Dynamic berth and quay crane allocation for multiple berth positions and quay cranes

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Dynamic berth and quay crane allocation for multiple berth positions and quay cranes*

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Abstract— **We study in this paper a dynamic berth and quay cranes allocation strategy in general seaport container terminals. We develop a dynamical model that describes the operation of berthing process with multiple discrete berthing positions and multiple quay cranes. Based on the proposed model, we develop a dynamic allocation strategy using the model predictive control (MPC) paradigm. The proposed strategy is evaluated using real data from a container terminal in Indonesia. The simulation results show that the MPC-based allocation strategy can improve the efficiency of the process where the total handling and waiting cost is reduced by approximately 20% in comparison to the commonly adapted method of first-come first-served (FCFS) (for the berthing process) combined with the density-based quay cranes allocation strategy.**

I. INTRODUCTION

Nowadays, over 60% of deep-sea cargo is transported by containers, as shown in [13]. The development of a standardized containerization system has marked the era of container terminals. High cost incurred in the operation processes and stiff competition among terminals have pushed terminal operators to improve their service. Two options that are commonly looked at are 1) investment in additional equipments; and 2) improvement of the operation of the current process. In this paper, we will study the latter option.

A common container terminal layout is shown in Figure 1 where 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 the ships for loading and unloading containers. There are internal trucks waiting beneath the QCs and they transport the containers to some specific destinations at container yard (CY). The containers are then stored in the CY and several straddle carriers (SC) work there to re-allocate them internally within the CY or to load/unload them to/from external trucks.

An important process in the terminal operations is the seaside operations-level decision making for berth and quay cranes allocation. The paper [3] presents an extensive review on the berthing allocation problem. The assignment of berth

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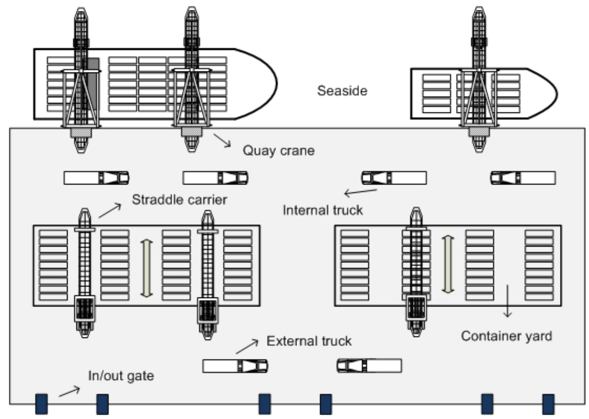

Fig. 1. An illustration of a container terminal layout with multiple berthing positions and multiple quay cranes (QC). Incoming ships can berth at different berthing position and several QCs can be allocated to the berthed ship. Internal trucks serve as the container carriers from the QCs to the container yard (CY) and external trucks are used to transport containers externally.

positions to incoming ships for handling their cargo plays an important role in minimizing the turnaround time.

In the current literature, there are mainly two classes of berthing allocation problems. They are the static berth allocation problem (SBAP) and the dynamic berth allocation problem (DBAP).

The SBAP, as discussed in [4], [7], [8], [10] and [15] is an allocation problem where the entire ships are assumed to have arrived at the port when the planning is being made. Hence the berthing allocation problem is solved based on a static set of ships arrival time. First come first served (FCFS) rule, which is the most common method in allocating berth positions and cranes also uses the similar philosophy. This method, which is simple and is easily adopted to the incoming ships, is not always efficient [10]. For instance, the FCFS can not be used if there is priority in seaport service where some ships can have higher priority than the others.

As opposed to the static arrival set, the DBAP takes into account the dynamic arrival of the ships within the planning horizon [9], [11] and [10]. Although the ships' arrival is considered to be dynamics (or time-varying), the berthing process in these works remains static. Hence, the allocation problem can be recasted into a linear programming for a fixed set of time interval, as proposed in [9]-[11]. For instance, in [10], the dynamic arrival is represented by a variable which is a time-gap between the departure of the current ship that occupies a berth position to the arrival of the next ship that will occupy the same position. This is in fact a static model with time-varying uncertainty. It does not incorporate dynamics of the whole process in berthing operations.

As reviewed in [3], the typical berth allocation process assumes that all ships arrival is precisely known apriori, so that linear programming can be applied for solving the berth allocation. However, this setting does not capture the operational-level decision making process where the set of ships arrival dynamically changes, the terminal operator knows about the ships arrival only for a brief time horizon and the berthing process itself is a dynamical process. Hence, the non-robustness and non-adaptiveness of this approach to the dynamically changing environment has led to the wide adoption of a heuristic approach that is a combination of the first-come first-serve strategy for the berthing allocation process and of the density-based strategy for the quay-crane allocation process.

On the other hand, for the decision making process in the tactical-level (i.e. weekly) or in the strategical-level (i.e. monthly)[1], dynamical models have been developed to describe the dynamics in container terminal operations, see e.g. [1], [2] and [5], [12]. These dynamical models are subsequently used for resource allocation in container terminals using model predictive control. In particular, the models are used as predictive models of the process during the optimization step. In these papers, resource allocation is expressed as percentage of servers (equipments) capacity to transport containers to the subsequent server. As an alternative to [1] and [2] where the percentage of servers is used as the decision variable, the control variables used in [5] are mainly the starting and finishing operation time of quay cranes, internal trucks and straddle carriers deployed in berth and container yard.

For an operational-level dynamical modeling, it has recently been studied in [16] where a finite-state machine is used to describe the discrete-event systems in the berthing process. It incorporates the dynamics of QC, automated guided vehicle (AGV), and automated stacking crane (ASC) employed in the terminal.

In this paper, we develop a dynamical model of the berthing process that improves the one used in the DBAP as in [9]-[10]. We include set dynamics describing the ships arrival and the dynamics of the berthing process with multiple berthing positions and multiple QCs. Based on the proposed model, we propose a dynamic allocation strategy of both the berth and quay cranes allocation, simultaneously, using model predictive control (MPC) and propose a novel heuristic, so-called N-level FCFS, which combines the FCFS and exhaustive search strategy to solve the MPC problem.

The outline of this paper is as follows. In Section 2 we explain the generic dynamical model of berthing process for multiple berthing positions and multiple quay cranes. We also provide performance criteria in this chapter. The application of MPC to our problem is presented in Section 3 based on the same performance criterion in prior section. The simulation result based on several scenarios is provided in Section 4. Finally, some concluding remarks and suggestions are provided in Section 5.

[1]There are three types of decision making in container terminal operations as in [14] i.e. strategical, tactical, and operational level. The strategical level and operational level have the largest and the smallest planning horizon, respectively. This classification also applies in other areas such as supply chain management and production system.

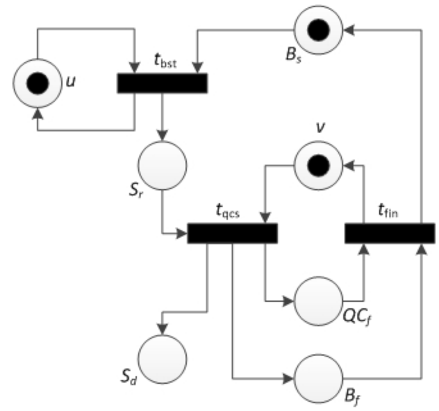

Fig. 2. A petri net of a simple berthing process involving one berthing position and one QC

II. DYNAMICAL MODELING OF BERTHING PROCESS

In this section, we explain a generic dynamical model of berthing process in general seaport container terminals. First, in order to simplify the presentation, let us consider a simple berthing problem where there is only one berthing position and one QC. In this particular case, the decision variable is the berthing ship that is chosen from the set of ships-ready-to-be-berthed. In the generalization of this simple problem to the multiple berthing positions and multiple QCs, we consider also the number of QC per berthing position as an additional decision variable.

A petri net diagram of this simple berthing problem is shown in Figure 2. The description of the transitions (as depicted in bar) and the places (as depicted in circle) can be found in Table I and Table II respectively. We refer interested readers to [6] for general exposition on petri net.

A. The dynamic modeling of a simple berthing process

We denote $\mathcal{S}(k)$ as the set of arriving ships to seaport at a berthing step $k \in \mathbb{Z}_+$. Here, arriving ships refers to all ships that has already reported to the port on their incoming. We denote the $i-$th element of $\mathcal{S}(k)$ by $\mathcal{S}_i(k)$. For instance, using the actual set of ships from our experimental dataset (see also Table III in Section IV), the set $\mathcal{S}(k)$ can be $\mathcal{S}(k) =$

TABLE I

DESCRIPTION OF TRANSITIONS

Transition	*Description*
t_{bst}	time of ship starts berthing at berth
t_{qcs}	time of QC starts loading/unloading containers
t_{fin}	time QC finishes loading/unloading containers, ship leaves berth

{"Berlian", "Fatima", "Meratus I"} and consequently $\mathcal{S}_2(k)$ refers to "Fatima".

Associated to $\mathcal{S}(k)$, we define two different measures, μ_a and μ_o which correspond to the arrival time and operations time, respectively. As an illustration using the above example of $\mathcal{S}(k)$, $\mu_a(\mathcal{S}_2(k))$ refers to the arrival time of the ship "Fatima". Similarly, $\mu_o(\mathcal{S}_1(k))$ and $\mu_o(\mathcal{S}(k))$ refer to the operation time of the ship "Berlian" and to the total operation time of all ships in $\mathcal{S}(k)$, respectively. Here, the measure $\mu_o(\mathcal{S}_i(k))$ refers to the i-th ship operations time for unloading and loading the entire containers by a single QC. This choice will be useful later when we take the number of QCs as another decision variable. The total operations time itself depends on the number of containers in a ship, represented by twenty-feet equivalent unit (TEU), number of QCs assigned to the ship, and quay crane capacity, that is usually in TEU per hour.

As shown in Figure 2, the token at the place $u(k)$ means that a ship has been chosen from the set $\mathcal{S}(k)$ for berthing at step k and is waiting to be berthed. Similarly, the token presents at the place B_s means that the previous ship has finished berthing and thus the berthing position becomes available. Whenever the tokens present in both places at the same time, the transition t_{bst} takes place, and leads to a new place S_r where the ship $u(k)$ is now ready for loading/unloading.

Similar interpretation to the rest of the diagram can be used for describing the whole berthing process. Now, if we use the time when the transitions occur as the state variables (see also Table I) and we use the arrival time of ship $u(k)$, the dynamics of t_{bst}, t_{qcs}, and t_{fin} at the k-th berthing step can be given by

$$t_{\text{bst}}(k) = \max\{\mu_a(u(k)), t_{\text{fin}}(k-1)\} \quad (1)$$

$$t_{\text{qcs}}(k) = \max\{t_{\text{bst}}(k), t_{\text{fin}}(k-1)\} \quad (2)$$

$$t_{\text{fin}}(k) = t_{\text{qcs}}(k) + \mu_o(u(k)) \quad (3)$$

$$\mathcal{S}(k) = \mathcal{S}(k-1)\backslash u(k) \cup \mathcal{U}(k)$$

One can further simplify (1)-(3) into only two state equations as follows

$$x(k) = \max\{\mu_a(u(k)), x(k-1)\} + \mu_o(u(k)) \quad (4)$$

$$\mathcal{S}(k) = \mathcal{S}(k-1)\backslash u(k) \cup \mathcal{U}(k) \quad (5)$$

where the state $x(k)$ denotes the finishing time $t_{\text{fin}}(k)$ and $\mathcal{U}(k)$ is the set of new arriving ships that comes at the berthing step k.

TABLE II

DESCRIPTION OF PLACES

Place	*Description*
S_b	ship needs berth
S_r	ship berthed ready for loading/unloading
S_d	ship departs from port
B_s	Berth ready for next ship to berth
B_f	Berth operation is finished
QC_f	QC departs from ship
QC_s	QC is ready for next ship

Remark 1: Compared to the existing literature ([1], [2], [5]), our dynamical modeling framework for the berthing problem has resulted into state equations involving set dynamics (c.f. (5)). The analysis of such dynamics in the context of seaports interconnection is not trivial and we will not treat this issue in this paper. However, we still take into account the set dynamics in our optimization problem later using the MPC algorithm.

B. Generalization to the multiple berthing positions and multiple QCs

In this subsection, we will extend the dynamical modeling of a simple berthing process in (4)-(5) into multiple berth positions and multiple QCs. For defining the domain of our decision variables, we denote the set of discrete berthing positions by $\mathcal{B}$ where $|\mathcal{B}|$ is the total number of positions and we denote $\mathcal{Q}$ as the set of QCs where $|\mathcal{Q}|$ defines the total number of available QCs. Note that we consider only discrete berthing positions in this paper. We denote $x_b(k)$ as the finishing time of the b-th berth position at berthing step k, for all $b = 1, .., |\mathcal{B}|$.

In this setting, every time an assigned QC has finished an operation at a particular berth position, a new berthing process (similar to the one in Figure 2) will commence where a new ship needs to be allocated and berthed. This means that this is an event-based dynamical model, since k is triggered from an completed event from previous $k-1$. As before, the finishing time for the b-th position will be denoted by $x_b(k)$.

In contrast to the dynamical modeling for the simple berthing process, we need at least three state variables for every berthing position that record the starting time t_{bst}, the estimated finishing time t_{fin} and the remaining operations time. For every $b-$ th berth position, we denote new state variables $z_b(k)$ as the berth starting time and $y_b(k)$ as the remaining operations time. We define an additional control variable $v_b(k) \in \mathbb{Z}_+$ which is the number of QCs allocated to the b-th berth position at step k and we assume that the total number of QCs is constant. For every berthing step k, the dynamics is given as follows. By letting

$$j = \arg\min_b [x_b(k-1)] \quad (6)$$

the dynamics of the j-th berth position is given by

$$z_j(k) = \max\{x_j(k-1), \mu_a(u(k))\} \quad (7)$$

$$y_j(k) = \mu_o(u(k)) \quad (8)$$

$$x_j(k) = z_j(k) + \frac{y_j(k)}{v_j(k)} \quad (9)$$

and the dynamics of the other berth positions $b \neq j$ is given by

$$z_b(k) = \begin{cases} x_j(k-1) & \text{if } x_j(k-1) > z_b(k-1) \\ z_b(k-1) & \text{otherwise} \end{cases} \quad (10)$$

$$y_b(k) = y_b(k-1) - [z_b(k) - z_b(k-1)]v_b(k-1) \quad (11)$$

$$x_b(k) = z_b(k) + \frac{y_b(k)}{v_b(k)} \quad (12)$$

$$\sum_{b=1}^{|\mathcal{B}|} v_b(k) = |\mathcal{Q}| \quad (13)$$

$$\mathcal{S}(k) = \mathcal{S}(k-1)\backslash u(k) \cup \mathcal{U}(k) \quad (14)$$

Equation (6) refers to the earliest available berth position (denoted by j) based on the finishing time of each berth position at the previous berthing step $k-1$. The state variable z in (7) and (10) defines the berthing-time for every berth position at every berthing step k. The state variable y in (8) and (11) is the remaining operations time at every berth positions. Finally, as in the simple berthing process, the state variable x describes the estimated finishing time for every berth position based on the allocated QCs given by the input variable v. The equation (13) ensures that the total number of QCs assigned to all berth positions is the same as the total number of available QCs.

From the state equation (9) and (12), one can deduce that the domain of the state space is

$$\{(x, y, z) \in \mathbb{R}_+^{|\mathcal{B}|} \times \mathbb{R}_+^{|\mathcal{B}|} \times \mathbb{R}_+^{|\mathcal{B}|} \mid x_i > z_i, i = 1, \ldots, |\mathcal{B}|\}.$$

It can also be seen from (7) and (10) that the state trajectories of the berthing time z is monotone non-decreasing.

C. Objective functions

The cost function of the berthing process, whether for the simple one or for the multiple berth positions and QCs, is based on both the operations cost and waiting cost. These two cost components are closely related to the time that the ships spend at the assigned berth positions for completing their berthing process.

The operations cost is the cost of operating the QCs that are allocated to a particular ship. Let us denote the operating cost of a QC unit (€/hour) by C_o. The operational cost between the step $k-1$ to step k is then defined by C_o multiplied by the time needed for unloading/loading containers from/to a ship. In other words, it is given by $C_o\mu_o(u(k))$ and

$$C_o\Big([x_j(k-1) - z_j(k-1)]v_j(k-1) + \sum_{b\neq j}[z_b(k) - z_b(k-1)]v_b(k-1)\Big),$$

for a single QC and multiple QCs case, respectively, where j is as in (6).

On the other hand, the waiting cost is associated to the total time that a particular ship spends at seaport, i.e. from the time it arrives until it leaves after the assigned QCs have completed the operations. It may happen that the particular ship has to wait after its arrival, since all berth positions are occupied. We denote C_w the waiting cost of a ship unit (€/hour).

For simplicity of notation, for the multiple berth positions and multiple QCs, we denote the earliest available berth position at berthing step k by $w(k)$ which is defined by

$$w(k) = \arg\min_b [x_b(k-1)]. \quad (15)$$

Based on this description, the cost functions (defined from the step k with horizon N) for the simple berthing process and for that with multiple berth positions and multiple QCs are given by

$$J(x, u) = \sum_{n=k}^{k+N} \mu_o(u(n))C_o + [x(n) - \mu_a(u(n))]C_w \quad (16)$$

and

$$J(x, y, z, u, v) \quad (17)$$

$$= \sum_{n=k}^{k+N} \Big([x_{w(n)}(n-1) - z_{w(n)}(n-1)]v_{w(n)}(n-1)C_o \quad (18)$$

$$+ \max\{x_{w(n)}(n-1) - \mu_a(u(n)), 0\}C_w + \sum_{b\neq w(n)} [z_b(n) - z_b(n-1)](v_b(n-1)C_o + C_w)\Big)$$

respectively.

In this formulation, we have explicitly defined the cost function as a function of state variables x, y and z and of input variables u and v that satisfy (6)–(14). Note that since $x > z$ (as remarked after (14)), the cost function J in (17) is positive definite.

III. MPC-BASED ALLOCATION STRATEGY

In this section, we propose a dynamic allocation strategy of both the berthing positions and the quay cranes using MPC approach. In this approach, the underlying dynamical process that has been captured by the proposed generic modeling framework of berthing process in Section II, is used to optimize the berthing control input u and quay cranes control input v for a finite step horizon in the future.

Let us now describe the MPC-based allocation strategy.

For every berthing step k, we denote $\hat{z}(l)$, $\hat{y}(l)$, and $\hat{x}(l)$, with the integer $l \geq 0$, as the predicted state variables at berthing step $k+l$ based on known/measured state variables at step k. Using this notation, $\hat{z}(0) = z(k), \hat{y}(0) = y(k)$ and $\hat{x}(0) = x(k)$. Also, $\hat{z}(-1) = z(k-1), \hat{y}(-1) = y(k-1)$ and $\hat{x}(-1) = x(k-1)$. Similar to (15), we define $\hat{w}(l) = \arg\min_b \hat{x}_b(l-1)$. Using these notations, the MPC algorithm for the berth and quay cranes allocation is given as follows where we use the step horizon $N > 0$. For generality, we will describe the algorithm for the multiple berthing positions and multiple QCs case. It is straightforward to adapt the algorithm for the simple berthing process.

MPC-based Allocation Strategy Algorithm

1) For a new berthing step k, we update the current state variables as in (6)–(14).

2) Solve the following MPC problem

$$\min_{\hat{u},\hat{v}} J(\hat{x}, \hat{y}, \hat{z}, \hat{u}, \hat{v})$$

subject to

$$\hat{z}_{\hat{w}(l)}(l) = \max\{\hat{x}_{\hat{w}(l)}(l-1), \mu_a(\hat{u}(l))\} \quad (19)$$

$$\hat{y}_{\hat{w}(l)}(l) = \mu_o(\hat{u}(l)) \quad (20)$$

$$\hat{x}_{\hat{w}(l)}(l) = \hat{z}_{\hat{w}(l)}(l) + \frac{\hat{y}_{\hat{w}(l)}(l)}{v_{\hat{w}(l)}(l)} \quad (21)$$

and for every $b \neq \hat{w}(l)$

$$\hat{z}_b(l) = \begin{cases} \hat{x}_{\hat{w}(l)}(l-1) & \text{if } x_{\hat{w}(l)}(l-1) > z_b(l-1) \\ z_b(l-1) & \text{otherwise} \end{cases} \quad (22)$$

$$\hat{y}_b(l) = \hat{y}_b(l-1) - [\hat{z}_b(l) - \hat{z}_b(l-1)]\hat{v}_b(l-1) \quad (23)$$

$$\hat{x}_b(l) = \hat{z}_b(l) + \frac{\hat{y}_b(l)}{\hat{v}_b(l)} \quad (24)$$

$$\sum_{b=1}^{|\mathcal{B}|} \hat{v}_b(l) = |\mathcal{Q}| \quad (25)$$

$$\hat{\mathcal{S}}(l) = \hat{\mathcal{S}}(l-1) \backslash \hat{u}(l), \quad (26)$$

where $\hat{u}$ and $\hat{v}$ are the predicted control input within the step horizon.

3) Implement the berthing control input $u(k) = \hat{u}(0)$ and the quay crane control input $v(k) = \hat{v}(0)$.
4) Increment the berthing step k by one and return to 1).

A. Numerical optimization

For solving the MPC optimization problem in step 2 of the MPC-based Allocation Strategy algorithm above, we need to find an optimal berthing control input $\hat{u}(0), \ldots, \hat{u}(N)$ from the space of $\mathcal{S}(k)$ and an optimal quay cranes control input $\hat{v}(0), \ldots, \hat{v}(N)$ from the available number of quay cranes $|\mathcal{Q}|$. If $|\mathcal{S}(k)|$ and $|\mathcal{Q}|$ are small, one can easily solve the optimization problem by using an exhaustive search. When they are large, one can use a heuristic method, such as, Genetic Algorithm, for finding a (sub)-optimal control input.

As an alternative to GA for solving the MPC problem as above, we propose another heuristic approach, called N-*level FCFS*, which is a quasi-exhaustive search that combines FCFS and exhaustive search approaches. The approach is detailed as follows.

N-level First-Come First-Served approach

1) Order the set of ships-to-be-berthed at step k, $\mathcal{S}(k)$ based on the measure of the arrival time μ_a such that

$$\mu_a(\mathcal{S}_1(k)) \leq \mu_a(\mathcal{S}_2(k)) \leq \ldots \leq \mu_a(\mathcal{S}_M(k))$$

holds where M is the dimension of $\mathcal{S}(k)$ and is assumed to be larger than the horizon N.

2) Pick the first N ships from the ordered set and denote such subset of ships as $\mathcal{D}(k)$.
3) Perform exhaustive search of optimal berthing control input $\hat{u}$ from $\mathcal{D}(k)$ and $\hat{v}$ from the available number of quay cranes that solves the MPC problem as above.

TABLE III

A SUBSET OF EXPERIMENTAL DATA OF SHIPS ARRIVAL AND THEIR LOADS IN AN INDONESIAN SEAPORT.

No	*Ship's name*	*TEU*	*Arrival time*	*Operations time (QC min)*
1	"Berlian"	665	20-01-14 23:59	1,995
2	"Fatima"	713	20-01-14 23:59	2,139
3	"Meratus I"	750	21-01-14 2:20	2,250
4	"Sejahtera"	463	21-01-14 3:00	1,389
5	"Vertikal"	894	21-01-14 8:00	2,682
6	"T. Rejeki"	429	21-01-14 8:15	1,287
7	"Meratus II"	318	21-01-14 8:30	954
8	"Meratus III"	392	21-01-14 16:00	1,176
9	"Perintis"	368	21-01-14 23:00	1,104
10	"Meratus IV"	807	20-01-14 23:59	2,421

IV. SIMULATION RESULTS

In this section, we provide simulation results for the multiple berthing positions and multiple QC case. We use a data set from a container terminal seaport in Indonesia to simulate our proposed dynamic allocation strategy for multiple berthing positions and multiple QCs. The data is obtained from the smallest terminal in the seaport which is consisted of 2 berth positions and 7 QCs with the same technical specification. There are 29 incoming ships to the terminal whose loads range from 327 to 2,156 TEU. A subset of the data for the first 10 ships is shown in Table III. From this data, we use the measure μ_a is based on the arrival time and the measure μ_o is based on the operations time (which is expressed in QC min).

We use the terminal standard for the C_o, i.e. the cost spent by the terminal operator to operate QCs for loading and unloading containers. For the waiting cost of C_w, since there is no data available, we use information from the terminal, i.e. the estimated hourly cost spent by every ship to wait for the completed operation in the seaport.

Equations (6)-(13) are used to simulate the data set with current policies in the terminal i.e. FCFS and density-based QCs allocation (DBQA). The DBQA is a method to allocate QCs proportionally according to number of containers in all ships that berth in the same berthing step interval. We compare this policy with the MPC-based Allocation Strategy where N-level First-Come First-Serve approach is adopted for solving the MPC problem. The simulation results is shown in Table IV. The graphical results for the FCFS and DBQA and for the MPC-based strategy with $N = 8$ is shown in Figure 3 and Figure 4, respectively. The small box in the right-upper part of every ship's schedule box represents number of QCs assigned to the particular schedule.

As shown in the table, the total cost from MPC monotonically decreases as the horizon N increases. The MPC with a horizon of 8 can already decrease the total cost of 20.56% compared with the traditional FCFS and DBQA methonds

One can notice that as the horizon N increases, the complexity has also increased and resulted in longer calculation time per berthing step. The complexity will also increase as the dimension of the problem increases, i.e. the number of

TABLE IV

SIMULATION RESULT OF THE BERTH AND QUAY CRANE ALLOCATION FOR MULTIPLE BERTH POSITIONS AND MULTIPLE QCS.

N	*Allocation Strategy*	*Total cost*	*Ave. Calc. time per step (s)*
1	FCFS & DBQA	3,921,923	0.0958
2	MPC	3,828,642	0.3634
3	MPC	3,642,352	1.2493
4	MPC	3,547,157	4.4727
5	MPC	3,364,535	12.884
6	MPC	3,230,941	29.783
7	MPC	3,162,912	70.548
8	MPC	3,115,403	155.92

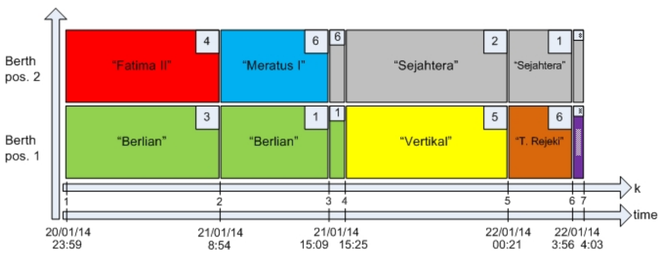

Fig. 3. The resulting berth and quay crane allocation using the commonly adopted FCFS and DBQA method for the first 7 berthing steps. The berth positions are shown in the vertical axis and the time (and the berthing step) is shown in the horizontal axis. Each box represents allocated ship at different berth position where the label describes the ship's name and the number on the top-right corner of every box gives the allocated QCs.

berth positions, quay cranes, and incoming ships. But, we can see that with N of 8 the numerical optimization only needs calculation time of 156 sec, which is relatively low in comparison to the average operational time for loading and unloading ships. It can be seen from Figure 3 and Figure 4 that the completed ship operational time is around four hours at the lowest. One can also argue it is not necessary to run the optimization for the whole incoming ships, which will result in shorter calculation time.

In Figure 3, the resulting planning using the commonly adopted FCFS with DBQA is shown. One can notice that the allocation of the berth position follows the order of arrival time as given in Table III. As a comparison, the resulting planning using our proposed strategy is shown in Figure 4. It can be seen from this figure that at the berthing step 2, the ship "Sejahtera" is given a priority to the ship "Meratus I", which arrives earlier, for berthing.

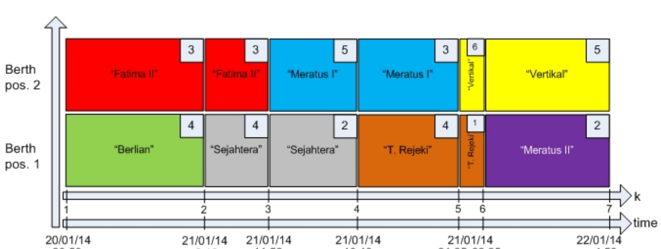

Fig. 4. The resulting berth and quay crane allocation using our proposed MPC-based strategy with N-level FCFS approach ($N = 8$) for the first 7 berthing steps. The berth positions are shown in the vertical axis and the time (and the berthing step) is shown in the horizontal axis. Each box represents allocated ship at different berth position where the label describes the ship's name and the number on the top-right corner of every box gives the allocated QCs.

V. CONCLUSION

We have formulated a dynamical modeling framework of berthing process for general seaport container terminals. The framework can capture the dynamics for multiple berthing positions and multiple quay cranes, as well as, asynchronous berthing time for different berthing positions. The dynamical model has been used in the development of a unified berth and quay cranes allocation strategy based on MPC. We have also proposed several numerical approaches to solve the MPC problems in the MPC-based Allocation Strategy. Simulation results have shown the efficacy of the dynamic berthing and quay crane allocation strategy.

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