



CSUN
 DAVID NAZARIAN
 COLLEGE OF BUSINESS
 AND ECONOMICS

MITIGATING SHIP DELAY IMPACTS ON STACKING OPERATIONS

A DATA ANALYTICS SOLUTION

Dr Amir Gharehgozli, David Nazarian College of Business and Economics,
 California State University, USA

The confluence of the availability of incredible amounts of data, methodological developments, the explosion in computing power and storage capacity have given rise to the popularity of “data analytics” in many industries. Many companies are now aggressively investing in data analytics tools to generate insights that can help them make well informed business decisions. The maritime industry, although somewhat behind other sectors, has also begun to take advantage of data analytics to aid the smooth running of the global supply chain. In automated container terminals with a turnover of hundreds of thousands of TEUs (twenty-foot equivalent units), data analytics can make a significant impact on stacking operations, especially in the era of mega-containerships and sudden changes in the container flow due to various events (e.g. weather, strikes, and so forth).

THE PROBLEM WE FACE

In the last few decades, the volume of global trade has dramatically increased. Consequently, the size of containerships to accommodate the need for transporting containerized cargo has drastically increased too. It was just a few years ago when ships could carry only 10,000 TEUs max. Today, mega-containerships with an 18,000-21,000 TEU capacity at has become the norm. In this circumstance, container terminals play an even more important role in the organization of efficient global trade. Many containers have to be stacked temporarily and even more land is needed for the related supply chain activities. Lack of space has driven container terminal operators to stack containers multi-high and this method of stacking containers often leads to reshuffling (the removal of a container stacked on top of a desired container).

RESHUFFLING

Since reshuffling is time consuming and increases the turnaround time of ships, reducing the number of reshuffles is a critical operational challenge for terminal operators. As shown in Figure 1, terminal operators first need to deal with reshuffling prior to the arrival of the ship by stacking containers in a specific sequence desired for loading the ship and reducing the turnaround time of the ship. On the other hand, reshuffles may occur when there is a delay in the arrival of a ship. This latter reshuffling, though not as common as former one, is another source of inefficiency.

Terminal operators have attempted to limit the number of prior and posterior reshuffles by using a dedicated stacking policy which assigns a section of the stack to each group of containers categorized based

on their weight, ship, and destination, and so forth. In light of the boom in the international freight transportation, terminal operators have been forced to shift toward a shared stacking policy in which containers of different groups are stacked tightly in multiple tiers. This policy helps terminal operators to increase the utilization of the stacking area and potentially stack more container but at the same time, any delay in the arrival of one ship can create numerous required reshuffles.

DATA ANALYTICS

Data analytics is a new powerful tool that can be used to limit the number of reshuffles, especially in the case of ship delays. Nowadays, container terminals collect data on a daily basis. Computers record all ship arrival times, container movements, container handling equipment movements, gate arrivals, and all the other departures, arrivals and movements. They also have access to the data of their clients and stakeholders including shippers, carriers, and consignees. Such databases can be used in order to forecast and mitigate disruption (Gharehgozli et al. 2017) as well as propose a method that can use this data in order to reduce the number of reshuffles when ships delay.

Computing also proposes a model to manage the risk and time lost in container stacking operations by estimating the expected number of reshuffles (ER). Inspired by the credit risk models common in the financial risk literature, they introduce a model which estimate ER based on the following three variables: probability of delay (PD), probability of delay of a ship; reshuffles given delay (RGD), magnitude of likely number of reshuffles in case of a delay; and call size at delay (CSD); the number of containers to be loaded on the ship. The following equation shows how ER can be estimated:

$$E(R) = \pi \times \xi \times \psi \tag{1}$$

Where, E(R) is the expected number of reshuffles, π is the probably of delay; ξ is the reshuffles given delay, and ψ is the call size at delay. Theoretically, E(R) can be 0 when $\pi=0\%$ or $\xi=0\%$. In the first case, the containership does not delay and in the second case the container terminal operators have used a dedicated policy to stack containers of each ship. E(R) can also be equal to ψ when $\pi=100\%$ and $\xi=100\%$. In order to calculate E(R), we need to estimate π , ξ , and ψ .

Data analytics can be used to estimate these variables using the historical data collected by terminal operators. In other words, estimating each variable needs data mining on the huge databases of

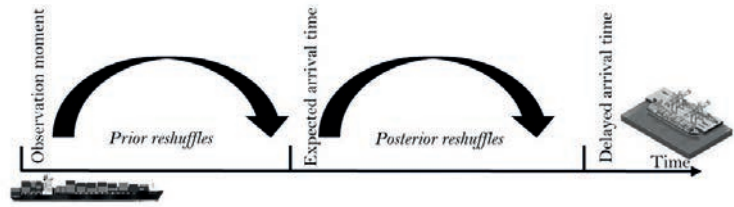


Figure 1. Two types of reshuffles: prior and posterior reshuffles.

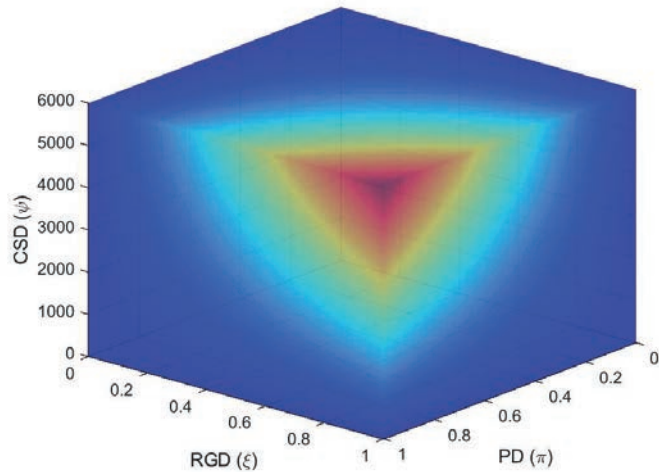



Figure 2. A thermal plot indicating expected number of reshuffles by means of different colors.

Note. Color scale is , where dark blue shows the smallest expected number of reshuffles and dark red shows the largest expected number of reshuffles.

container terminals. In some instances, external databases may also be necessary to get a holistic picture. For example, as is common in the banking literature, ‘Logistics Regression’ can be used to estimate probability of delay for ships. Building such a model requires defining and collecting data on variables such as ship size, shipping line, ship age, fuel type, flag of convenience, et cetera. Similar models can be built for the other two variables using a terminal’s internal and external data.

In practice, data may not be available, or the terminal may not be willing to provide the required data. Furthermore, the variables estimated based on the data of a specific terminal cannot be generalized to other terminals. Therefore, Gharehgozli et al. (2017) use a simulation model to estimate the variables for a numerous number of scenarios. Estimating ER helps container terminal operators to evaluate the robustness of the stacking policy chosen and to mitigate the risk of extra reshuffles.

THE SIMULATION MODEL

To run the simulation model, it is assumed that there is one delayed ship with a call size, ψ , which can vary in a range from 0 to 6,000 TEU. Furthermore, the probability of

delay, π , and reshuffles given delay, ξ , are in a range from 0% to 100%. Figure 2 shows ER for different values of model variables. The values of ER are shown by means of different colors.

Based on the simulation study the following conclusions can be made:

Impact of probability of delay (PD): If a carrier is reliable and always on time (i.e., $\pi=0\%$), then ER is 0. Therefore, because based on equation (1), ER is estimated by multiplying π , ξ , and ψ , regardless of the stacking policy, no extra reshuffles will occur since the carrier is always on time. However, if the carrier is less reliable in terms of punctuality (i.e., $\pi>0\%$), then ER increases. Therefore, terminal operators need to analyze their historical data and evaluate the punctuality of the carriers with whom they work. If a carrier is always late (i.e., $\pi=100\%$), then it is recommended to use a dedicated policy to stack containers of that carrier in order to avoid unexpected reshuffles in the future, if and when the ships of that carrier delay.

Impact of reshuffles given delay (RGD): If container terminal operators implement a dedicated policy then no reshuffles will occur even if the ship delays (i.e., $\xi=0\%$). Again, since ER is estimated by multiplying

π , ξ , and ψ , regardless of the stacking policy, it will equal 0. Therefore, the punctuality of the carrier does not have any impact on the efficiency of the terminal since the expected number of reshuffles will not change. Mathematically speaking, the number of reshuffles becomes independent of PD. By using a shared stacking policy and mixing different container groups together, RGD increases (i.e., $\xi > 0\%$). Therefore, if a ship delays, then more reshuffles will be needed in the terminal which its scale depends on the magnitude of PD, RGD, as well as CSD that will be discussed next.

Impact of call size at delay (CSD): last but not the least, size matters. Larger ships with larger call sizes can create more reshuffles in case they delay as compared with smaller ships (also see equation 1). Therefore, terminal operators can use a shared policy to stack containers of ships with smaller CSDs without being much concerned with the inefficiency that may be created by handling the reshuffles in case of delay. On the other hand, they need to carefully take the punctuality of larger ships with larger CSDs into consideration before mixing their containers with the other ones.

In calculation, the results discussed in this article confirms that while carriers may benefit from the increased economies of scale, mega-ships introduce new challenges to terminal operators. Mega-

containerships (even if always punctual) can potentially increase the expected number of reshuffles and as a result, increase their own turnaround times. Terminal operators need to rethink their stacking operations not only to increase

their utilization and make better use of the limited land available at terminals but also to decrease the number of reshuffles which can significantly hurt their productivity. Data analytics seems to be key to address this new challenge at terminals.

REFERENCES

- [1] Gharehgozli, A., Mileski, J., Duru, O. (2017). Heuristic Estimation of Container Stacking and Reshuffling Operations under the Containership Delay Factor and Mega-Ship Challenge. *Maritime Policy and Management*, 44(3), 373-391.

ABOUT THE AUTHOR

Amir Gharehgozli is an Industrial Engineer who has got his PhD in Logistics and Operations Management from Rotterdam School of Management. His research interests are Facility Logistics Management, Distribution Logistics Management, Supply Chain Management, and Maritime Logistics; in particular, studying recent innovations in these areas. He is now the associate editor of *Maritime Policy and Management*. He is currently an assistant professor in David Nazarian College of Business and Economics at California State University Northridge.

ABOUT THE ORGANIZATION

David Nazarian College of Business and Economics at California State University Northridge is dedicated to educating the leaders of tomorrow. By offering a challenging curriculum, smaller class sizes, state-of-the-art facilities, and nationally recognized programs, the College offers a unique educational experience. Access to prominent alumni and influential business leaders provides students the opportunity to network with and learn from successful individuals.

ENQUIRIES

amir.gharehgozli@csun.edu



Designing for the Future

The equipment designs and standards Liftech developed 50 years ago revolutionized global shipping.

We have never stopped dedicating our curiosity and skills to structures that touch the lives of people in communities around the world.

Innovation, Experience, Integrity

Liftech
LIFTECH CONSULTANTS INC.

www.Liftech.net