

Workload Forecasting in a Container Terminal

Chen Chuanyu^{*}, Stuti Nautiyal[†] and Ye Rong[‡]

Maritime & Port Simulation, SimPlus Private Limited,

10 Anson Road #31-10, International Plaza, Singapore 079903

Accurate workload forecasting is the fundamental and most important step of resource and staff planning. Unfortunately, often encountered in a container terminal is the problem of uncertainty and drastic variation in demand patterns that leads to planning inefficiency. This is particularly true when it comes to predicting the number of containers to be handled by a yard block, which receives work from both the quayside by internal trucks and the gate by external trucks.

In this paper we discuss how to tap on the information system to forecast workload in a container terminal for day-to-day resource and staff planning purpose. Historical and online data from the terminal operating system can be retrieved to form the distributions of daily container arrivals and departures for individual vessels. Aggregating these container moves, based on the vessel schedule, yields an estimation of workload from the gate on a particular day. Workload from the quayside can be forecast by time-series analysis techniques, using the historical handling volumes of individual vessels. A planning tool based on the outlined methodology is being developed to help port operators effectively and efficiently plan their resources.

1. Introduction

Workload forecasting is the fundamental aspect of resource planning for day-to-day operations in a container terminal. An accurate forecast of the work expected allows port operators to provide just enough resources, be it manpower, equipment, or container movers etc. The avoidance of over-providing and under-providing would have cost and efficiency implications. Excess resource will result in unproductive operations and resultantly higher operating cost. Insufficient resource can cause long queues to build up, and congestions inside or even outside the terminal, leading to unhappy customers.

In order to provide high quality service to customers at a low cost, port operators must be able to accurately predict container moves over the planning horizon. Typically three types of container moves decide the level of activity at a terminal. Import containers are those unloaded from vessels and picked up by trucks or trains to leave the port. As most ports provide a free storage period for import

E-mail: ^{*}chuanyu.chen@simplus.sg; [†]stuti.nautiyal@simplus.sg; [‡]ye.rong@simplus.sg.

containers, their departure from the port usually follows certain patterns that are associated with the length of free storage period. Such patterns form the basic of the workload forecasting at import yard and are of paramount importance for equipment and staff planning.

Export containers arrive by land transport e.g. on trucks and trains and leave by vessels. Similar to the departure of import containers, the arrivals of export containers also follow certain time diagrams that can be used for workload forecasting. Unlike import containers for which yard planning is done more in an online fashion, one or more designated yard area is opened for containers to be loaded to an individual vessel well before its arrival. The expected number of export containers belonging to the vessel therefore needs to be forecast for yard planning to designate adequate space for the vessel.

Transshipment containers arrive and leave by vessel. Similar to export containers, when a transshipment container arrives at the port to be loaded to another vessel, the expected number of transshipment containers belonging to the vessel needs to be forecast for assigning the right amount of space.

In summary, the task of workload forecasting is twofold, namely to predict the discharging and loading volumes of individual vessels, and to predict the patterns in which these containers reach and leave the yard. The forecasted loading volume is first used for allocating yard space to a vessel, and then for allocating the right number of equipment, along with the forecasted discharging volume as well as container movement patterns. The procedure of workload forecasting is illustrated in Fig. 1, which is then elaborated further in the subsequent sections.

2. Forecasting Handling Volume of a Vessel

The number of containers associated with a vessel voyage is affected by several factors related to global and regional economics, as well as seasonal demand variations etc, and could vary a lot for different calls. Therefore an approach to predict the handling volume for a vessel is to establish, from historical data, a correlation between the numbers and the factors. When a change in a certain factor is expected, the corresponding change in the container number can be estimated by the correlation model. Such a multivariate approach explains the variation in demand and works well when accurate information of the influencing factors is available. Unfortunately most likely such information itself can only be estimated, either by domain experts or based on data. In such cases the forecast of one parameter is dependent upon that of a set of parameters, which could possibly introduce more chances for errors and biases.

When accurate information of the influencing factors is not available, an alternative way of forecasting the container number associated with a vessel is to build a univariate model that depends only on the past and present information of the number itself. The model should be able to capture such characters as seasonal variation, the trend, and other cyclic variations. An accompanying assumption of the approach is that the past is representative of the future. A working model

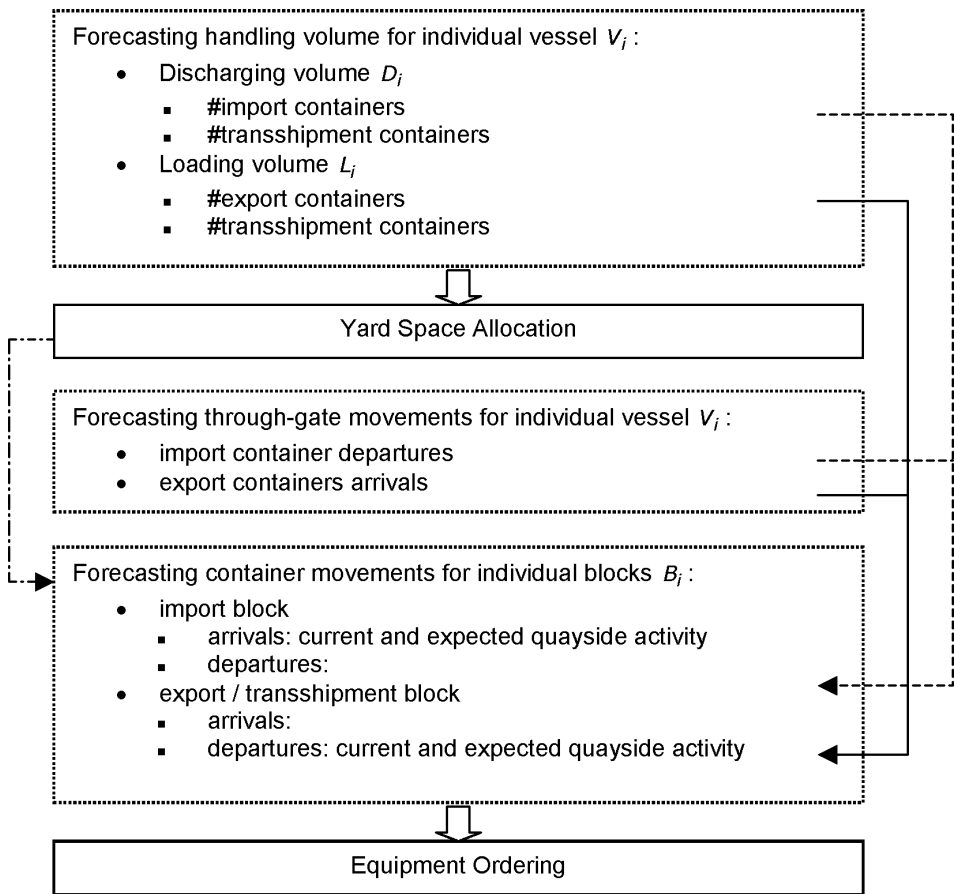


Fig. 1. Workload forecasting procedure.

will thus require updating when there is a structural change or sudden change. Time-series analysis techniques, such as Holt-Winters, Exponential Smoothing, and Damped Trend Exponential Smoothing (refer to the work by Gardner Jr. in 1985 and 2006 for excellent reviews on various Exponential Smoothing methods), can be applied to forecast the handling volume.

The forecast is done for individual vessels when the first loading container arrives, either from the gate or from its first carrier. The forecast volume should be updated and adjusted until the day of vessel's scheduled arrival, whenever more accurate information is available, e.g. expected numbers obtained from shipping companies who are required to report in advance the related information.

3. Forecasting Through-Gate Movements for a Vessel

Container moves associated with vessel operations are more predictable as vessels normally call on a fixed schedule, and the stowage plan (or even

discharging/loading list) is made available before a vessel arrives. Therefore workload from a vessel alongside or expected to berth during the planning period can be estimated from its discharging and loading list and expected or real-time gross quay crane rate (GCR).

Forecasting container moves associated with gate operations, on the other hand, is more challenging, due to the unpredictable scheduling of haulier vehicles. Import containers discharged from vessels normally stay in the yard for a certain period of time, which is highly related to the free storage duration a port offers. Most of the import containers are trucked out before or on the day when the storage charge starts being incurred. The departure patterns can be investigated by mining the historical gate operations data that are readily available in the information system of most ports. In particular, for each vessel voyage, the number of import container departures on day i after vessel call, n_{ij} , can be collected for each vessel call instance j . The probability of an import container leaving on day i after vessel call can thus be estimated by

$$p_i = \frac{\sum_j n_{ij}}{\sum_i \sum_j n_{ij}}$$

A similar approach can be applied to forecast the distribution of export container arrivals. Again the forecasted moves should be adjusted by comparing them with the live operations data for a higher accuracy of prediction.

4. Forecasting Workload for Individual Yard Blocks

Forecasting block workload for resource planning requires distributing the forecasted container moves to individual blocks over different time periods. Overlaying the forecast moves associated with all vessels gives the forecast workload distribution at the yard during the planning period, which forms the basis for equipment ordering. Figure 2 illustrates the aggregation procedure for forecasting the workload in a block on a particular day. Basically it aggregates the volumes from the vessels that are expected to be related to the operations of the day of interest, and then distributes the volume to individual blocks based on the yard allocation rules adopted by the terminal.

5. Applications

The approaches were implemented and tested in a number of SimPlus consulting projects. Holt-Winters and Exponential Smoothing were applied to forecast the handling volumes that were categorized by container type. Data mining was also conducted to unearth the patterns of container arrivals and departures through the gate. With this, along with the prediction of container moves associated with vessel operations by using real time GCR and discharging/loading list, workload in each block can be predicted with an accuracy that is adequate for resource planning. Such guided forecasts performed better than reactive planning or assuming the volume similar to that of last visit. Possible enhancements to the models would

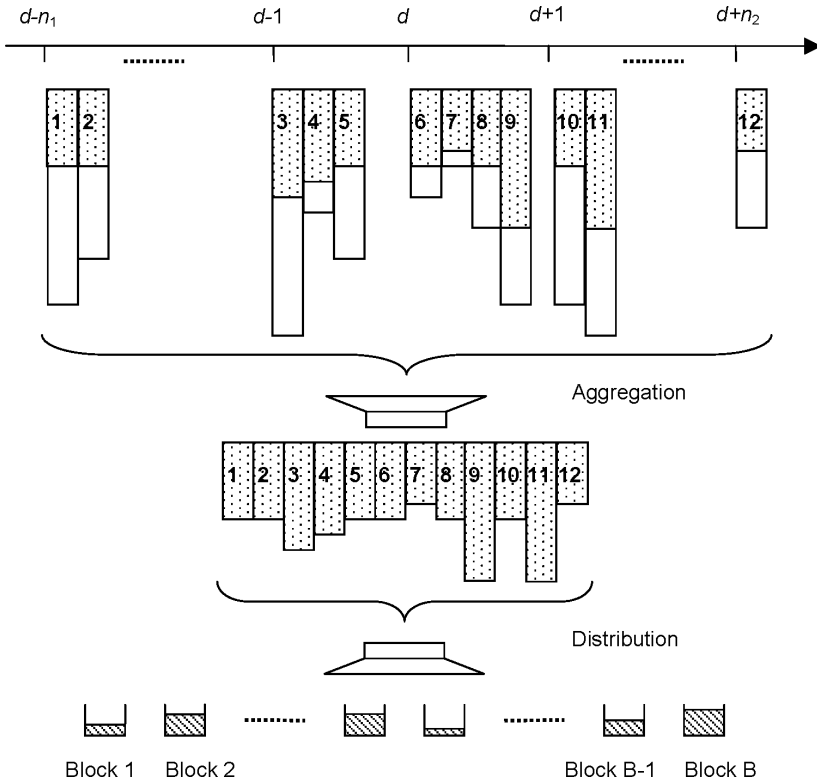


Fig. 2. Aggregating workload for individual blocks.

include finding ways to factor in other parameters such as “holiday effects” and daily fluctuation, or evenly hourly fluctuation. A comprehensive forecasting tool, SimCast, being developed, captures the features and is tailored for container port operations.

References

1. Gardner Jr. E. S. (1985), Exponential smoothing: The state of the art. *Journal of Forecasting*, 4, 1–28.
2. Gardner Jr. E. S. (2006), Exponential smoothing: The state of the art – Part II. *International Journal of Forecasting*, 22, 637–666.