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Simultaneous Allocation and Scheduling of Quay Cranes, Yard Cranes, and Trucks in Dynamical Integrated Container Terminal Operations

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***Abstract*— We present a dynamical modeling of integrated (end-to-end) container terminal operations using finite state machine (FSM) framework where each state machine is represented by a discrete-event system (DES) formulation. The hybrid model incorporates the operations of quay cranes (QC), internal trucks (IT), and yard cranes (YC) and also the selection of storage positions in container yard (CY) and vessel bays. The QC and YC are connected by the IT in our models. As opposed to the commonly adapted modeling in container terminal operations, in which the entire information/inputs to the systems are known for a defined planning horizon, in this research we use real-time trucks, crane, and container storage operations information, which are always updated as the time evolves. The dynamical model shows that the predicted state variables closely follow the actual field data from a container terminal in Tanjung Priuk, Jakarta, Indonesia. Subsequently, using the integrated container terminal hybrid model, we proposed a model predictive algorithm (MPA) to obtain the near-optimal solution of the integrated terminal operations problem, namely the simultaneous allocation and scheduling of QC, IT, and YC, as well as selecting the storage location for the inbound and outbound containers in the CY and vessel. The numerical experiment based on the extensive Monte Carlo simulation and real dataset show that the MPA outperforms by 3-6% both of the policies currently implemented by the terminal operator and the state-of-the-art method from the current literature.**

***Index Terms*— Containers, discrete-event systems (DESs), logistics, mathematical model, predictive control.**

I. Introduction and Literature Review

CONTAINER terminals have been important nodes in global maritime transportation network for the past six decades. The standardization and low cost of container boxes have made them the foremost choice of transportation means in the international trade [22]. The trend of containerization growth has been twice the growth of the total world and maritime trade for the past decade [25]. The increasing demand in container trade has made the terminal operators to put efforts to optimize and streamline their operations in order to guarantee an efficient service to the shipping liners, as well as the inland shippers and consignees as the terminal's main customers [24].

The general layout of a container terminal is shown in Figure 1. It is shown that a number of ships can dock at various berth positions along the seaside and several quay cranes (QC) can be assigned to every berthed ship for loading and unloading containers. There are internal trucks (IT) waiting beneath the QC and they transport the containers to some specific destinations at container yard (CY). On the other way around, IT also deliver containers from CY to QC, which will load them to the pre-determined stacking point at the vessels. The CY is divided into two parts. The section which is closer to the berth is dedicated to the export (hence, outbound) containers, and the other part is for the import/inbound ones. The containers are stored in the CY and several yard cranes (YC) re-allocate them internally within the CY (known as housekeeping/re-handling) or load/unload them to/from external trucks (ET), which finally deliver the containers to their owners (consignees) in the factories or warehouses.

Container terminal operations are typically divided into three main areas, namely seaside, storage, and transfer [24], [25]. The seaside is a section where incoming ships arrive at the seaport and the terminal operator allocates berth positions and QC(s) to each vessel. This is known as the integrated berth and crane allocation problem (I-BCAP), where a detailed review is provided in [11]. A ship's load is represented by its number of containers, where each box of container is measured as a twenty feet equivalent unit (TEU), approximately six meters long, while the longer container is forty feet (FEU). The typical decisions in BCAP are allocation of berth positions and QCs to the incoming ships [11]. In more detailed levels, the terminal planners determine the exact positions of outbound containers should be at the vessels, which usually identified by bays and tiers [11].

The storage operations is the management of containers in the CY and we refer to [9] for a review on this specific operations. A container position in the CY is defined by its row, bay, and tier, which is comparable to $x - y - z$ axis in

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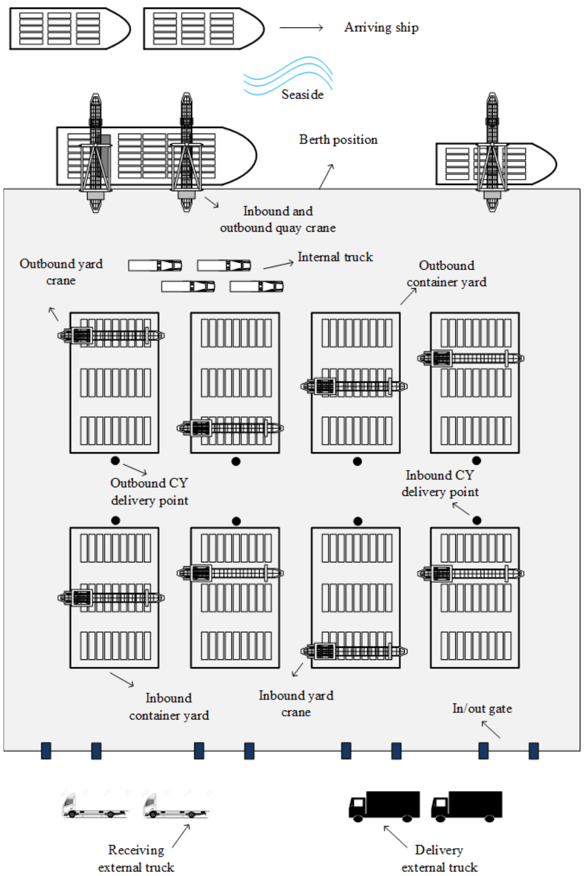

Fig. 1. A general layout of a container terminal. Incoming ships can berth at different berthing position and several QCs can be allocated to the berthed ship. ITs carry the containers from the QCs to the CYs to be handled by the YCs, and vice versely in the other direction. The ETs are used to transport containers externally to the hinterland.

the Cartesian systems. There are three typical decisions in this sub-operations. Firstly, the positions where a group of containers should be stored. Secondly, the allocation of YC to handle them from/to IT. The container placement at the right positions in the CY is important. Thirdly, if an ET comes to the CY for pick-up operations, and the targeted container is not in the top tier, the terminal operators has to assign YC to re-arrange the containers positions. This situation therefore leads to the third process, which is known as housekeeping/marshalling. Due to its cost-inefficiency, marshalling is highly avoided in terminal operations [9].

The seaside and storage sub-systems are connected with the transfer operations, whose review is discussed in [10]. In this sub-operations, transporters handle the container delivery between QC and CY area. Common transporters in container terminals are rail-mounted gantry crane (RMGC), rubber-tyre gantry crane (RTGC), reach staker (RS) and internal trucks (IT). In this paper, we will focus on the IT. The decisions in this sub-sytems are the allocation of IT to serve as the link between QC and YC, and vice versa. The scheduling of IT to QC or YC is also important, therefore we found significant works of vehicle routing problems (VRP) in the container terminals. The most common method for scheduling is currently performed in daily basis, where the schedule of IT is created at the beginning of each day, based on ships' arrivals, outbound containers' stowage plans, and inbound containers' external delivery. In this setting, variations of these three inputs are often neglected [10].

In accordance with the complex seaport operations, the aim of the terminal operators is to operate the container terminal efficiently in the least possible cost with minimal dissatisfaction level from its customers [16], [17], [22], [25]. The purpose of the terminal operators can be summarized into container delivery whose destinations are to: 1) CY, for the inbound boxes, and 2) vessels, for the outbound boxes [16], [17]. The storage configuration of the inbound containers in the CY and of the outbound containers in the vessels are known as the storage plan and stowage plan, respectively [13], [30].

The complexity of container terminal operations has been studied extensively in literature and some literature reviews in this topic are presented in [24], [25]. The container terminal operations in the three sub-systems as above are dependent to each other. For instances, the exact deployment of IT can only be executed after the QC and YC allocation are definitive. For allocating cost-effective QC and YC themselves, the detailed knowledge on the schedule is required.

To make an optimal operations planning, the entire sub-systems in the terminal have to be considered [16], [17]. However, in practice, the complexity of the operations makes the state-of-the-art research in container terminal operations limited only to each sub-system [24], [25]. Excellent reviews for the seaside, storage, and transfer operations are provided in [9]–[11]. To the best of authors knowledge, there is no literature review dedicated for the container terminal integrated operations.

In the practical level, the terminal operators almost exclusively rely on the non-integrated decision making process to produce planning in each sub-system of the terminal operations. The QC, YC, and IT are allocated according to the first-come first-served (FCFS) criteria, which does not guarantee the optimality of the planning [9]–[11], [22].

There are indeed several works on the integrated terminal operations such as [1], [2], [5], [16], [17], [28]. Although the end-to-end operations process is modeled in [1], [2], the problems are more in the tactical level, which relate to resource allocation. In these papers, resource allocation is expressed as percentage of servers (equipment) capacity to transport containers to the subsequent server. In [17], a genetic algorithm (GA)-based pseudo code is used to create the planning. The non-existence of mathematical models makes the test-ability of the problems can not be guaranteed.

One noticeable drawback of the state-the-art models is the static approach, in which the inputs are known apriori. In the state-the-art (static), operations research is the main technique used in the container terminal operations modeling [9]–[11], [24], [25], and linear programming (LP) can be applied for solving the equipment allocation in the seaport. One assumption of LP is the inputs have to be deterministic, which implies that the changing of inputs during solution searching is not permitted. This means that real-time input changing is not accommodated. In [27], a dynamic programming technique is used to find the optimal policy of a berth allocation problem. The models in [23] and [27] incorporate stochastic aspect, which is done through some statistical functions for the inputs (ship arrivals, berth positions and cranes availability). But, the problem itself is modeled in a static way. The consequence is, for instance, no new ship can be added to the pre-determined stochastic set of ship arrivals during solution searching.

For instance, in [16], the IT are pre-determined before the schedule of QC, IT and YC are solved through linear programming technique. In fact, during terminal operations, there are chances of disruption of the equipment conditions [10], [22]. This dynamic behavior is not yet represented in [16]. The discussion of modeling approach in seaport operations is heavily discussed in [7], which concludes that the dynamical approach is more suitable to capture the changing environment. A discrete-event system (DES) model is developed in [7] and it is important to note that the DES here is not the same terminology that commonly used in operations systems, where some probabilistic functions are employed to represent the random behavior of systems. The latter approach is know as discrete-event simulation as exemplified in [26].

Some works in terminal operations have tried to incorporate dynamical modeling as studied in [5], [28], [29]. In these three works, a partially dynamical aspect in the lower-level controllers is included, which is the detail movement of QC, YC and IT/rail in terminal. However, prior to this step, the allocation of the three equipment to berth and CY are solved from a static model so-called the higher-level controllers, where a similar concept of LP is used to find the solutions. In [5], [28] the mixed-integer linear programming model (MILP) technique is used to find the optimal allocation of QC, YC, and rail.

This setting does not completely capture the real equipment allocation problems in the terminal. In the beginning of each planning period, the terminal operators allocate the QC, YC, and IT based on available information in the terminal, namely vessel arrivals and CY storage status. But later on, the equipment detail scheduling in [5], [28] is handled via a linear programming technique which in reality is static. The changing in berth and CY configuration will be seen by the terminal operators as a new possible storage/stowage plan, and will subsequently change the entire previous allocation and scheduling of QC, YC, and IT. This dynamics behaviour in container terminal operations is not considered in the modeling framework in [5], [16], [28].

As opposed to the static modeling, we employ a dynamical model based on discrete-event systems (DES) in this paper. The DES framework is suitable for describing the terminal operations problems, since each job completed by either QC, YC, or IT can be seen as a discrete-event time step [12]. The DES is suitable in operational and tactical level decision making [7]. The example can be found in [1], [2], [28], [29]. While for the strategical level decision making, such as capacity planning, the use of static modeling is more suitable. Strategic decision making is usually done less frequently than the tactical and operational ones. Therefore, one does not need to frequently measure the states as they evolve at each time/event, as in the tactical/operational cases. Instead, the analysis is only based on the length of the planning horizon, which is indeed one of the characteristic of static (LP) modeling techniques.

For terminal operations, the DES modeling framework has been successfully applied to a sub-system of terminal operations, namely the berth and quay crane allocation [6], [7]. As stated in [6], [7], the generalization of the work to the complete terminal operations remains open. The lack of dynamical models in container terminal operations as mentioned before has motivated us to study dynamical modeling in integrated terminal operations. In particular, we also use finite state machine (FSM) framework, where the DES formulation is represented in each of the state machine formulation. As discussed in [21], FSM framework incorporates a set of several discrete variables. In this regard, the FSM suits our problems where the complex systems of terminal operations can be represented by discrete variables.

As our first main contribution of this paper, we extend the modeling framework in [6], [7] to the integrated container terminal setting. Subsequently, we propose a simultaneous allocation and scheduling of QC, YC, and IT in the operations planning as our second contribution. The approach is based on the model predictive algorithm (MPA) as presented in [6], [7] and its efficacy is demonstrated in a real experiment in Jakarta's main seaport, Tanjung Priok. The MPA is based on model predictive control (MPC) which is often used to find optimal solution of DES models [14]. Recently, a preliminary mathematical analysis of the MPA algorithm has been reported in [8]. This proposition is a prominent aspect that can not be completely achieved in [5], [28], where only the lower-level controllers of equipments' scheduling are modeled dynamically while the allocation itself is done via a deterministic and static perspective with linear programming techniques.

The rest of this paper is organized as follows. After research motivation is presented in the first section, Section II is devoted for the explanation of container terminal operations, which will serve as the foundation of the dynamical mathematical models presented in the Section III. The allocation strategy of the models is given in Section IV. Subsequently, we describe the simulation set-up and results in Section V. The simulations use the MPA method from our previous research and the benchmarking methods from the state-of-the-art literature. Finally concluding remarks and possible future works are discussed in Section VI.

II. Container Terminal Operations

We present the generalization of integrated container terminal operations framework in this section. The framework will serve as the basis for the dynamical models development in the Section III.

A. General Assumptions

Based on the previous studies in [1], [16], [17], [28], [29], we summarize the integrated container terminal operations which is defined as the sequential series of processes to unload inbound containers from ships to CY, and correspondingly,

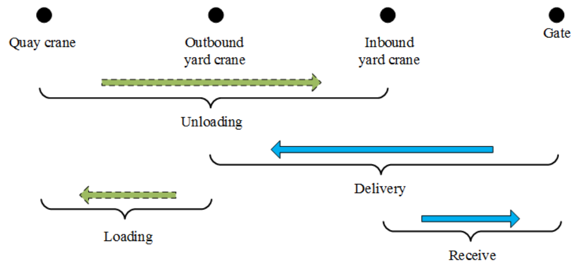

Fig. 2. An illustration of an integrated container terminal operations. The bracket refers to the two (begin and end) parties which are involved in every process. The arrows show the direction of container flow. The green-dashed arrow refers to transportation process of a container by an IT. The blue-solid arrow represents the transportation of a container by an ET, which is not considered in this paper.

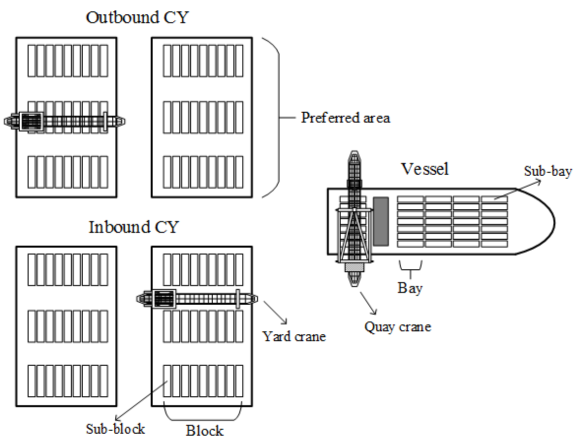

Fig. 3. A top view layout of the CY (left) and vessel (right). Both of CY and vessel serve as temporary storage in a container terminal. CY is usually divided into inbound (import) and outbound (export) sections, where the storage positions are identified by blocks. Vessels carry both of import and export containers where the storage positions are identified by bays. CY and vessels are served by YCs, and QCs, respectively.

the set of processes to load outbound containers from CY to vessels, where in both types of operations, the vessels are already allocated berth positions in the terminals. The schematic diagram of an end-to-end container terminal operations is depicted in Figure 2.

This paper discusses the loading and unloading and loading processes in container terminals which will be focused for the inbound containers. The reasoning for the omission of outbound containers is presented in Section III. The receiving and delivery operations, which are performed by the ET, are neglected in this research. This limitations operations framework can also be found in [5], [16], [28] due to complexity of ET operations, which includes random aspects of time to pick and deliver containers to/from hinterlands [20].

Regarding the handling operations of containers, the goals of the terminal operators are to, firstly, locate the inbound containers into import sub-blocks in CY, which is known as the unloading process, and secondly, place the outbound containers into vessels, which is reversely the loading process. The output the first and second goals are the CY's storage plan and vessel's stowage plan, respectively. Examples of operations and modeling for CY's storage and vessel's stowage plan are discussed in [13] and [30], and the illustrative example is given in Figure 3.

TABLE I

THE SUBSET OF INBOUND CONTAINERS HANDLING SEQUENCE FROM A VESSEL'S BAYS. THE SEQUENCE ARE CREATED BY THE TERMINAL OPERATORS AND BASED ON THIS INFORMATION, THE STEVEDORE PICK THE CONTAINERS FROM THE VESSEL AND TRANSPORT THEM INTO APPROPRIATE CY BLOCKS WITH ITS

Sequence	*Container ID*	*Vessel bay*	*Row*	*Tier*
1	MAL-110	53	1	3
2	MAL-113	53	1	2
3	MAL-109	53	1	1
4	GOT-580	52	3	3
5	GOT-582	52	3	2

TABLE II

THE SUBSET OF OUTBOUND CONTAINERS HANDLING SEQUENCE FROM SEVERAL BLOCKS IN THE OUTBOUND CY. THE SEQUENCE ARE CREATED BY THE TERMINAL OPERATORS AND BASED ON THIS INFORMATION, THE STEVEDORE PICK THE CONTAINERS FROM THE CY'S BLOCKS AND TRANSPORT THEM INTO APPROPRIATE VESSEL'S BAYS WITH ITS

Sequence	*Container ID*	*CY block*	*Row*	*Tier*
1	HUT-904	12	5	3
2	HUT-907	12	5	2
3	HUT-910	12	5	1
4	MAE-881	11	2	3
5	MAE-880	11	2	2

In a ship, the smallest unit to store containers is the sub-bay, whose capacity is more than 5 TEU [30]. A group of several sub-bays is the bay. The containers in the seaside are handled by QCs. Some QCs work on several berthed-ships, and in practice the QCs do not have some specific working areas, as long as their movement do not interfere among each other [11]. In this research, we assume that a bay at a vessel is allocated by a QC which handles the container from the beginning of unloading/loading until finished.

A container yard consists the areas for the outbound and inbound containers. The smallest unit to place containers in the CY is the sub-block, whose capacity is more than 20 TEU [30]. A group of some sub-blocks in the same ordinate is defined as a block, where a set of blocks in physically marked region is the preferred area, which is usually designated for specific customers (shipping liners). A yard crane is assigned to some specific specific preferred areas. An inbound YC cannot move to the outbound CY preferred areas, and vice versa. We assume in this research that a YC is allocated to a specific block in the CY. Figure 3 shows an illustration of a CY configuration.

A storage plan is the set of decisions that the terminal operators know to which CY's sub-blocks the inbound containers will be allocated. On the other hand, a stowage plan is the information on vessel's sub-bays where the outbound containers will be allocated. The inputs to create those two plans for the inbound and outbound containers are the handling sequences, which are illustrated in Tables I and II, respectively.

The direction of handling sequence in Tables I and II are from and to vessels, respectively. In Table I the terminal operators have to create CY storage plan, while in Table II, the vessel stowage plan need to be devised. The range of container numbers that can be handled each ship is 1,000 to 10,000 TEU per ship [7]. The two examples in Tables I and II do not necessarily belong to the same vessel. The alphabetical characters in the container ID in Tables I and II usually refer to the customers/owners of the containers. As have been explained in Section I, the container handling sequences may dynamically change. Therefore, the information given to load or unload containers has to be updated regularly based on latest condition in the field.

For modeling purpose, we assume that the X, Y, and Z coordinate (position) of each inbound container in the CY blocks and each outbound container in the vessel bays are not stipulated. Instead, we determine the CY's sub-block and the vessel's sub-bay to which the containers will be located, and the exact placement of containers in CY's blocks and in vessel's bays are assumed to be properly managed. This limitation is also found in [2] and [5]. We believe that the dynamical models of integrated terminal operations which still in the initial phase in this research will be too complicated if this setup is considered. For detail treatment in the modeling of CY's storage plan and ship's stowage plan, we refer interested readers to [13] and [30].

The assumptions that we use for the modeling purpose in this paper are based on the definition from [1], [16], [17], [28], [29]. The modeling framework in this research is in the tactical level which usually deals with the allocation of equipment [9]. The more detail decision making process is categorized as the operational level, which requires further works in the modeling.

B. Job Definition

As explained in the previous subsection, the container handling sequence is performed by three main equipment in the terminal, namely QC, YC, and IT. Correspondingly, we define a job as an operation/work that is either 1) to unload each of inbound container from the vessel to the inbound CY; or 2) to load each of outbound container from the outbound CY to the vessel. For the former one, Table I presents a subset of jobs for the inbound container handling sequence, and similarly, for the latter one, Table II shows a subset of jobs for the outbound container handling sequence. In both cases, a job is performed by the terminal operators by pairing a QC and a YC, which is connected by an IT, as exemplified in Figure 4.

In this paper, we focus mainly on the modeling and optimization of the former one, e.g., the unloading processes of inbound (import) containers. Hence we incorporate detailed model for the inbound container sequence while the outbound one is simplified by a lumped model.

Figure 4 illustrates the container handling sequence in both types of job. As shown in Figure 4a, *an unloading job* for the inbound container is initiated by the unloading of an assigned container with the prescribed QC from the vessel to the empty IT chassis, which is mostly located beneath the QC. Subsequently, the loaded IT brings the inbound container to a pre-determined inbound CY's sub-block location before it is picked up by the allocated YC. This particular job is completed when the YC has successfully placed the container into the allocated sub-block in the inbound CY.

The reverse process is applied for the outbound container as shown in Figure 4b. *A loading job* starts when a YC at the export CY picks up an already assigned outbound container from the outbound CY and places it on an empty IT's chassis, which is normally situated under the YC. The loaded IT will then transport the outbound container to the allocated QC. When the QC is ready, it takes the container from the IT and brings it to a prescribed sub-bay location in the vessel. Once the outbound container is positioned at the right location in the vessel, the loading job is completed.

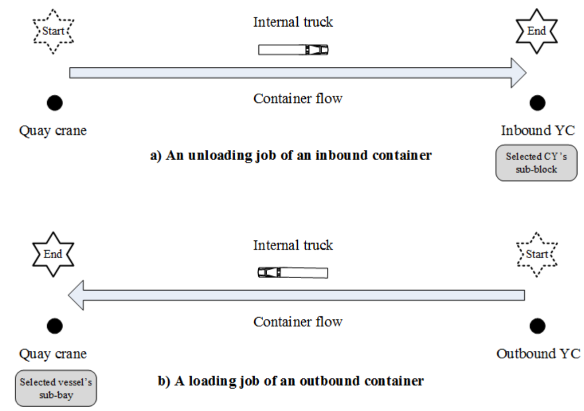

Fig. 4. An illustration of two kinds of job available in the integrated container terminal operations. An unloading job refers to the terminal operations of an import/inbound container with the start and end operations at QC (vessel's sub-bay) and YC (CY), respectively. A loading job refers to the handling of an export/outbound container with the start and end operations at YC (CY) and QC (vessel's sub-bay), respectively. In both types of jobs, internal trucks need to be allocated to transport the containers between the two cranes.

It is important to note that the YC in the unloading job is different with the YC used in the loading job, while a QC can perform operations both for unloading and loading jobs.

The same job definition is also used in the works of [5], [16], [28], where IT act as connectors between QC and YC for handling the containers. As have been discussed in Section I, the allocation and scheduling are done separately in all these works. Particularly, the dynamics of the integrated container terminal operations problems is only used for the scheduling. In this paper, we perform simultaneous allocation and scheduling where the process' dynamics play an important role in both types of decision.

We also assume in this research that the detail movement of the QC, YC, and IT is not included in the modeling. For instances, in the operations of seaside cranes, the hoist and release operations are not considered. Instead, we will later assume that each QC and YC operations requires a constant operational time. The speed of each IT when transporting is also assumed to be constant.

III. Dynamical Modeling of Integrated Container Terminal Operations

As have been introduced in Section I, we follow the modeling framework in [7] using DES for describing the operations of the cranes and trucks and it is combined with a finite-state machine (FSM) for distinguishing between the loading and unloading jobs. The DES model in our present work uses a discrete event time $k \in \mathbb{N}$ which corresponds to the start or initiation of an unloading or a loading job as explained in Section II-B.

As briefly mentioned before, we focus the DES modeling effort on the inbound handling sequence in the present work while for the outbound sequence, we simplify the DES modeling of it by simply assuming a block of area in CY instead of detail sub-blocks of area as in the inbound case.

The involvement of external parties (e.g. the external trucks (ET)) adds to the complexity of the DES modelling. Due to the schedule constraints of the departing vessels, the terminal operators usually apply stricter schedule for ET to deliver outbound containers than for ET to bring the inbound containers to the hinterland [20]. Some traditional terminals, as later shown in our case in Section V, do not have the truck appointment systems for notifying IT that the import containers are ready for clearance from the CY. The random aspect on hinterland container transport by trucks introduces complexity for the inbound operations [20]. Consequently, we focus on a detailed modelling of the inbound CY in this paper that represents closely to the integrated operations of container terminals in practice.

In the following subsections, we will firstly described the general setup of the DES and FSM model. It is followed by the DES-FSM model development of the integrated terminal operations. Lastly, we present the predictive model that is used for the development of model predictive control along with the associated cost function.

A. General DES & FSM Setup

Throughout the paper, we will use various mathematical notations in our modelling and methods that are summarized in Table III. The discrete-event time is denoted by k that corresponds typically to the start of a discrete event in the operations, such as, the start operation of a QC, IT or YC.

Let us define the variables of sets involved in such integrated operations based on the three main operating areas in the terminal, namely, the seaside (berth), the storage (CY), and the transporter (IT). For the seaside operations, $\mathcal{S}(k)$ denotes the set of available sub-bays in ships at an event time k. The set of all sub-bays in all berthed vessels is denoted by $\mathcal{S}_{\text{tot}}(k)$. As before, it follows that $\mathcal{S}(k) \subset \mathcal{S}_{\text{tot}}(k)$ for all discrete-event time k. We emphasize here that both $\mathcal{S}(k)$ and $\mathcal{S}_{\text{tot}}(k)$ accumulate sub-bays information from all berthed vessels at any given discrete-event time k.

As discussed in the Introduction, the seaside and the storage operations are connected by the transporters. While there are different forms of transporter, we restrict ourselves to the use of internal trucks (IT) in this work since it is still the dominant mode of internal transportation in many terminals worldwide, particularly, those in the developing countries [10], [20]. We denote the set of indices of internal trucks by $\mathcal{T}_{\text{tot}} = \{1, 2, \ldots, L\}$.

It has been mentioned before that there are two jobs for the import/inbound and export/ outbound containers and we will associate each job with a state in the FSM. Correspondingly, we denote $\mathcal{J} = \{l, u\}$ as the state space of the FSM where l refers to the state of loading job and u corresponds to the state of unloading job. The set $J(k) \subset \mathcal{J}$ denotes the state of the FSM at event time k. The guard condition for the FSM will be given later in subsection III-B which is based on the state variables of the DES.

TABLE III

LIST OF MATHEMATICAL NOTATIONS USED IN THE DYNAMICAL MODELS OF INTEGRATED CONTAINER TERMINAL OPERATIONS

Notation	*Description*
	Decision variables
$u(k)$	Control variable for assigning job from the set $\mathcal{J}(k)$
$t(k)$	Control variable for assigning an inbound truck from the set of IT $\mathcal{T}_{\text{in}}(k)$
$\bar{t}(k)$	Control variable for assigning an outbound truck from the set of outbound IT $\mathcal{T}_{\text{out}}(k)$
$s(k)$	Control variable for assigning a vessel's sub-bay from/to which an inbound/an outbound container is sent/delivered
$n(k)$	Control variable for assigning a CY sub-block from the set $\mathcal{Y}(k)$ for inbound operations
	Parameters
L	The number of inbound internal trucks
M	The number of positions of QCs
N	The number of positions of inbound CYs
v	Average speed of an IT
$\mathrm{d}(a, b)$	Distance between point a and b in the terminal
α	Average time needed by a QC to handle a container
β	Average time needed by a YC to handle a container
	State variables
$x_t^i(k)$	The state variable of the position of the i-th IT
$x_q^i(k)$	The state variable of finishing time of the i-th QC
$x_c^i(k)$	The state variable of finishing time of the i-th YC
	Sets
$\mathcal{S}_{\text{tot}}(k)$	Set of all sub-bays in ships at event time k
$\mathcal{S}(k)$	Set of available sub-bays in ships at event time k
$\mathcal{S}_{\text{arr,tot}}(k)$	Set of new sub-bays from newly berthed vessels
$\mathcal{S}_{\text{arr,empty}}(k)$	Set of available sub-bays from newly berthed vessels
$\mathcal{S}_{\text{dep,tot}}(k)$	Set of new sub-bays from recently departed vessels
$\mathcal{S}_{\text{dep,empty}}(k)$	Set of available sub-bays from recently departed vessels
$\mathcal{T}_{\text{tot}}$	Set of all internal trucks
$\mathcal{T}_{\text{in}}(k)$	Set of all available IT assigned for unloading jobs at event time k
$\mathcal{T}_{\text{out}}(k)$	Set of all available IT assigned for loading jobs at event time k
$\mathcal{J}$	State space of the FSM for jobs: loading job (l) and unloading job (u)
$J(k)$	The state of the machine/job at event time k
	Indices
k	Event time
K	Planning horizon time
j	Index of the first earliest available QC
l	Index for a loading job
u	Index for an unloading job

At each event-time k, when a job is assigned (e.g., loading or unloading), all assigned internal trucks proceed to their next position. As described before, we will focus on the detailed modeling for the unload jobs for the inbound containers. Therefore, we assume that the inbound and outbound CY are located in different area of the terminal, as commonly found in practice [9]. We also assume that there is only one block of outbound CY with its own dedicated crane. At any given event time, we have the set $\mathcal{T}_{\text{out}}$ which is a set of trucks that are positioned and readily available at the outbound CY. Hence, in this paper, the outbound job depends only on the availability of cranes in QC and of sub-bays in the vessel. When a loading job is executed, we can replenish the truck in $\mathcal{T}_{\text{out}}$ to replace the assigned outbound truck. However, for the set of inbound IT $\mathcal{T}_{\text{in}}$, they are not necessarily available at all cranes of QC. Thus when an unloading job is executed, we need to allocate a truck from $\mathcal{T}_{\text{in}}$ that will move from its current position in the terminal to the assigned QC crane. Note that at any given event time k, the sets of IT satisfies the following relations

$$\mathcal{T}_{\text{tot}} = \mathcal{T}_{\text{in}}(k) \cup \mathcal{T}_{\text{out}}(k) \tag{1}$$

with $\mathcal{T}_{\text{in}}(k) \cap \mathcal{T}_{\text{out}}(k) = \emptyset$. Due to this conservative relation, for the rest of this paper, we will only describe the dynamics of $\mathcal{T}_{\text{out}}(k)$ while the state of $\mathcal{T}_{\text{in}}(k)$ can be deduced directly from (1).

For each truck index $i = 1, \ldots, L$, we denote

$$x_t^i(k) \in \{0, 1, 2, \ldots, M, M+1, M+N\} \tag{2}$$

as the position state of $i-$th truck where 0 refers to the outbound CY position, $1, \ldots, M$ refer to each of M cranes of QC and the rest represent each of N cranes in the inbound CY. For example, $x_t^i(k) = 2$ corresponds to the state of $i-$th truck at event time k which is located at the 2nd crane in QC while $x_t^i(k) = M + 2$ means that the $i-$th truck is located at the 2nd yard crane in the inbound CY at event time k. The position of each truck x_t^t is initialized at $x_{t,0}^i \in \{1, 2, \ldots, M, M+1, M+N\}$ for all $i \in \mathcal{T}_{\text{in}}(0)$ and $x_{t,0}^i = 0$ otherwise.

Following the modeling framework for berth and quay-crane allocation in [7], the state variables will be given by the finishing time of the two equipment (the cranes in both QC and YC) and the position of all IT at each event-time k. Namely, $x_t^i(k)$ describes the position state of the $i-$th IT at event-time k, $x_q^i(k)$ refers to the finishing time of the $i-$th QC at event-time k and $x_c^i(k)$ denotes the finishing time of the $i-$th yard crane in the inbound CY at event time k.

B. DES-FSM of Integrated Container Terminal Operations

Based on the description of variables and sets in the previous subsection, we can now present the DES-FSM modeling of integrated container terminal operations. Firstly, a new event time k is triggered whenever a QC has finished unloading/loading job from/to an assigned IT from the previous event time $k-1$. Thus the actual time associated to the new event time k is given by

$$j = \arg\min_i [x_q^i(k-1)]. \tag{3}$$

Simultaneously, a guard condition is used to determine the transition of state machine at the new event time k. Before defining the guard condition, we denote $\mathrm{d}(a, b)$ as the distance between the two points a and b in the container terminal, and the route from a to b has to follow pre-defined possible paths in the terminal. We also assume that the operations time needed by a QC to handle a 20-feet container at the sub-bay $s \in \mathcal{S}$ (loading or unloading) is described by the function $\mu : \mathcal{S}_{\text{tot}} \to \mathbb{R}_+$. It is dependent on the location of the sub-bays in the vessel, e.g., the Cartesian coordinate of the sub-bays on the vessel. Using these notations and given j as in (3), the guard condition and the transition of state machine are as follows.

Guard: If there exist $n \in \{1, \ldots, N\}$, $s \in \mathcal{S}_{\text{tot}} \backslash \mathcal{S}(k-1)$ and $\ell \in \mathcal{T}_{\text{tot}} \backslash \mathcal{T}_{\text{out}}(k-1)$ such that

$$\begin{aligned} x_c^n(k-1) < x_q^j(k-1) &+ \mu(s) \\ &+ \frac{1}{\upsilon}[\mathrm{d}(x_t^\ell(k-1),\ j\text{-th QC}) \\ &+ \mathrm{d}(j\text{-th QC},\ n\text{-th YC})] \end{aligned} \tag{4}$$

then

$$J(k) = u, \tag{5}$$

or otherwise

$$J(k) = l, \tag{6}$$

where υ is the constant velocity of an IT.

Roughly speaking, the inequality (4) in the guard condition means that there will be an available yard crane in the inbound CY (the n-th CY crane) at the next event time when we allocate the ℓ-th truck (which is not currently located in the outbound CY) to unload a container at the s-th sub-bay in the vessel from their current position $x_t^\ell(k-1)$ to the final destination of the n-th YC. As we have explained in Section II-B, an inbound container can be processed in the inbound CY only when both the YC and the IT are ready. When these conditions hold, then the empty IT moves from its current position to the QC, holds its position at QC until it has received the container from the crane, and subsequently the loaded IT proceeds on to the designated YC.

After the new event time and the associated state machine have been updated, we proceed to the decision making process. Based on the guard condition as before, if $J(k) = l$ then three decision variables for the outbound process have to be made, namely, the outbound internal truck $\bar{t}(k)$ taken from $\mathcal{T}_{\text{out}}(k-1)$, the internal truck $t(k)$ taken from and $\mathcal{T}_{\text{tot}} \backslash \mathcal{T}_{\text{out}}(k-1)$ for marshalling trucks in $\mathcal{T}_{\text{out}}(k)$ and the vacant sub-bay in the vessel $s(k)$ taken from $\mathcal{S}(k-1)$.

Otherwise, when $J(k) = u$ then three decisions for the inbound process have to be made. They are the inbound internal truck $t(k)$ taken from $\mathcal{T}_{\text{tot}} \backslash \mathcal{T}_{\text{out}}(k-1)$, the available yard crane $n(k)$ that satisfies (4) and the inbound container sub-bay $s(k)$ in the vessel that belongs to $\mathcal{S}_{\text{tot}} \backslash \mathcal{S}(k-1)$. We note that as there can be more than one solution of n and ℓ that satisfy (4), a combinatorial optimization on the truck and the crane may be required to optimize the operations. In the next section, we will return back to the allocation strategy.

Subsequently, after these decision variables (depending on the particular job) have been taken, the state variables x_t^i, x_q^i, x_c^i and the dynamic sets $\mathcal{S}$, $\mathcal{T}_{\text{in}}$ and $\mathcal{T}_{\text{out}}$ are updated as follows.

On the one hand, when the system is in the loading mode with $J(k) = l$, we have the following update rule:

$$x_q^j(k) = x_q^j(k-1) + \mu(s(k)) + \frac{1}{v}\mathrm{d}(j\text{-th quay, outbound CY crane}) \quad (7)$$

$$x_t^{\bar{t}(k)}(k) = j, \quad x_t^{t(k)}(k) = 0 \quad (8)$$

where j is as in (3), $\mu(s(k))$ denotes the crane operations time for loading the container to the sub-bay $s(k)$ and

$$x_q^i(k) = x_q^i(k-1) \quad \forall i \neq j \quad (9)$$

$$x_c^i(k) = x_c^i(k-1) \quad \forall i \quad (10)$$

$$x_t^i(k) = x_t^i(k-1) \quad \forall i \neq \bar{t}(k) \text{ or } t(k) \quad (11)$$

$$\mathcal{T}_{\text{out}}(k) = \mathcal{T}_{\text{out}}(k-1) \cup t(k) \backslash \bar{t}(k) \quad (12)$$

$$\mathcal{S}(k) = \mathcal{S}(k-1) \backslash s(k) \cup \mathcal{S}_{\text{arr,empty}}(k) \backslash \mathcal{S}_{\text{dep,empty}}(k) \quad (13)$$

$$\mathcal{S}_{\text{tot}}(k) = \mathcal{S}_{\text{tot}}(k-1) \cup \mathcal{S}_{\text{arr,tot}}(k) \backslash \mathcal{S}_{\text{dep,tot}}(k), \quad (14)$$

where $\mathcal{S}_{\text{arr,tot}}(k)$ and $\mathcal{S}_{\text{arr,empty}}(k)$ is the set of new sub-bays and available sub-bays from the newly berthed vessel(s), respectively, and correspondingly, $\mathcal{S}_{\text{dep,tot}}(k)$ and $\mathcal{S}_{\text{dep,empty}}(k)$ are those from the recently departed vessel(s).

On the other hand, when the unloading job occurs (e.g., $J(k) = u$), these variables are updated according to

$$x_q^j(k) = x_q^j(k-1) + \mu(s(k)) + \frac{1}{v}\mathrm{d}(x_t^{t(k)}(k-1), j\text{-th quay}) \quad (15)$$

$$x_c^{n(k)}(k) = x_q^j(k-1) + \frac{1}{v}\mathrm{d}(x_t^{t(k)}(k-1), j\text{-th quay}) + \mu(s(k)) + \frac{1}{v}\mathrm{d}(j\text{-th quay}, n(k)\text{-th CY crane}) + \beta \quad (16)$$

$$x_t^{t(k)}(k) = n(k) + M \quad (17)$$

where j is as in (3), $\mu(s(k))$ gives the crane operations time for unloading the container from the sub-bay $s(k)$ and

$$x_q^i(k) = x_q^i(k-1) \quad \forall i \neq j \quad (18)$$

$$x_c^i(k) = x_c^i(k-1) \quad \forall i \neq n(k) \quad (19)$$

$$x_t^i(k) = x_t^i(k-1) \quad \forall i \neq t(k) \quad (20)$$

$$\mathcal{T}_{\text{out}}(k) = \mathcal{T}_{\text{out}}(k-1) \quad (21)$$

$$\mathcal{S}(k) = \mathcal{S}(k-1) \cup s(k) \cup \mathcal{S}_{\text{arr,empty}}(k) \backslash \mathcal{S}_{\text{dep,empty}}(k) \quad (22)$$

$$\mathcal{S}_{\text{tot}}(k) = \mathcal{S}_{\text{tot}}(k-1) \cup \mathcal{S}_{\text{arr,tot}}(k) \backslash \mathcal{S}_{\text{dep,tot}}(k). \quad (23)$$

In contrast to the quay crane operations, the operations time for the yard crane is approximately constant and is given by β (c.f. (16)). It is assumed here that the yard cranes are well-placed in the container yard such that the operations time for unloading any container to the yard is relatively constant.

Roughly speaking, the dynamics of the state variables and the sets of IT and sub-bays in (7)-(23) can be described qualitatively as follows.

During the loading mode, Eq. (7) describes the finishing time of loading process at the j-th quay crane that comprises of the standard crane operations time and the travel time of the internal truck $\bar{t}(k)$ from outbound CY to the crane. The latter is described in (8) along with the marshalling of an IT truck $t(k)$ to the outbound CY. The rest of the state variables of the quay cranes, yard cranes and internal trucks are the same as the previous event time as presented in (9)-(11). Due to the use and marshalling of trucks from and to the container yard, respectively, the set of available outbound trucks $\mathcal{T}_{\text{out}}$ is updated accordingly as in (21). Lastly, the used sub-bay is removed from the set of available sub-bays in the vessel $\mathcal{S}(k)$ in (22).

Similarly, for the unloading mode, Eq. (15)-(17) describe the unloading process. In (15), the finishing time of j-th quay crane x_q^j is updated according to the unloading operations time $\mu(s(k))$ and the travel time from the current position of $t(k)$-th truck to the crane. The finishing time of the $n(k)$-th yard crane is computed in (16) based on the accumulation of total quay crane operations time, the travel time from the j-th quay crane to the yard crane and the yard crane operations time β. The final position of $t(k)$-th truck position will be at the $n(k)$-th yard crane as given in (17). The rest of equations (18)-(22) can be understood similarly to those for the loading job as before.

The transition of this finite state machine is shown in Figure 5. The illustration explains the guard condition and the state machine transition as given in (4).

Similar to our previous work in [7], the model considers the set dynamic of available trucks and of ship's sub-bays at each event time k. The dynamic aspect of these sets is not yet considered in the state-of-the-art approaches, as found for example in [16], [17]. In these works, it is commonly assumed that the entire information is known and can directly be used in its entirety for the whole planning horizon. Whereas in practice, the availability of vessels' bays and trucks in a terminal is very dynamic which can be due to disruptions, such as, the equipment breakdowns or the non-existence of human operators [3], [13], [19] or due to an incomplete/incorrect container manifest in the vessel. The integration of the above model with the following model predictive allocation strategy will allow us to monitor the operations and to adjust the planning in real-time in dealing with such dynamically changing environment.

IV. Model Predictive Allocation Method for Integrated Terminal Operations

In this section, we will use the integrated terminal model from the previous section as a predictive model for optimizing the allocation of trucks, cranes and sub-bays. We will present the adaptation of model predictive allocation strategy as presented in [7] to such integrated terminal operations.

In general, the model predictive allocation strategy can be described as follows. As shown in the previous section, at each event time k, we have to make a decision for a number of operational variables according to the admissible jobs at the time and based on which, the state will transition to the next state.

Instead of making decision to these variables based only on the information at each event time k, we can use the model to predict the outcome of the future states within a finite horizon of event time when a given sequence of decisions is being evaluated. Subsequently, the first action from the optimal sequence of decisions can be implemented in the terminal operations for the current event time. This allocation strategy is recursively done for all subsequent events. We note that the update of the states based on the available information at any given time ensures that the model will always be up-to-date with the current terminal operations.

We will firstly describe the objective functions that will be optimized by our proposed model predictive allocation algorithm. We will then describe the algorithm and the pre-conditioning steps to solve the recursive optimization problem. As there are two sets of decision variables that correspond to two possible jobs, the predictive model will take into account all possible future machine states that depend on the outcome of a particular sequence of decisions within a finite horizon of event time.

A. Cost Function

The cost function used to evaluate policies in our dynamical models is related to the operations time. The use of operations time in the cost function for the optimization has been used extensively in literature, see for instance, [17]. Other types of cost function, such as, the length of queue [5] and the energy expenditure [16], [28], can be considered as well in our setting as the dynamical model described in the previous section can include information on the queue of IT and fuel consumption of IT by tracking the distance travelled.

We recall from the previous section that $n(k)$ is one of the decision variables on the yard crane unit that will be assigned for processing an inbound container in CY. Let us denote $w(k)$ the earliest available QC at the next event time k for unloading/loading job based on the available information/predicted state at $k-1$:

$$w(k) = \arg\min_i [x_q^i(k-1)] \tag{24}$$

As we are interested with the total operations time, the objective function for the optimization of terminal operations can be the total time to unload the entire import containers and to load all the export containers starting from the initial event time $k = 0$ up to the event time equal to the total number of inbound and outbound containers. By Bellman's principle of optimality, the optimization of this operations is equivalent to the optimization of the cost-to-go or Bellman value function at every event time k, which will be the total operations time from the event time k until the end of operations. We note that, the latter involves combinatorial optimization that includes future machine states $\mathcal{J}(k)$ whose number of states can grow exponentially with the future event time. By adopting the receding horizon control (known also as the model predictive control (MPC)) approach, instead of using the aforementioned cost-to-go, we can consider a (shorter) finite horizon of event time for the cost function.

Consequently, at every event time k, we consider the following receding horizon-based cost function

$$Z(k) = \sum_{m=k}^{K} z(m) \tag{25}$$

where K is the length of horizon, $z(m)$ in (25) is the total time spent in the container terminal to allocate a single inbound/outbound container that is defined by

$$z(m) = \begin{cases} x_q^{w(m)}(k) - x_q^{w(m)}(k-1) & \text{if } \mathcal{J}(k) = l \\ x_c^{n(m)}(k) - x_c^{n(m)}(k-1) & \text{if } \mathcal{J}(k) = u, \end{cases} \tag{26}$$

where the future state and decision variables follow the model as in (7)–(22). From (26), we have that the total operational time for loading an outbound container is given by the difference of finishing time of QC at k and $k-1$. Similarly, the time for unloading an inbound container is based on the difference of finishing time of the assigned yard crane at k and $k-1$.

B. Allocation Algorithm and Pre-Conditioning Steps

We follow the framework of model predictive allocation (MPA) as provided in [7], where the mathematical analysis is provided in [8]. At every event time k, we denote $\hat{x}_t^i(h)$, $\hat{x}_q^i(h)$, $\hat{x}_c^i(h)$ and $\hat{w}(h)$ with integer $h \geq 0$ as the predicted state variables and the predicted available quay crane, respectively, at event time $k+h$ computed using a copy of the model. Using these notations, the MPA algorithm is given as follows.

MPA algorithm (for integrated terminal operations):

1) For a new event time k, identify the available quay crane j according to (3) and evaluate the **Guard** condition for determining the current job $\mathcal{J}(k)$.
2) Based on the previous information of the state variables, j and $\mathcal{J}(k)$, solve the following receding horizon optimization problem

$$\min_{\hat{n},\hat{t},\hat{\bar{t}},\hat{s}} Z(k)$$

subject to the following state equations for all $h = 0, 1, \ldots K$ with K be the length of the horizon

$$\left.\begin{aligned} \hat{x}_q^{\hat{w}(h)} &= \hat{x}_q^{\hat{w}(h-1)} + \mu(\hat{s}(h)) \\ \hat{x}_{t,p}^{\hat{\bar{t}}(h)}(h) &= \hat{w}(h) \\ \hat{x}_{t,p}^{\hat{t}(h)}(h) &= 0 \\ \hat{x}_q^i(h) = \hat{x}_q^i(h-1), &\quad \forall i \neq \hat{w}(h) \\ \hat{x}_c^i(h) = \hat{x}_c^i(h-1), &\quad \forall i \\ \hat{\mathcal{T}}_{\text{out}}(h) = \hat{\mathcal{T}}_{\text{out}}(h-1) &\cup \hat{t}(h) \\ &\backslash \hat{\bar{t}}(h) \\ \hat{\mathcal{S}}(h) = \hat{\mathcal{S}}(h-1) &\backslash \hat{s}(h) \\ \cup \hat{\mathcal{S}}_{\text{arr,empty}}(h) &\backslash \hat{\mathcal{S}}_{\text{dep,empty}}(h) \\ \hat{\mathcal{S}}_{\text{tot}}(h) &= \hat{\mathcal{S}}_{\text{tot}}(h-1) \\ \cup \hat{\mathcal{S}}_{\text{arr,tot}}(h) &\backslash \hat{\mathcal{S}}_{\text{dep,tot}}(h) \\ \hat{n}(h) &= \emptyset \end{aligned}\right\} \text{ if } \hat{\mathcal{J}}(h) = l$$

or else (whenever $\hat{\mathcal{J}}(h) = u$)

$$\begin{aligned} \hat{x}_q^{\hat{w}(h)} &= \hat{x}_q^{\hat{w}(h-1)} + \mu(\hat{s}(h)) \\ \hat{x}_c^{\hat{n}(h)}(h) &= \hat{x}_q^{\hat{w}(h-1)} \\ &\quad + \frac{1}{v}\mathrm{d}(\hat{x}_{t,p}^{\hat{t}(h)}, \ \hat{w}(h)\text{-th quay}) + \mu(\hat{s}(h)) \\ &\quad + \frac{1}{v}\mathrm{d}(\hat{w}(h)\text{-th quay}, \ \hat{n}(h)\text{-th CY crane}) \end{aligned}$$

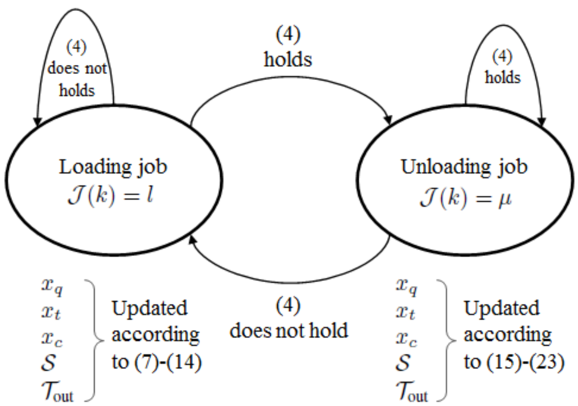

Fig. 5. An illustration of the state machine transition for the two types of jobs and the update of state variables after each transition.

$$
\begin{aligned}
&+\beta\\
\hat{\mathcal{T}}_{\text{out}}(h) &= \hat{\mathcal{T}}_{\text{out}}(h-1)\\
\hat{\mathcal{S}}(h) &= \hat{\mathcal{S}}(h-1) \cup \hat{s}(h) \cup \hat{\mathcal{S}}_{\text{arr,empty}}(h)\\
&\quad \setminus \hat{\mathcal{S}}_{\text{dep,empty}}(h)\\
\hat{\mathcal{S}}_{\text{tot}}(h) &= \hat{\mathcal{S}}_{\text{tot}}(h-1)\\
&\quad \cup \hat{\mathcal{S}}_{\text{arr,tot}}(h) \setminus \hat{\mathcal{S}}_{\text{dep,tot}}(h)\\
\hat{x}_q^i(h) &= \hat{x}_q^i(h-1), \quad \forall i = \hat{w}(h)\\
\hat{x}_c^i(h) &= \hat{x}_c^i(h-1), \quad \forall i \neq \hat{n}(h)\\
\hat{\bar{t}}(h) &= \emptyset
\end{aligned}
$$

3) Using the optimal solution in 2), assign the inbound yard crane $n(k) = \hat{n}(0)$, the outbound vessel's bay $s(k) = \hat{s}(0)$, the inbound internal truck $t(k) = \hat{t}(0)$ and the outbound internal truck $\bar{t}(k) = \hat{\bar{t}}(0)$. When $\hat{n}(0)$ or $\hat{\bar{t}}(0)$ is an empty set, it means that there is no assignment of yard crane or outbound internal truck, respectively.
4) Increment the event time k by one and return to 1).

For solving the optimization problem in Step 2 of the above-mentioned MPA algorithm with the event horizon $h = \{0, 1, \ldots K\}$, we need to compute the optimal inbound yard cranes $\hat{n}(0), \ldots, \hat{n}(K) \in \{1, \ldots, N\}$, the vessel's sub-bays $\hat{s}(0), \ldots, \hat{s}(K) \in \mathcal{S}_{\text{tot}}(k)$, the inbound internal trucks $\hat{t}(0), \ldots, \hat{t}(K) \in \mathcal{T}_{\text{tot}} \setminus \mathcal{T}_{\text{out}}(k)$ and the outbound internal trucks $\hat{\bar{t}}(0), \ldots, \hat{\bar{t}}(K) \in \mathcal{T}_{\text{out}}(k)$. Solving this combinatorial optimization for a finite length of horizon will still be non-trivial when the horizon length K is large. In order to facilitate this, we introduce preconditioning, similar to that used in [7]. The preconditioning is based on the ordering of the elements in the discrete sets of the decision variables (according to some measures), and followed by a truncation of the ordered sets. The optimization is then performed based on the truncated sets. In particular, we consider the following optimization steps using the above mentioned preconditioning:

1) Let $\mathcal{S}_{\text{ordered}}^{\text{unload}}(k) \subset \mathcal{S}_{\text{tot}}(k)$ be the ordered set of sub-bays containing the remaining containers to be unloaded at time k, which are ordered based on the container handling sequence predetermined by the terminal operator (as exemplified in Table I and II). Set $\mathcal{A}(k)$ as the first K elements of $\mathcal{S}_{\text{ordered}}^{\text{unload}}(k)$.
2) Similarly, we define $\mathcal{S}_{\text{ordered}}^{\text{load}}(k) = \{s_1, s_2, \ldots\} \subset \mathcal{S}(k)$ as the ordered set of the available sub-bays at time k, which is ordered based on the quay-crane operations time such that
$$\mu(s_1) \leq \mu(s_2) \leq \mu(s_3) \leq \ldots.$$
Set $\mathcal{B}(k)$ as the first K elements of $\mathcal{S}_{\text{ordered}}^{\text{load}}(k)$.
3) Let $\mathcal{Y}(k) = \{y_1, y_2, \ldots, y_N\}$ be the ordered set of inbound yard cranes at time k such that
$$x_c^{y_1}(k) \leq x_c^{y_2}(k) \leq \ldots \leq x_c^{y_N}(k)$$
holds where N is the number of yard cranes. Accordingly, set the truncated ordered set $\mathcal{C}(k)$ as the first K elements of $\mathcal{Y}(k)$.
4) Define $\mathcal{T}_{\text{ordered}}(k) = \{t_1, t_2, \ldots\}$ as the ordered set of internal trucks at time k based on the distance to the $w(k)$-th quay crane where $w(k)$ is as in (24), e.g.,
$$\mathrm{d}\big(x_{t,p}^{t_1}, w(k)\big) \leq \mathrm{d}\big(x_{t,p}^{t_2}, w(k)\big) \leq \ldots$$
holds. Based on this ordered set, set $\mathcal{D}(k)$ as the first K elements of $\mathcal{T}_{\text{ordered}}(k)$.
5) Using the truncated ordered sets $\mathcal{A}(k), \mathcal{B}(k), \mathcal{C}(k), \mathcal{D}(k)$, compute the optimal sequence of sub-bays $\hat{s} \in \mathcal{A}(k)$ (for unloading) or $\mathcal{B}(k)$ (for loading), optimal sequence of inbound yard cranes $\hat{n} \in \mathcal{C}(k)$ and optimal sequence of inbound trucks $\hat{t} \in \mathcal{D}(k)$ that solve the receding horizon optimization problem in step 2) of the MPA algorithm.

The above optimization with pre-conditioning algorithm replaces then step 2) of the MPA algorithm as given before. The preconditioning step that is described above is similar to the one used in [7]. In particular, the model predictive allocation algorithm in [7] uses also the truncated ordered set of berthed ships prior to finding an optimal sequence of ships that solves the receding horizon optimization problem for allocating berth and quay cranes. Instead of dealing with a truncated ordered set, the proposed algorithm above involves four truncated ordered sets, which makes it harder to solve the problem. Yet this preconditioning step facilitates significantly the search of optimal sequences, in comparison to solving the combinatorial optimization using the whole sets of sub-bays, internal trucks and yard cranes. In the following section, we will compare the performance of our proposed algorithm above with the state-of-the-art genetic algorithm and particle swarm optimization.

V. Simulation

In this section, we present the simulation use to evaluate the effectiveness of the model-based allocation algorithm proposed in Section IV, which is developed based on the model presented in Section III. We present two kind of simulations. Firstly, we simulate the dynamical models based on real-data collected from a real container terminal and compare the results from the MPA algorithm with the results obtained from the existing policies in the terminal. Secondly, we use Monte Carlo simulation based on large datasets to test the efficacy of the algorithm.

TABLE IV

SIMULATION PARAMETERS USED TO TEST THE DYNAMICAL MODELS OF INTEGRATED CONTAINER TERMINAL OPERATIONS. THE PARAMETERS ARE EMPIRICALLY OBTAINED FROM OBSERVATION IN PORT OF TANJUNG PRIUK, JAKARTA, INDONESIA. IN EACH OF THE EQUIPMENT, WE MEASURED 100 CONTAINER HANDLING OPERATIONS AND TOOK THE AVERAGE OPERATIONS TIME

Parameter	Value	Unit
QC 1 operations time	180.03	seconds/container
QC 2 operations time	171.37	seconds/container
QC 3 operations time	154.85	seconds/container
YC export operations time	128.53	seconds/container
YC import 1 operations time	115.78	seconds/container
YC import 2 operations time	114.94	seconds/container
Average IT speed	21.02	km/hour

A. Simulation Set-Up

The parameters which are used in the simulation are collected from a field observation in international container terminal of Port of Tanjung Priuk, Jakarta, Indonesia. The terminal consists of two berth positions, three quay cranes, two yard cranes in the import side of container yard for the inbound containers, one yard crane in the export side of container yard for the outbound containers, and ten internal trucks. The parameters are shown in Table IV.

The parameters are obtained from one hundred observations of operations time for each equipment. As an example, for obtaining the quay crane operations time, we assume that

$$\mu(s) = \alpha + \frac{1}{\upsilon_{\mathrm{QC}}}\mathrm{d}(s, 0)$$

where α is the average time for a QC to unload/load a container, υ_{QC} is the average travel speed of the crane and $\mathrm{d}(s, 0)$ is the distance between the sub-bay s to the crane. For the first QC, we measured the time needed by the QC to unload/load 100 set of containers, and by taking the average, we obtain the parameter $\alpha = 180.03$ seconds/container (c.f. Table IV). The corresponding speed υ_{QC} is obtained by literature studies from [4], [15] with value of 90 meter/minute. This value is also confirmed by the terminal. The operational time variances among cranes are caused by the difference in specifications or equipment's ages. To obtain the parameters of IT speed, we collected one hundred observations for each of the ten trucks and subsequently, based on the average, we set $\upsilon = 21.02$ km/hour.

The parameters will be used to simulate the dynamical models of the integrated container terminal operations. To compare with the state-of-the-art methods in this topic, we select two benchmark methods from [16] and [17]. We would like to compare the solutions from the dynamical modeling approach in this research with the static approach as presented in these two benchmark methods. These two papers use heuristic methods to find the solution and similar recent method can also be found in [18]. In [16], LP problems are defined for determining the allocation and scheduling of QC, YC, and IT. The problems are solved through genetic algorithm (GA) and particle swarm optimization (PSO) approach. We present the summary of the GA and PSO below, and for the completeness the readers can refer to [16].

1) Select randomly q initial routes of job to handle containers to a QC where $\theta_j^q = 1$ as in [16]. Calculate the insertion cost as in [16] to obtain one of the decision variables, which is the IT selected to perform the operations for the QC, which is represented by $C_{12}(j, u, j') = aq_{j'u} - aq\, j'$. Calculate the best insertion task, and select the set of jobs for the QC. Repeat the process for all the QC.
2) Select randomly y initial routes of job to handle containers to a YC where $\psi_j^y = 1$ as in [16]. Calculate the insertion cost as in [16] to obtain one of the decision variables, which is the IT selected to perform the operations for the YC, which is represented by $C_{12}(j, u, j') = aq_{j'u} - aq\, j'$. Calculate the best insertion task, and select the set of jobs for the YC. Repeat the process for all the YC.
3) Select randomly j initial routes of job to handle containers to an IT. Calculate the insertion cost as in [16] to obtain two of the decision variables, which are the QC and the YC to which the IT will operate, which is represented by $C_{12}(j, u, j') = S_{j'u} - S_{j'}$, and $S_j = (1 - \lambda_y).ay_j + \lambda_y.aq_j$. Calculate the best insertion task, and select the set of jobs for the IT. Repeat the process for all the IT.
4) The sets of jobs selected for the QCs, YCs, and ITs in Step (1), (2), (3) by the GA algorithm will be the initial inputs for the PSO. Select the S best individuals from the GA as a particle. Calculate and update the particle to find the best position according to $x_{pj}(t+1) = x_{pj}(t) + \upsilon_{pj}(t+1)$ as in [16]. Evaluate the fitness of the sets of the particles of PSO with the same procedure as GA, by the equation $F = 1/(CP.\sum_{i\in X} f_{1i} + CE.f_2)$, and select the best jobs.

The second benchmark is from [17]. We slightly modify the problem setting in [17], which considers the operations of automated container terminals, while we consider in this paper a modeling framework for generic terminals. The solution in [17] is obtained through GA, and the procedure is summarized as follows:

1) Select initial populations of the tasks for the cranes (QC and YC), the vehicle (IT), and the storage (CY position) for the sets of inbound and outbound containers.
2) Consider the precedence of tasks/operations and select a random string of numbers whose dimension is $N = \sum_{k=1}^{K}\sum_{i=1}^{Q_k} T_{ki} = \sum_{m=1}^{M}\sum_{n=1}^{N_m} O_{mn}$ as in [17].
3) Evaluate the chromosomes in Step (2) with fitness criterion from objective functions in [17], perform mutation and crossovers and repeat until no task with better fitness is obtained.

B. Simulation Results and Validation

In this section we will present the simulation results based on data which has been collected from the international container terminal of Port of Tanjung Priuk, Jakarta. The terminal is the smallest in the seaport and the regular vessels that call to the terminal historically range from 300 to 1,000 TEU. To comply with the settings in the dynamical models that we

TABLE V

DATASET COLLECTED FROM OBSERVATION AT THE PORT OF TANJUNG PRIUK, JAKARTA, INDONESIA. THE OBSERVATIONS ARE CONDUCTED FOR A WEEK PERIOD, WHERE FOUR VESSELS ARRIVED WITH EACH ITS LOADS OF INBOUND AND EXPORT CONTAINERS

Vessel	Total load (TEU)	Import load (TEU)	Export load (TEU)
A	473 TEU	283 TEU	190 TEU
B	312 TEU	209 TEU	103 TEU
C	527 TEU	358 TEU	169 TEU
D	323 TEU	171 TEU	152 TEU

TABLE VI

SIMULATION RESULTS BASED ON DYNAMICAL MODELS OF INTEGRATED CONTAINER TERMINAL OPERATIONS IN (3)-(19) WITH PARAMETERS AND DATASET IN TABLE IV AND V. THE MPA IS PERFORMED UNTIL $K = 8$, AND THE OBJECTIVE FUNCTIONS OF TOTAL OPERATIONS TIME IS COMPARED WITH THE EXISTING METHOD IN THE TERMINAL, AND TWO BENCHMARKING METHODS FROM [16] AND [17]

K	Allocation strategy	Total operations time (minutes)	Ave cal. time per step (s)
-	FCFS & DBQA (ex.)	2,572.16	0.18
1	MPA	2,713.64	2.87
2	MPA	2,667.82	7.13
3	MPA	2,614.92	18.79
4	MPA	2,605.51	39.12
5	MPA	2,541.84	68.03
6	MPA	2,535.33	89.56
7	MPA	2,469.03	105.39
8	MPA	2,405.78	133.63
-	GA [17]	2,502.06	50.87
-	GA & PSO [16]	2,435.15	53.92

have developed in Section III-A, export and import containers refer to the outbound and inbound containers, respectively.

The terminal operators currently employ density-based quay crane allocation (DBQA) method to allocate QC to the vessels. With this method, the QCs are allocated proportionally with the container density along the quay/berth, or in other words, the number of container per meter berth. The detail explanation of DBQA can be found in [7]. For allocating the YC, the terminal operators use first-come first-served (FCFS) policy where a job to handle a container is assigned to the earliest available YC. The existing allocation method for IT is also based on FCFS, where a container to be handled is assigned to the earliest and nearest IT. The latter criterion is observed since the ITs always move between the QCs and the YCs.

We use a dataset which is collected from a week observations at the terminal. During that period, four vessels arrived, where the specifications are provided in Table V. The entire containers in Table V are simulated with 1) terminal's existing policy, 2) MPA algorithm as explained in Section IV, 3) two benchmark methods as explained in Section V-A. The simulation results are presented in Table VI.

We can see in Table VI that the MPA algorithm with $K \geq 5$ improves the performance of the existing method by 1.69%. With $K = 8$, MPA's result is 6.48% better than the existing methods used by the terminal operators. The two benchmarking methods from [17] and [16] also have better performances than the FCFS & DBQA methods. With $K = 8$, our MPA method is 3.21% and 1.03% better than the GA in [17] and the GA and PSO in [16], respectively. When $K \geq 8$ is used, the proposed method can yield a further reduction in operations time than the two benchmarking methods, but at the expense of larger computational time.

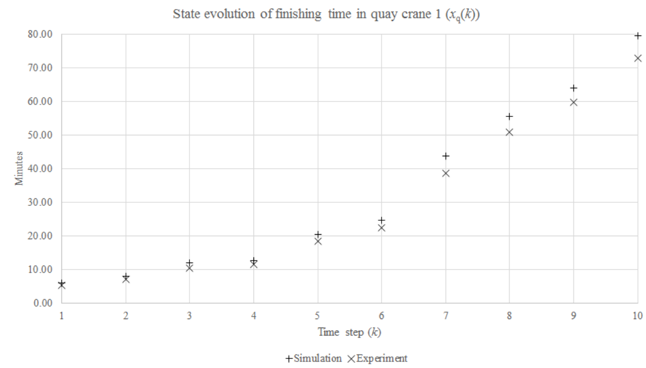

Fig. 6. The plot of trajectory of the state variable $x_1^1(k)$ which describes the finishing time of the first quay crane. The horizontal axis is the discrete time step (k). The vertical axis is the time in minutes. In each k, two $x_c^1(k)$s are plotted, where the crosses ($\times$) refer to the actual data recorded from the observation in the terminal, and the plusses ($+$) show the evolution of corresponding state variable from the simulation using (3)-(19) with the same dataset as the former observation.

To validate the dynamical models, we compare the one of the state variables, which is the finishing time of the first QC ($x_q^1(k)$). The state variables in each time k are obtained from the observation and the outputs from the simulation as provided in Figure 6.

From the one week observation, we recorded the realization of QC, YC, and IT allocation in the terminal, where the total operations time needed to handle 1,635 TEU in Table V was 2,624.84 minutes. From the same dataset, we then find the optimal control inputs according to dynamical models in (3)-(19) and the total operations time for the existing FCFS & DBQA methods is 2,576.28 minutes as presented in Table VI. The evolution of state variables from both of the observation and simulation of the existing allocation methods were recorded, and the evolution of the state variable of the finishing time of the first internal truck ($x_t^1(k)$) for the first ten discrete time steps (k) is presented in Figure 6.

It can be seen that the dynamical models are able to mimic the dynamic in the container terminal operations. This implies that the studied real systems (in the tactical level) can be modeled well. There are indeed discrepancies between those two state variables. This mainly caused by variations in container handling by QCs and YCs. From one operations to another, the time needed by a QC or a YC to handle a container varies slightly, where we use constant parameters as in Table IV. The variations are rooted from the detail operations of the cranes which are not modeled yet in our dynamical models of integrated container terminal operations.

An example of container handling sequence by the three cranes using the MPA algorithm is presented in Table VII. It can be seen from the subset of the results that the job sequence do not necessarily follow the FCFS rule as now being applied by the terminal operators in the observed seaport.

TABLE VII

THE SUBSET OF YARD CRANES ALLOCATION RESULTS USING MPA ALGORITHM, WHERE THE SEQUENCE OF CONTAINER HANDLING IS SHOWN IN EACH WORKING CRANES. THE NUMBER SHOWS THE INDEX OF EACH CONTAINER

Crane	Container handling sequence
YC 1 import	01 - 02 - 03 - 04 - 12 13 - 14 - 15 - 16 - 20
YC 2 import	05 - 06 - 07 - 08 - 18 19 - 25 - 26 - 30 - 31
YC export	284 - 285 - 286 - 287 - 288 303 - 304 - 305 - 310 - 311

TABLE VIII

THE SETTING OF SIMULATION SCENARIO USING REALISTICALLY GENERATED DATASETS. THIS TABLE PRESENTS VESSELS' LOADS CONFIGURATION FOR EACH SCENARIO

Scenario	Lower bound ship load (TEU)	Upper bound ship load (TEU)
Light load	300	800
Normal load	800	1,500
Heavy load	1,500	3,000

TABLE IX

THE SETTING OF SIMULATION SCENARIO USING REALISTICALLY GENERATED DATASETS. THIS TABLE PRESENTS NUMBER OF EQUIPMENT CONFIGURATION IN THE TERMINAL FOR EACH SCENARIO

Scenario	Number of QC	Number of YC	Number of IT
Light load	3	3	10
Normal load	6	6	20
Heavy load	10	10	30

C. Simulation Results Using Generated Data

For evaluating further the performance of dynamical models in (3)-(19) and MPA algorithm that has been developed, in this section we present the simulation results using realistically generated terminal data inputs. We generate three scenarios with a total of 150 datasets of container operations as presented in Table VIII and IX. There are three scenarios of the loads of the vessels in the terminal, which is classified as light, normal, and heavy. The other sources of variability also come from the terminal equipment size. The scenario is reflected from the common terminal operations configuration. For instance, the terminal observed in this paper can be classified into a terminal with light loads.

In each scenario, 50 datasets are generated, with 100 vessels' loads in each dataset. The examples of the subset of a dataset for each scenario is presented in Table X, XI, XII. The total loads in every vessel are randomized with uniformly distributed numbers whose lower and upper bounds parameters are presented in Table VIII. The lower and upper bound parameters of import and export loads percentage are determined from observations and discussion with the terminal operators. For the import load percentage, the lower and upper bound are 40% and 70%, respectively, and the parameters for the export load percentage are 25% and 40%, respectively. In each load, the percentages for the import and export loads are randomized based on the bounds and weighted so the summation of both of the loads percentages are 100%.

We use constant parameters for the QC and YC operations time, with the time to handle a container for both of the two types of cranes are 180 and 170 seconds, respectively. This parameters are obtained from the standard (manufacturing) specifications of the cranes. The summary of the Monte Carlo simulation results with the large datasets are presented in Table XIII. The average of total operations time in each scenario shows that MPA always outperform the existing FCFS and DBQA methods, as well as the two benchmarking methods from [16] and [17], although it can be seen that the difference between MPA and GA & PSO method is slight.

The graphical representations of the simulation results are provided in Figure 7 and 8. With $K = 8$, the average cost reduction from the existing FCFS & DBQA methods of MPA are greater than GA and GA & PSO. The MPA indeed has obvious setback, where the calculation time is much greater than the other three methods. This due the problems complexity, in which five control variables (job, YC, vessel's

TABLE X

A SUBSET OF DATASET OF LIGHT LOAD SCENARIO, WHERE THE LOADS OF THE FIRST 10 VESSELS ARE PRESENTED

Vessel	Total load (TEU)	Import load (TEU)	Export load (TEU)
1	342	209	133
2	677	417	260
3	306	178	128
4	537	275	262
5	650	389	261
6	507	358	149
7	526	344	182
8	334	197	137
9	658	406	252
10	708	456	252

TABLE XI

A SUBSET OF DATASET OF NORMAL LOAD SCENARIO, WHERE THE LOADS OF THE FIRST 10 VESSELS ARE PRESENTED

Vessel	Total load (TEU)	Import load (TEU)	Export load (TEU)
1	1,228	734	494
2	1,013	741	272
3	1,313	854	459
4	881	581	300
5	1,211	829	382
6	1,287	659	628
7	1,140	755	385
8	1,072	580	492
9	1,297	865	432
10	927	643	284

TABLE XII

A SUBSET OF DATASET OF HEAVY LOAD SCENARIO, WHERE THE LOADS OF THE FIRST 10 VESSELS ARE PRESENTED

Vessel	Total load (TEU)	Import load (TEU)	Export load (TEU)
1	2,418	1,500	918
2	2,299	1,505	794
3	1,922	1,343	579
4	2,130	1,273	857
5	1,601	1,061	540
6	2,326	1,456	870
7	1,909	1,285	684
8	1,548	951	597
9	1,766	957	809
10	2,111	1,438	673

TABLE XIII

SIMULATION RESULT OF DYNAMICAL MODELS IN (3)-(19) USING THE GENERATED DATASETS WITH OUR PROPOSED MPA METHODS WHICH ARE COMPARED WITH THE EXISTING METHOD OF FCFS & DBQA AND TWO STATE-OF-THE-ART METHODS

Allocation Strategy	*Average total opr. time (min.)*	*Ave. calc. time per step (s)*
Sc. 1: Light load		
FCFS & DBQA	841.85 ± 6.18	0.111
GA as in [17]	824.95 ±4.18	51.876
GA & PSO as in [16]	813.84 ±4.14	53.784
MPA (with $K = 8$)	799.36 ±4.66	128.875
Sc. 2: Normal load		
FCFS & DBQA	1,754.94 ±9.45	0.120
GA as in [17]	1,713.59 ±8.62	52.095
GA & PSO as in [16]	1,699.22 ±8.99	53.284
MPA (with $K = 8$)	1,658.61 ±10.08	135.899
Sc. 3: Heavy load		
FCFS & DBQA	3,570.89 ±15.75	0.123
GA as in [17]	3,508.87 ±14.58	51.996
GA & PSO as in [16]	3,415.64 ±14.88	53.853
MPA (with $K = 8$)	3,395.64 ±15.32	137.088

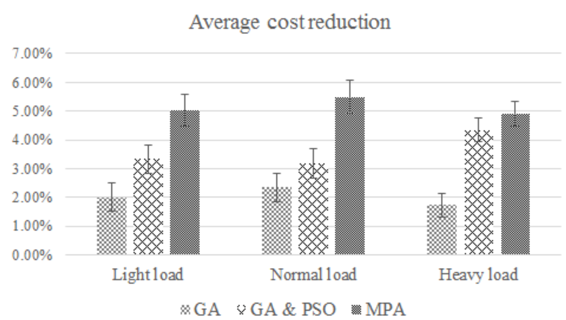

Fig. 7. Average cost reduction of GA, GA & PSO and MPA methods when compared to the existing FCFS & DBQA method. The vertical axes in each bar are the error bars.

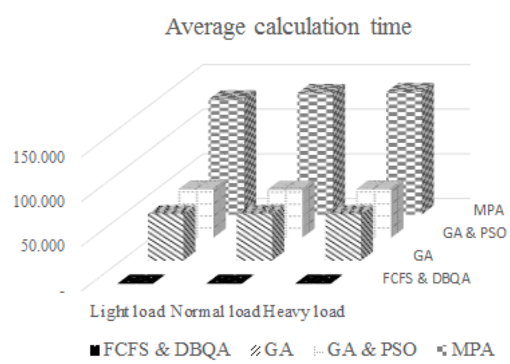

Fig. 8. Average calculation time per step (in minutes) for each method in each scenario.

bay, and IT) have to be solved simultaneously. In comparison to the total operations time of a single container, which takes more than fourteen minutes (see Table XIII), the computational time of our proposed algorithm (which is slightly more than two minutes) is still acceptable.

VI. CONCLUSION

We have formulated dynamical models of integrated container terminal operations based on DES modeling framework. The operations is an end-to-end processes that include the seaside, storage, and transfer sub-systems, which are usually analyzed independently in the state-of-the-art literature. The difficulty in the optimization caused by the asynchronous operations among quay cranes, yard cranes, and internal trucks is overcome in this research.

The proposed MPA method allows us to plan the terminal operations integratively and simultaneously: the allocation and scheduling of QC, YC, and IT, as well as, the placement of the boxes in the CY and ship, based on ship's and CY's unloading plan for the inbound and outbound containers, respectively.

We have also conducted data collection from a real container terminal. The simulation shows that given the same inputs, the state variables obtained from the dynamical model, can closely follow the actual state variables collected from the realization of equipment allocation in the seaport by the terminal planner. This implies that the modeling framework can be used to describe any general integrated container terminal operations. Moreover, we solved the optimization problem using our proposed MPA algorithm with preconditioning. We have shown that the proposed approach performed better than: 1) the existing FCFS & DBQA methods used in the studied terminal, 2) the GA-based method from literature, 3) the GA & PSO-based method from the literature, in which the former two methods use commonly static modeling approach using operations research. Based on the Monte Carlo simulation with large datasets, the MPA outperforms those three methods, although the high computational time of the MPA needs to be taken into account in the trade-off with the cost reduction of the operational time.

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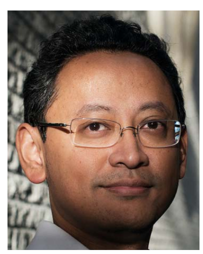

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