry bulk ships. Based on an agreement between the terminal and the shipping company in most cases, the terminal receives revenue from the shipping company (see the first term of J_1) when unloading the material completely before the due time. After the due time, if the unloading process is not completed, the ship has to wait in the terminal, and the terminal has to pay a demurrage fee until the ship leaves the terminal. Here, we consider a linear function based on [34] to describe the total demurrage fee with respect to the waiting time, as illustrated in Fig. 4. To minimize the demurrage fee, the terminal makes every attempt to complete

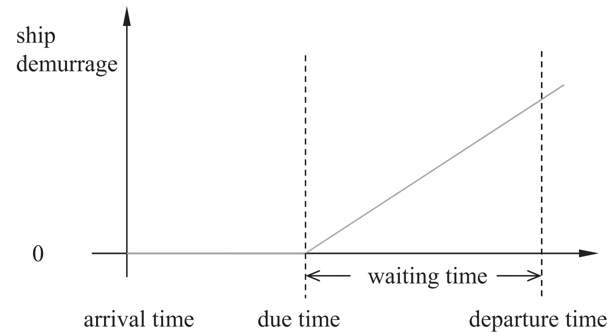

Fig. 4. Cost function of the ship demurrage over time.

the unloading operation at the terminal before the due time. J_2 is detailed as follows:

$$J_2 = \sum_{i=1}^{N_{\text{p}}} \sum_{p\in P} c_p^{\text{quay}}(k+i) \delta_p^{\text{quay}}(k+i) \Delta T \tag{27}$$

where the parameter $c_p^{\text{quay}}(k+i)$ ([euro/h]) is the unitary penalty of a particular material p to be unloaded at time instant $k+i$ within the prediction horizon. The shape of $c_p^{\text{quay}}(k+i)$ is a step function depending on the due time.

For the MPC controller, because the due time may not be within the prediction horizon (see Fig. 5), it is necessary to introduce a parameter N_{d} to indicate the due time horizon, which is used for calculating the cost associated with the penalty under different conditions.

1) The due time horizon is ahead of the prediction horizon, $N_{\text{p}} \le N_{\text{d}}$ [see Fig. 5(a)]

$$c_p^{\text{quay}}(k+i) = 0 \quad 1 \le i \le N_{\text{p}}. \tag{28}$$

2) The due time horizon is within the prediction horizon, $N_{\text{p}} > N_{\text{d}}$, $N_{\text{d}} > 0$ [see Fig. 5(b)]

$$c_p^{\text{quay}}(k+i) = \begin{cases} 0, & 1 \le i \le N_{\text{d}} \\ c_p^{\text{due}}, & N_{\text{d}} < i \le N_{\text{p}}. \end{cases} \tag{29}$$

3) The due time cannot be met, $N_{\text{p}} > N_{\text{d}}$ $N_{\text{d}} \le 0$ [see Fig. 5(c)]

$$c_p^{\text{quay}}(k+i) = c_p^{\text{due}} \quad 1 \le i \le N_{\text{p}}. \tag{30}$$

Fig. 5 illustrates these three different conditions for computing the penalty $c_p^{\text{quay}}(k+i)$ within the prediction horizon of the MPC controller. When the prediction horizon precedes the due time of material p, $c_p^{\text{quay}}(k+i)$ is equal to zero [see Fig. 5(a)]; when the due time is within the prediction horizon, the trajectory of $c_p^{\text{quay}}(k+i)$ is a piecewise function [see Fig. 5(b)]; and when the due time of material p cannot be met, $c_p^{\text{quay}}(k+i)$ is a constant value [see Fig. 5(c)].

In addition to J_1 and J_2, J_3 is associated with the storage revenue when materials are stored in the stockyard. The composition of J_3 is given as follows:

$$J_3 = \sum_{i=1}^{N_{\text{p}}} \sum_{p\in P} c_p^{\text{yard}} \sum_{q\in Q} x_{pq}^{\text{yard}}(k+i) \tag{31}$$

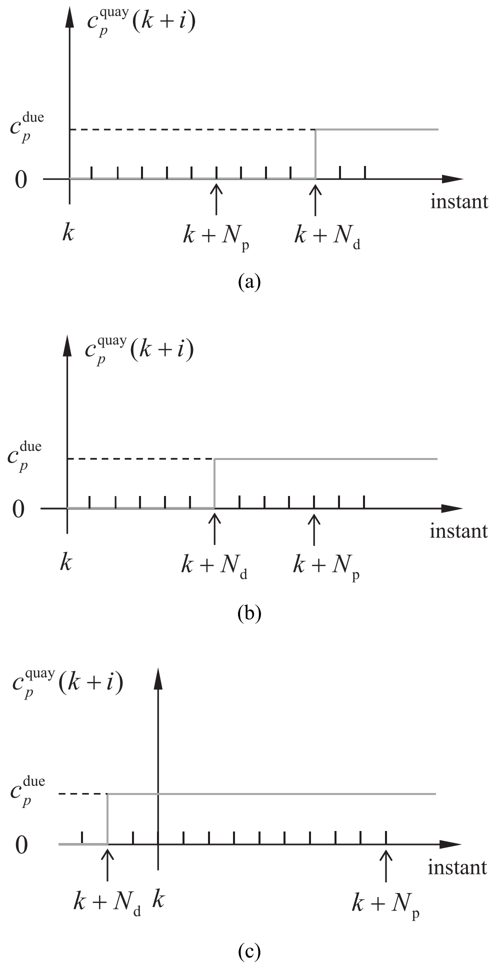

Fig. 5. Curves of $c_p^{\mathrm{quay}}(k+i)$ under three different conditions. (a) Due time horizon is ahead of the prediction horizon ($N_{\mathrm{p}} \leq N_{\mathrm{d}}$). (b) Due time horizon is within the prediction horizon ($N_{\mathrm{p}} > N_{\mathrm{d}}$, $N_{\mathrm{d}} > 0$). (c) Due time cannot be met ($N_{\mathrm{p}} > N_{\mathrm{d}}$, $N_{\mathrm{d}} \leq 0$).

where the parameter c_p^{yard} is a constant unitary storage revenue for material p at time instant $k+i$. Note that a client of the dry bulk terminal can request that the terminal store its material for an extended period of time by paying a high value of c_p^{yard}.

The MPC control problem can be rearranged as a standard mixed integer linear programming (MILP) problem as follows:

$$\min_{\tilde{u}} \quad f^{\mathrm{T}}\tilde{\mathbf{u}} \tag{32}$$

$$\text{s.t. } \mathbf{b}_{\min} \leq \tilde{\mathbf{A}}\tilde{\mathbf{u}} \leq \mathbf{b}_{\max} \tag{33}$$

$$\tilde{\mathbf{u}}_{\min} \leq \tilde{\mathbf{u}} \leq \tilde{\mathbf{u}}_{\max} \tag{34}$$

where $\tilde{\mathbf{u}} = \left[\tilde{\delta}^{\mathrm{T}} \quad \tilde{\mathbf{z}}^{\mathrm{T}}\right]^{\mathrm{T}}$ is the vector of the decision variables [$N_{\mathrm{p}}(3NN_{\mathrm{s}}+N+1)$ binary variables and $N_{\mathrm{p}}NN_{\mathrm{s}}$ continuous variables], and the matrix $\tilde{\mathbf{A}}$ has $N_{\mathrm{p}}(7NN_{\mathrm{s}}+6N+N_{\mathrm{s}}+2)$ rows and $N_{\mathrm{p}}(4NN_{\mathrm{s}}+N+1)$ columns. This MILP problem can be solved by commercial solvers (e.g., CPLEX [35]) or free solvers such as SCIP [36].

IV. Case Study

In this section, we perform a real case study to demonstrate the potential of the proposed MPC controller. The case study considers a busy terminal wherein a vessel may have to wait when the terminal is busy allocating materials. Given the detailed configuration and parameters for simulating the dry bulk terminal, a number of Monte Carlo simulations will be conducted to analyze the proposed MPC controller based on the MLD model. The simulation experiments include four parts considering the three scenarios shown in Fig. 6. A brief description of these three scenarios is given as follows.

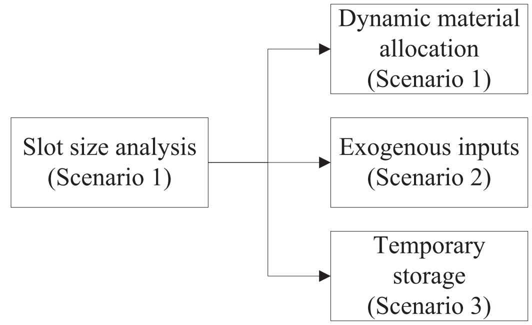

Fig. 6. Flow diagram of the simulations.

- Scenario 1 considers a fundamental case involving two materials in which one material is stored in the stockyard, whereas the other material has just arrived to be unloaded. This scenario is used to analyze the effects of the slot sizes on the terminal performance and show the advantage performance of the MPC controller in comparison with the static allocation method.
- Scenario 2 also considers a case of two materials in which one material is stored in the stockyard and the other material will arrive in the near future. This scenario illustrates the economic benefit of the extended MLD model that incorporates exogenous inputs for addressing new materials arriving in the near future.
- Scenario 3 considers a case of three materials in which two materials are stored in the stockyard and the third material is just arriving to be unloaded. This scenario emphasizes temporary storage for more flexible material handling in the dry bulk terminal using the proposed MPC controller.

A. Setting of the Dry Bulk Handling System

The hardware for the simulation is an Intel Core 2430 (2.4 GHz) with 4 GB of memory. CPLEX is used to solve the MILP problem of the MPC controller. Several assumptions are made in this simulation:

1) The initial quantity of materials in the stockyard is given randomly.
2) The quantity of the newly arriving material is assumed to be in the range [10,30] (kt) following a typical capacity of the Handysize ship for small bulk carriers [7].
3) The shape of the stockpile is assumed to be trapezoidal (see Fig. 7 for illustration), and the capacity of the stockpile is calculated using the associated parameters [7] given in Table I for arranging the layout.
4) For the sake of simplicity, the handling capacities of stacking and reclaiming are assumed to be identical, both being 2 [kt/h], as suggested in [7].

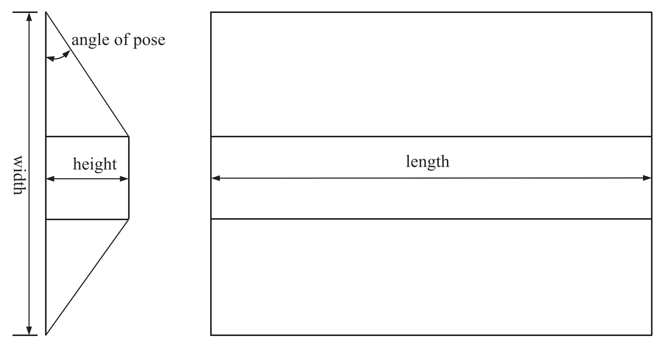

Fig. 7. Side and top views of the trapezoidal stockpile.

TABLE I
KEY PARAMETERS OF THE MATERIAL STOCKPILE

Description	Value	Unit
Length	300	[m]
Width	60	[m]
Height	18	[m]
Angle of repose	38	[°]
Bulk density	0.8	$[\mathrm{t/m^3}]$

TABLE II
KEY PARAMETERS OF THE OBJECTIVE FUNCTION

Parameter	Value	Unit
c_p^{in}	1,500	[euro/kt]
c_p^{out}	1,000	[euro/kt]
c_p^{due}	625	[euro/h]
c_p^{yard}	10	[euro/h]

5) The key parameters of the objective functions are given in Table II based on data from terminal operators.
6) Since the dynamics of the flow model is relatively slow, the time step ΔT is set to be 1 h, similarly as considered in [22] and [23].
7) The simulation length is considered to be 24 h, as 24-h operation is preferred by the terminal operator, similarly as considered for freight transport in [37].
8) The prediction horizon N_{p} is set to be 8 h, as a longer horizon is not needed due to the large uncertainties associated with the arrival of the vessels [7], and for the sake of simplicity, the control horizon N_{c} is equal to N_{p} [20].

B. Slot Size Choice

As discussed in Section II, the slot volume M_{yard} (kt) determines the variable numbers of the dry bulk terminal dynamics, leading to a different computational complexity in solving the MILP optimization problem of the MPC controller. Furthermore, the slot volume M_{yard} alters the storage layout for allocating different materials, which could influence the economic performance of the MPC control. To analyze these influences, we use Scenario 1 where one material is stored in the stockyard and the other material has just arrived to be unloaded. For this scenario, we conduct 50 Monte Carlo simulations, in which the quantities of these two materials follow an independent uniform distribution, as suggested in [7]. The quantity of the newly arriving material follows the second assumption in Section IV-A, while the quantity of the other material in the stockyard is assumed to be in the range [210, 240] (kt) to simulate a busy terminal scenario in which the total quantity of these two materials could exceed the maximum storage capacity.

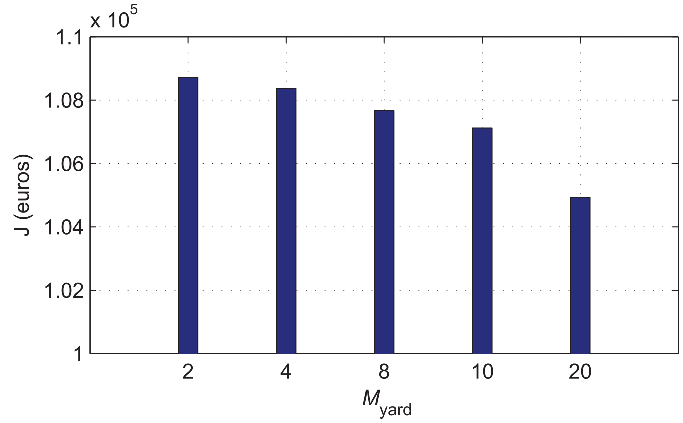

Fig. 8. Total profit of the MPC controller when varying the slot volume M_{yard}.

TABLE III
COMPOSED PROFITS OF THE MPC CONTROLLER WHEN VARYING THE SLOT VOLUME M_{yard} (UNIT: EURO)

M_{yard}	J_1	J_2	J_3
2	57,920	2,490	53,280
4	57,900	2,710	53,190
8	57,840	3,140	52,970
10	57,780	3,490	52,830
20	57,440	4,490	51,980

1) Economic Performance Comparison: Fig. 8 and Table III give the economic performance of the MPC controller when the slot volume M_{yard} is varied. In Fig. 8, the total profit of the dry bulk terminal J is presented, and in Table III, the compositions of the total profit (the handling revenue J_1, the penalty J_2, and the storage revenue J_3) are compared.

It can be observed from Fig. 8 that the total profit of the dry bulk terminal decreases as the slot volume M_{yard} increases. By the definition in Section II, a given slot can only be occupied by one material. Given the finite capacity, when the slot volume M_{yard} increases, the material stored in a particular slot has to be removed completely to accommodate the newly arriving material. As a result, the ship with the new material has to wait longer until there is an available slot for sufficiently accommodating the arriving material from the vessel.

The total profit J consists of the handling revenue J_1, the demurrage cost J_2, and the storage revenue J_3, and the effect of the slot volume M_{yard} on each part (J_1, J_2, and J_3) is illustrated in Table III. When M_{yard} increases, for a particular slot, the stored material has to be removed to accommodate the arriving material from the vessel if the new material cannot be unloaded completely. As a result, the vessel has to wait in the terminal until the material is completely unloaded, and therefore, a higher demurrage fee is paid to the shipper.

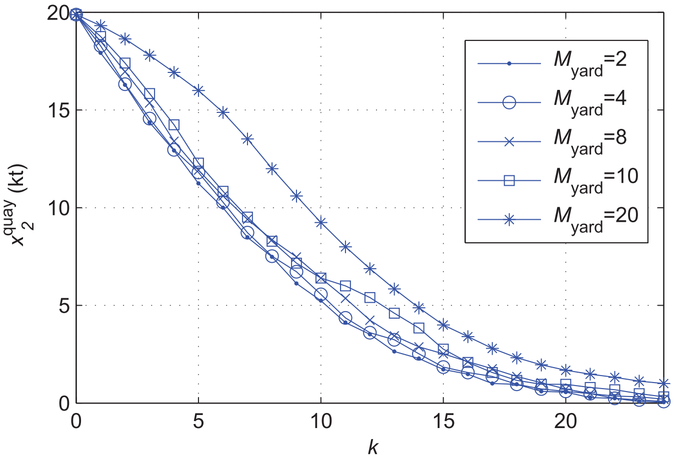

Fig. 9. Average quantity of the arriving material still to be unloaded when varying the slot volume M_{yard}.

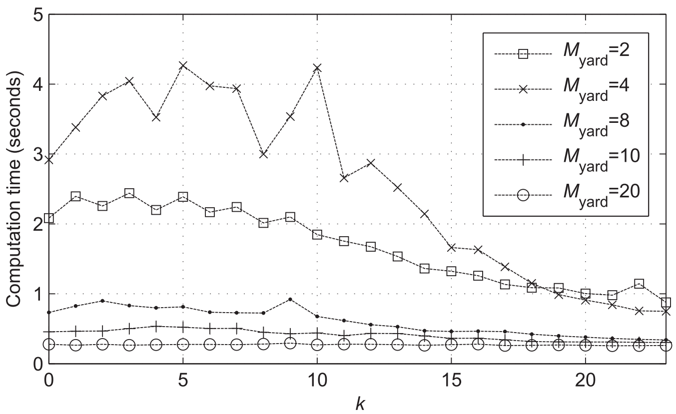

Fig. 10. Average computation time of the MPC controller at each time instant under different M_{yard} values.

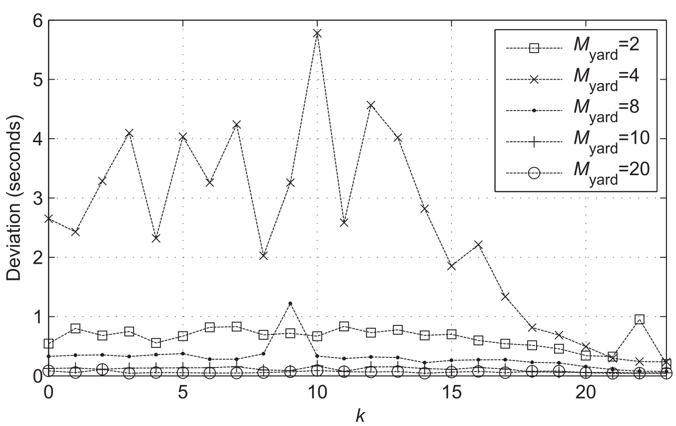

Fig. 11. Deviation of the computation time of the MPC controller at each time instant under different M_{yard} values.

Simultaneously, all the materials are stored in the stockyard, leading to a lower storage revenue, as can be seen in Fig. 9.

2) Computational Analysis: Figs. 10 and 11 give the average and deviation of the computation time for solving the optimization problem of the MPC controller at each time instant. In addition to the computation time, the preprocessing time consumed for formulating standardized matrices before solving the optimization problem is presented in Fig. 12.

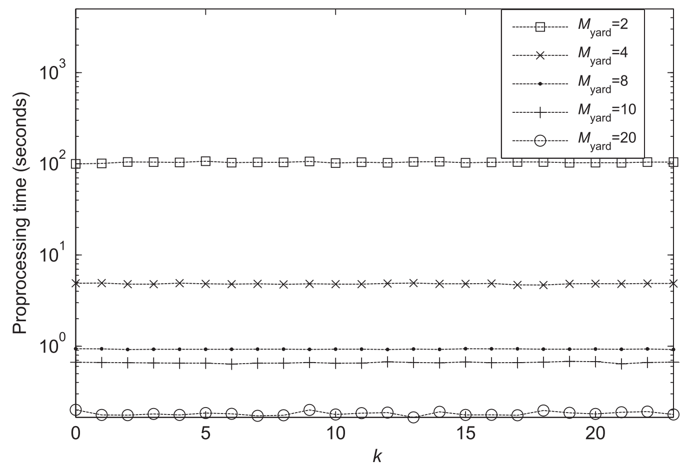

Fig. 12. Average preprocessing time of the MPC controller at each time instant under different M_{yard} values.

In Figs. 10 and 11, both the average and deviation of the computation time with respect to each M_{yard} tend to decrease from the start of the simulation until the end of the simulation. As less material remaining in the vessel needs to be unloaded into the stockyard, the computational complexity of the MILP problem decreases, and therefore, both the average and deviation for each slot volume reach their minimal values at the end of the simulation. Despite the fact that the control variables grow significantly when the slot volume decreases, the smallest slot volume ($M_{\text{yard}} = 2$) does not achieve the maximal value of the average and deviation of the computation time.

Fig. 12 presents the average preprocessing time for solving the optimization problem of the MPC controller at each time instant. Unsurprisingly, when each slot is more refined, the number of control variables grows significantly such that computing the matrices for formulating the optimization problem takes considerably more time. It should be noted that all the optimization problems are implemented in MATLAB and that the preprocessing time could be reduced in C or through direct implementation in the CPLEX code. If more materials are considered ($N > 2$), the computational complexity will grow considerably causing increasing both computational times and preprocessing times.

The biggest slot volume ($M_{\text{yard}} = 20$) obtains both the shortest computation time and the shortest preprocessing time due to the fewest decision variables. The smallest slot volume ($M_{\text{yard}} = 2$) achieves the best economic performance of the proposed hybrid MPC controller, despite the high preprocessing time for solving the optimization problem. In the following parts, we set $M_{\text{yard}} = 2$ for the slot volume for the MLD model when the hybrid MPC controller is compared with other approaches.

C. Dynamic Material Allocation

Based on the optimal slot volume, this section compares the performance of the hybrid MPC controller with the results

TABLE IV

COMPARISON OF THE AVERAGE ECONOMIC PERFORMANCE WHEN $M_{\text{yard}} = 2$ (UNIT: EURO)

Approach	J	J_1	J_2	J_3
Hybrid MPC	10,8720	57,920	2,490	53,280
SSA	66,260	17,820	6,088	54,528

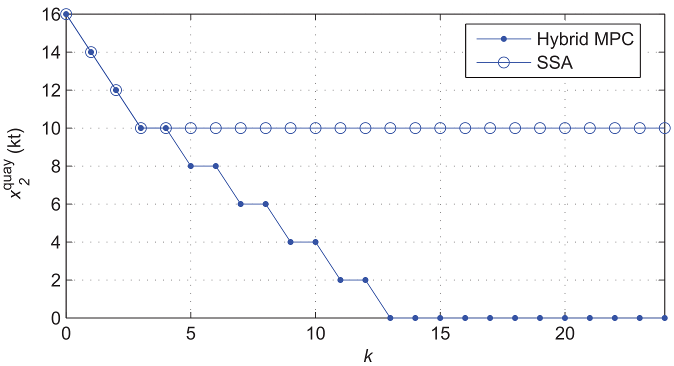

Fig. 13. Quantity of the newly arriving material remaining to be unloaded in one simulation.

TABLE V

AVERAGE ECONOMIC PERFORMANCE COMPARISON OF THE MPC CONTROLLER WITH RESPECT TO THE EXOGENOUS INPUT (UNIT: EURO)

Approach	J	J_1	J_2	J_3
with the exogenous input	113,172	57,920	950	54,302
without the exogenous input	107,785	49,660	2,490	55,635

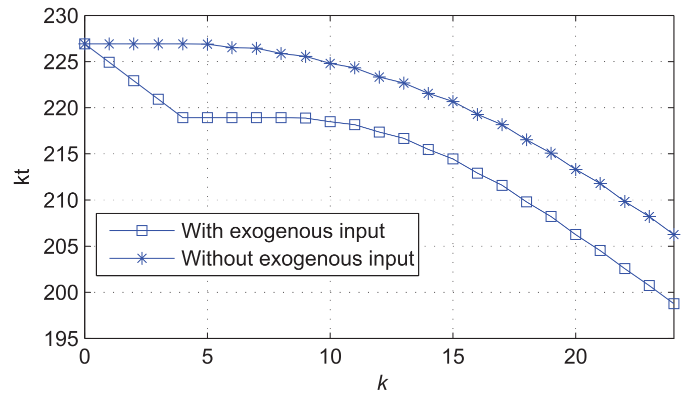

Fig. 14. Average quantity of material 1 in the stockyard by the hybrid MPC controller.

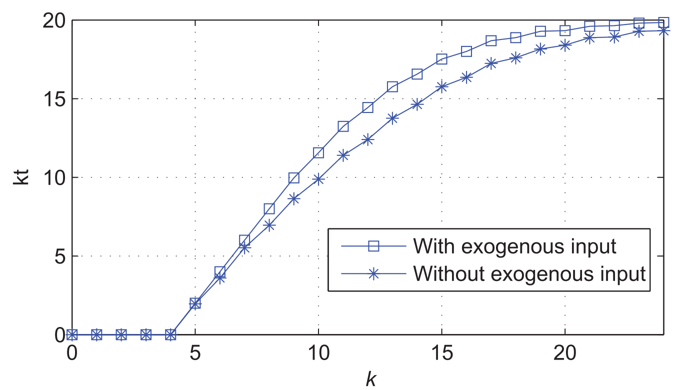

Fig. 15. Average quantity of material 2 in the stockyard by the hybrid MPC controller.

under SSA. The SSA method [17] solves a static optimization problem in which sufficient capacity is assumed for accommodating newly arriving materials and no outgoing actions are considered. The comparison is made under Scenario 1, and the result of the hybrid MPC controller for Scenario 1 is used for the comparison.

Table IV compares the average economic performance of the hybrid MPC controller and the SSA method. This economic performance is obtained by calculating the average result of each simulation using Scenario 1 of allocating two materials in Section IV-B. Table IV clearly indicates that the profit of the SSA method is significantly lower than under the hybrid MPC approach by 39%. The SSA method does not consider the control action for removing materials in the stockyard causing congestion such that there is no longer sufficient space for accommodating all the material of the vessel. Therefore, the vessel has to wait in the terminal, and the terminal pays a higher demurrage fee to the shipper (see Fig. 13).

D. Exogenous Inputs

The previous sections are concerned with Scenario 1 where the decision-making process of the hybrid MPC controller starts from when the ship just arrives. It remains unclear if the exact arrival time of the material can be known in advance. With the newly extended model [see (19) and (20)], it is possible for the MPC controller to take the future arrival time of the material into account. The MPC controller can take actions for decreasing the waiting time of the vessel such that the demurrage fee can be reduced. To demonstrate this potential, we conduct 50 Monte Carlo simulations using Scenario 2 where the quantities of the two materials follow the independent uniform distribution. It is assumed that the exact arrival time of the new material is provided 4 h before it arrives.

Table V compares the average economic performance of the MPC controller regarding the exogenous input. It can be observed from Table V that the MPC controller achieves a higher increment of the total profit J of 5% when the extended MLD model is considered. For the results of the MPC controller within the simulation length, the extended MLD model performs better in terms of the handling revenue J_1 and the demurrage fee J_2 than the original MLD model despite the fact that the extended MLD model leads to a lower storage revenue J_3.

Figs. 14 and 15 present the average quantities of both material 1 and material 2 in the stockyard by the hybrid MPC controller regarding the exogenous input. Since the exogenous input represents the future information of the dry bulk terminal system, actions can be taken in advance when the material time can be provided in advance. This allows the terminal to remove material 1 in advance, as shown in Fig. 14, to increase the handling revenue J_1. This also leads to less congestion when material 2 is stacked in the stockyard (see Fig. 15), resulting in a lower demurrage fee J_2.

TABLE VI

STORAGE PARAMETERS OF THREE MATERIALS IN THE STOCKYARD WHEN $M_{\text{yard}} = 2$

Parameter	Value	Unit
c_1^{yard}	2,000	[euro/h]
c_2^{yard}	10	[euro/h]
c_3^{yard}	10	[euro/h]

TABLE VII

COMPARISON OF THE AVERAGE ECONOMIC PERFORMANCE WHEN $M_{\text{yard}} = 2$ (UNIT: EURO)

Approach	J	J_1	J_2	J_3
Hybrid MPC	530,060	57,860	3,213	542,600
FIFO	481,990	57,860	3,213	476,530

E. Temporary Storage

Unlike dry bulk export terminals, the dry bulk import terminal can store material temporarily as requested by the client. This temporary storage requirement must be satisfied using the proposed hybrid MPC controller. This section exclusively discusses the results of the hybrid MPC controller for providing temporary storage and compares its result with a typical heuristic method [first in first out (FIFO)] used for the stacking and reclaiming of materials [38].

For this section, we consider three different materials ($N = 3$) using Scenario 3 where material 1 and material 2 are already stored in the stockyard and material 3 has just arrived to be unloaded. For the case of these three materials, the associated storage parameters are given in Table VI. Initially, the quantities of material 1 and material 2 in the stockyard are equal, and their total quantity is equal to the material in the stockyard for the case of two materials ($N = 2$). It is also assumed that material 1 arrives earlier than material 2. Similarly as in the previous sections, we conduct 50 Monte Carlo simulations.

Table VII compares the economic performance of the hybrid MPC controller for temporary storage with the FIFO method. It can be observed in Table VII that the total profit J using the hybrid MPC controller is significantly higher, 14% higher, than when using the FIFO method. The handling revenue J_1 and the demurrage fee J_2 of the two approaches are the same, and the gap in the storage revenue J_3 between these two approaches leads to the difference in J.

Fig. 16 illustrates how the average quantities of the three materials change over the course of the simulation using the hybrid MPC controller and the FIFO method. When the hybrid MPC controller is employed, due to its high storage c_1^{yard}, the quantity of material 1 in the stockyard does not change, whereas some of material 2 is removed, although it arrives late. The hybrid MPC controller obtains a higher profit than the FIFO method, which allows material 1 to leave the terminal earlier.

It should be noted that for temporary storage, as multiple materials are considered, the dimensions of the matrices for formulating the MILP optimization problem could increase significantly. The high matrix dimensionality leads to a high requirement in terms of memory.

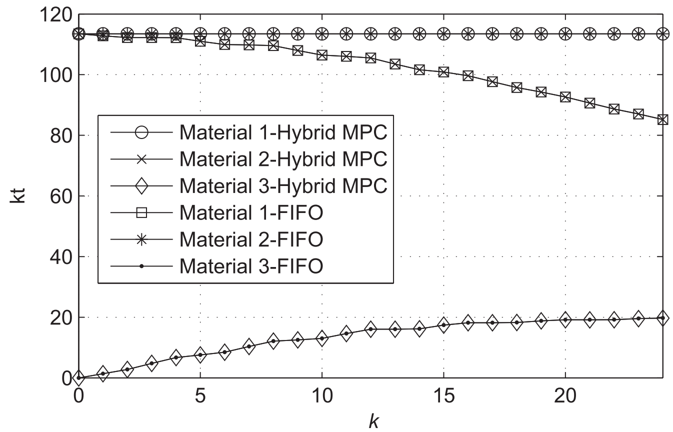

Fig. 16. Comparison of the average quantities of three materials in the stockyard over the course of the simulation.

V. CONCLUSION AND FUTURE RESEARCH

For a dry bulk terminal, current methods for allocating materials consider sufficient storage space, which could result in unnecessary economic losses when a finite storage capacity is considered. To address this problem, this paper proposes a new methodology for allocating materials in the stockyard of a small dry bulk terminal. This methodology captures the continuous-time and discrete-event dynamics of the dry bulk terminal, thereby allowing one to model the behavior of the dry bulk terminal in a dynamical manner. The dynamical model partitions the stockyard into several slots using an MLD representation. Based on the MLD model, an MPC is proposed for real-time decision making. The simulations assess the effect of the slot volume on the economic performance and the computational complexity of the MPC controller. It is demonstrated via simulation that for the scenario with two materials, the hybrid MPC controller has reduced the economic losses by 39% compared with the SSA method, and the economic profit has been increased by 5% when the exogenous input is considered. The simulations also show that for temporary material storage, the hybrid MPC controller achieves 14% greater profit than the FIFO method.

In future research, a large intermodal terminal, in which different transport modalities (vessels, barges, and railways) are coordinating incoming and outgoing material flows through the terminal, will be investigated. In particular, rail transport [39] in practice has fixed time schedules, increasing the difficulty of the problem. For a large terminal, an advanced optimization method is expected to reduce the computational burden and the required memory. Future research will also model the position of the stacker-reclaimer in the dynamical terminal system and investigate the planning of multiple stacker-reclaimers considering collision avoidance.

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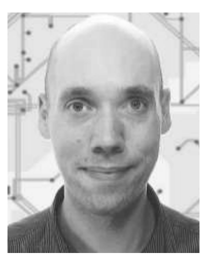

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