BUNCHING INDEX FOR BULK CARGO PORTS

Hai-Yan Xu [a], Xiuju Fu [b], Ruthu Shree Ragavan [c], Lee Jek Suen [d] , Xiao Feng Yin[e], Rick Siow Mong Goh[f]

[a],[b],[e],[f] Computing Science, Institute of High Performance Computing, Singapore
[c],[d] Jurong Port Pte Ltd, Singapore

[a] xuh@ihpc.a-star.edu.sg, [b] fuxj@ihpc.a-star.edu.sg, [c] ruthu@jp.com.sg
[d] jeksuen@jp.com.sg, [e] yinxf@ihpc.a-star.edu.sg, [f] gohsm@ihpc.a-star.edu.sg

ABSTRACT

In this study, we propose a novel Bunching Index (BI) model to derive a useful parameter for quantifying instantaneous information of congestion degree of ports based on number of vessels waiting for berths, waiting time and vessels size. Further analysis based on the data of port calls, port processes, and cargo demands from a general and bulk cargo port in Southeast Asia shows that the proposed bunching index well reflects the impact of vessel bunching at ports. It is found that bunching index is significantly correlated to certain types of port processes, cargo storage balance, and number of trucking trips for the cargo with time lags. Our study demonstrates that bunching index can be used for predicting time-ahead bunching, detecting the impact of bunching and factors affecting operations, and evaluating the effectiveness of counter measures for reducing bunching. We believe that bunching index can be used for other ports to detect hidden patterns and provide insights for improving port operation efficiency and optimizing resource utilization.

Keywords: bunching, bulk cargo ports, port operation efficiency, Berth on arrival rate

1. INTRODUCTION

Port congestion happens when the number of vessels waiting for berthing is accumulated to a certain level that exceeds the port capacity and the affected vessels have to wait longer than expected. Considering the detrimental impact of port congestion on port operator, shipping agents, and consignees, many researchers have studied possible factors that cause port congestion, cost associated with port congestion, and the ways to avoid and eliminate port congestion (Gidado 2015; Naudé 2016; Pani 2013).

Port congestion related studies could be more effective only when the severity of port congestion at any given time can be properly quantified. From the literature, the quantification of the degree of port congestion may be measured from different perspectives. One is from the view of ports, such as congestion index defined by Abe and Wilson (2011), i.e., the ratio of throughput handled in the port to the whole capacity of the port, which can also be considered as ports utilization rate. High value of this index implies high possibility of congestion. Berth on Arrival (BoA) rate, the percentage of vessels berthed within a certain time window since arrival, is usually used at ports, representing the performance of berthing at a port over a certain time period (Dai et al. 2004; Huang et al. 2008; Yang, Zhang, and Lam 2013). Lower BoA represents that the percentage of vessels not berthed within the specific time window is higher at ports. It also implies higher possibility of a long queue waiting for berths.

However, both congestion index and BoA cannot provide timely information for port berthing status and ignores the evaluation of berthing service from the view of vessel owners and consignees, i.e., the volumes of cargo on the vessels coupling the waiting duration matter, which is related to the demurrage cost occurred and the potential cost of cargo shortage due to the delayed unloading schedule, and affects vessels' next schedule etc.

The second one is from the view of ports' customers, i.e., shipping companies and consignees. UNCTAD (1976) proposed average waiting time to represent port congestion. This index cannot reflect the impact of the number of waiting vessels. If average waiting time is same, more waiting vessels implies a more severe congestion. Naudé (2016) improved the index by considering both average waiting time and number of waited vessels. Two indices are not convenient to be used to quantify the impact of the congestion situation and the vessel DWT are not reflected either.

It is obvious that port congestion at the moment is not properly quantified to reflect the real-time severity of congestion and the factors that concern various stakeholders. In this paper a novel Bunching Index (BI) model is proposed to derive a composite parameter for quantifying instantaneous information of congestion degree of ports based on the number of waiting vessels, waiting time and vessels size. The association between the proposed index and port operation parameters, and cargo demands is investigated based on the data of port calls from a general and bulk cargo port in Southeast Asia. We found that BI is significantly correlated to some port operations, cargo storage balance, and number of trucking trips for the cargo with time lags.

The rest of this paper is organized as follows: the details of the bunching index is formulated in Section 2; the influence of bunching index to other port loading/unloading processes is explored in Section 3; the study and discussions of factors that could affect bunching index is presented in Section 4; conclusions and further study directions are discussed in Section 5.

2. BUNCHING INDEX DEFINITION AND FORMULATION

2.1. Definition of bunching index in general and bulk cargo port

Bunching index is a concept that can be generally found to define regularity assessment in scheduled transportation system (Daganzo 1997), such as flight traffic (Dravecka 2006), bus transport (Li, Yang, and Ma 2013) and container liners. Different from scheduled transportation system where vehicles/vessels/planes are scheduled to arrive regularly, the berthing of vessels at general and bulk cargo port is usually irregular, i.e., vessels arrive with FCFS (first come and first served) mode. As such, bunching of vessels for berthing is expected, especially when there is higher throughput and limited number of berths available. Hence, bunching index for general and bulk cargo port is important to reflect the degree of port congestion.

Upon defining bunching index for general and bulk cargo port, we have the following considerations:

1. Vessels' waiting time threshold. Only vessels whose waiting time exceeds the threshold are accounted in bunching index calculation. This threshold can be changed according to different ports' regulation. Usually, it can be set the same as the threshold adopted for calculating BoA rate. For example, a 1-day time window is used in this study.
2. Accumulative effect of the number of waiting vessels and their waiting time. The longer the vessels wait and the more the vessels at port, the higher the bunching index is. As different vessels contribute differently to bunching index, bunching index is defined as the product of all vessels' contributions. We further assume that congestion severity increases exponentially as the increase of waiting time.
3. Impact of vessel size. Here vessel size is its deadweight. We choose deadweight instead of vessel throughput as deadweight directly links with the demurrage fee. The contribution of each vessel to bunching index is a power with the base of a function of vessel size. To avoid a too high and obtain a reasonable bunching index, the function of vessel size is defined as the sum of one and standardized vessel size, which is the ratio of vessel size divided by its maximum possible value of vessel size at the port. Here, maximum possible value is the biggest vessel deadweight at the port in history.

Let t denote current time, w_i denote the deadweight of vessel i, $t_i(t)$ denote waiting time of vessel i until time t, t_0 denote BoA threshold, the bunching index at time t is defined as

$$B(t) = \prod_{i\in\Omega_t} l_i(t) \qquad \text{Eq. 1}$$

where

$$l_i(t)=l(w_i,t_i)=(1+g(w_i))^{f(t_i(t))}$$

Ω_t is the set of all vessels at the port at time t; $l_i(t)$ is the contribution of vessel i to bunching index; $g(w_i)$ reflects the impact of vessel's deadweight, and it is in (0, 1) with $g(w_i)=\alpha w_i/W$, α is an adjustment parameter, $W=max\{w_i|i\in\Omega\}$, Ω is the set of all vessels at the port in history; $f(t_i)$ is to reflect the impact of vessel's waiting time, $f(t_i)=max\{0, t_i\text{-}t_0\}$. It implies that $B(t)$ is 1, if there is no bunching at time t; $B(t) > 1$ if bunching presents.

2.2. Application of bunching index to a general cargo port

To check the reasonability and effectiveness of the proposed bunching index, we compared bunching index with the number of vessels at port and vessels' waiting time based on port calls data from a general and bulk cargo port in Southeast Asia. The data from April 2011 until June 2015 is used to verify the bunching index. Figure 1 depicts the time series of bunching index, number of vessels and waiting time calculated upon each vessel arriving at berth.

Figure 1: Bunching index, number of vessels and waiting time from April 2011 until June 2015 calculated upon each vessel arriving at berth. First panel: bunching index obtained based on Eq. 1; Second panel: number of vessels at port; third panel: waiting time before a vessel arriving at berth. BOA rate is calculated at annual basis.

From the Figure 1, it is clear that the bunching index reaches its highest point in 2013, when exceptional long waiting time erupts and the BoA rate is the lowest among all studied years. The bunching index is closely related to the BoA as the same threshold is used for both bunching index and BoA calculation. On the other hand, the number of vessels in the queue does not significantly affect bunching index. It is because the bunching index gives allowance for the vessel to be waiting in the queue. It affects the bunching index only when queuing time is longer than expected. Meanwhile, it also indicates that the fluctuation of the number of vessels is not the only factor affecting congestion degree and it works together with the duration of waiting time. It will be further discussed in Section 4.

3. HOW DOES BUNCHING INDEX AFFECT PORT PROCESSING

In this section, we explore how does bunching index associate with port operations through the port calls data from the general and bulk cargo port in Southeast Asia. We investigate the impact of bunching index on all non-working hour components for cement cargo unloading, including gantry (gantry moving and positioning), lubricant, trimming (trimming and cleaning of vessel cargo hole), silo stoppage (unloading stoppage due to silo capacity limitation), rain, port breakdown, others by consignee (others stoppage caused by consignee) and others by port (other stoppage caused by port).
Among all the non-working hour components, gantry and trimming are found having significant relationship to the bunching index after controlling other factors, such as cargo throughput, shipping agent, cargo type, net-working hour and non-working hour components other than the interested component using port stay data from April 2011 until June 2015 (see **Table 1**).

Table 1: Significant impact of bunching index on non-working hour components

Non-working hour components	Bunching index coefficient	p-value
Gantry (day)	1.449e-02	0.01430
Trimming (day)	-1.900e-02	0.01496

For net-working hour (NWH), we found that the impact of bunching index on NWH is not significant after controlling the effect of port and cargo relevant factors and non-working components. On the other hand, if we associate bunching index with NWH without controlling other factors, significant relationship between bunching index and NWH is detected. It implies that NWH might be affected by port of loading and/or cargo relevant factors (e.g., the type of cargos).

4. WHICH FACTORS CAN AFFECT BUNCHING INDEX

We further explore the factors that could affect or indicate bunching index through the cement vessel port calls data from the port. High cement demand implies high volume of cement and more vessels required by cement consignees, which would trigger possible high bunching index. The number of daily cement trucks passing through the port gates may reflect cement demand. To remove the periodic fluctuation of the number of cement trucks, a monthly moving average is used. The cross-correlation between cement trucks and daily maximum bunching index from August 2013 to August 2015 is calculated (see **Figure 2**). It is detected that cement trucks number 28 days ago has highest correlation coefficient with the current bunching index.

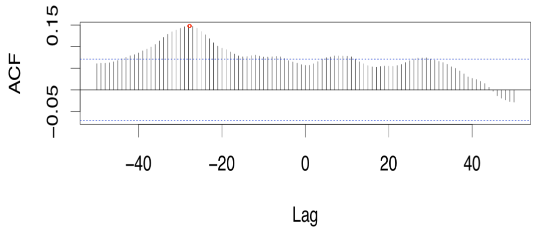

Figure 2: Cross-correlation between cement trucks (monthly moving average) and daily maximum bunching index

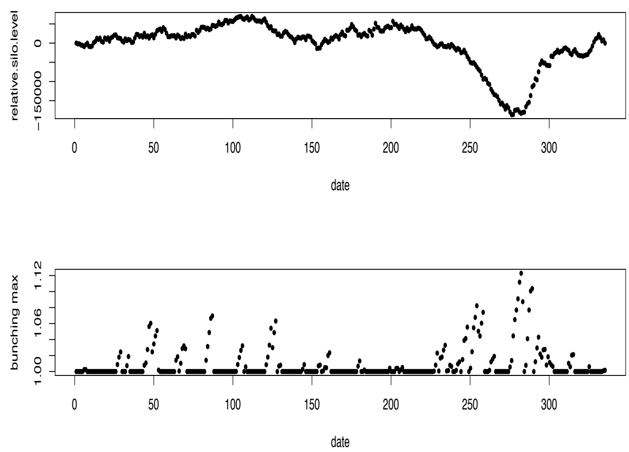

Figure 3: Estimated relative silo level and bunching index from April 2014 to February 2015

Silo balance can be another factor to reflect cement demand and also a more direct indicator to bunching index compared with the number of trucks running in the port's yard. Figure 3 illustrates the comparison of time series of estimated relative silo level and bunching index from April 2014 to February 2015. Furthermore, the cross-correlation between estimated relative silo level and daily maximum bunching index from April 2014 to February 2015 is calculated and depicted in **Figure 4**. Compared with the correlation between truck number and bunching index, higher correlation coefficient is detected between relative silo level and bunching index. It is detected that relative silo level one day ago has highest correlation coefficient with current bunching index.

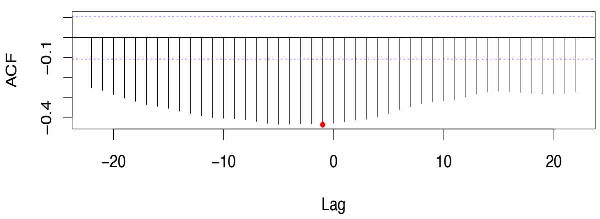

Figure 4: Cross-correlation between silo balance and daily maximum bunching index

5. CONCLUSIONS AND FUTURE WORK

In this paper, we propose a novel bunching index that takes into consideration the number of waiting vessels, vessel sizes and their waiting time. As a useful parameter for port and port efficiency study, the association between BI and other port operation parameters is indeed detected in this study. Significant relationship is found between bunching index and non-working hour components in port operation: gantry and trimming after controlling other factors. More specifically, higher bunching index associates longer gantry time and shorter trimming time. Silo balance and number of cement trucks entering into port have lagged effect on bunching index. Silo balance one day ago has highest negative correlation to bunching index, while number of trucks one month ago has the highest positive correlation to bunching index considering all lags.

Our study demonstrates that bunching index can be used for predicting time-ahead bunching, detecting the impact of bunching and factors affecting operations, and evaluating the effectiveness of counter measures for reducing bunching. It suggests that advanced booking is one option to reduce bunching besides increasing port resources. We believe that BI can be used for other ports to detect hidden patterns and provide insights for improving port operation efficiency and optimizing resource utilization. The BI can also be extended to include other relevant factors, such as cargo size, to better reflect the significance of vessels affected. A version II BI might be realized in the near future that is able to be used not only in bulk cargo terminal but in general and container cargo terminals.

REFERENCES

Abe K., Wilson S.J., 2011. Investing in Port Infrastructure to Lower Trade Costs in East Asia, Journal of East Asian Economic Integration. Vol. 15, pp. 3-32.

Daganzo F.C., 1997. Scheduled transportation systems, Fundamentals of Transportation and Traffic Operations, pp.285 – 321.

Dai J., Lin W., Moorthy R., Teo C.-P., 2004. Berth allocation planning optimization in container terminal. Unpublished manuscript. Available from: https://people.orie.cornell.edu/jdai/publications/daiLinMoorthyTeo08.pdf [accessed 1 June 2017]

Dravecka L., 2006. Operational feasibility of traffic synchronisation in central Europe – results, in 25th Congress of the International Council of the Aeronautical Sciences. Hamburg, Germany: ICAS.

Gidado, U., 2015. Consequences of port congestion on logistics and supply chain in African ports. Developing Country Studies. 5(6): 160–167.

Huang S.Y., Hsu W.J., Chen C., Ye R., Nautiyal S., 2008. Capacity analysis of container terminals using simulation techniques, International Journal of Computer Applications in Technology, 4(32), pp. 246-253

Li F., Yang D., Ma, K., 2013. Bus Rapid Transit (BRT) Bunching Analysis with Massive GPS Data. Fourth International Conference on Transportation Engineering, October 19-20, Chengdu, China

Naudé J., 2016. A Multi-Phase Model to Forecast Congestion at Brazilian Grain Ports: a Case Study at the Port of Paranagua, Thesis (Master). Stellenbosch University.

Pani C., 2013. Managing vessel arrival uncertainty in container terminals: a machine learning approach. Thesis (PhD). University of Cagliari, University of Antwerp.

UNCTAD, 1976. Port performance indicators. United nations Conference on Trade and Development. New York, US.

Yang D., Zhang A., Lam J.S.L., 2013. Impacts of port productivity and service level on liner shipping operating cost and schedule reliability. International Forum on Shipping, Ports and Airports (IFSPA). Trade, Supply Chain Activities and Transport: Contemporary Logistics and Maritime Issues.

AUTHORS BIOGRAPHY

Dr. Hai-Yan XU is a research scientist with the Institute of High Performance Computing, Singapore. She received her B.S. (1999) in Mathematics, M.S. (2002) and Ph.D. (2005) in Statistics from Shanghai Normal University, China. She has published more than 20 papers in peer-reviewed conferences and journals such as PLOS Neglected Tropical Diseases, PLOS One, IEEE Transactions on Reliability, IIE Transactions, Computational Statistics & Data Analysis, and The International Journal of Advanced Manufacturing Technology. Her research interests include applied statistics and probability, longitudinal data analysis, discrete time series analysis, accelerated life and degradation testing, optimal design, and large-scale data analysis with applications in maritime port, logistics and supply chain, public health, manufactury, and city planning.

Dr. Xiuju FU is Senior Scientist in Department of Computing Science at Institute of High Performance Computing, A-STAR. She received her bachelor and master degrees in Beijing Institute of Technology in 1995 and 1999, respectively. And she received her Ph.D. in Information System, School of EEE, Nanyang Technological University, 2003. Her research areas are in intelligent modelling and simulation based on data analysis, modeling/simulation and optimization techniques, with the applications in maritime port and transportation, logistics and supply chain, and public health.

Ms. Ruthu Shree Ragavan is an Assistant Manager, Strategic Planning Office at Jurong Port Pte Ltd. During her 6 years in the port industry, she has also served in Operational and Customer Service roles. She majored in International Transportation and Logistics Management and received her Master of Business Administration (2011) from Indian Maritime University, India

Mr. Lee Jek Suen is an Assistant Vice President, Strategic Planning Office at Jurong Port Pte Ltd. He received his B.A Oxon (1996) in Politics, Philosophy & Economics from the Oxford University (UK), and MSc International Relations (1997) from the London School of Economics (UK). Over the past decade, besides Strategic Planning, he has served in Business Development and Operational roles in Singapore, China, other ASEAN as well as African ports.

Dr. Xiao Feng YIN is Scientist for the Institute of High Performance Computing, A*STAR Singapore. He received both his PhD and his Master's degrees from Nanyang Technological University (NTU), Singapore. His research interests include maritime, logistics and supply chain optimization, planning and scheduling, knowledge discovery and artificial intelligence.

Dr. Rick Siow Mong GOH is the Director of the Computing Science (CS) Department at the A*STAR's Institute of High Performance Computing (IHPC). At IHPC, he leads a team of more than 60 scientists in performing world-leading scientific research, developing technology to commercialization, and engaging and collaborating with industry. The research focus areas include high performance computing (HPC), distributed computing, artificial intelligence, and complex systems. His expertise is in discrete event simulation, parallel and distributed computing, and performance optimization and tuning of applications on large-scale computing platforms. Dr. Goh received his Ph.D. in Electrical and Computer Engineering from the National University of Singapore. More details on Rick can be found at: http://www.a-star.edu.sg/ihpc/People/tid/2/Rick-Goh-Siow-Mong.aspx