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Modeling Shipment Spot Pricing in the Australian Container Shipping Industry: Case of ASIA-OCEANIA trade lane

Ayesha Ubaid a,*, Farookh Hussain a, Jonathan Charles b

a University of Technology Sydney, 15 Broadway, Ultimo, 2007, Australia
b Mizzen Group, Cicada Innovation, Sydney, NSW, Australia

ABSTRACT

The shipping industry is fairly volatile pertaining to shipment pricing. To handle this volatility, two types of pricing strategies are employed in the shipping sector, contract market pricing and spot pricing. The contract market offers a fixed shipment price for a known cargo task over a set period, with secured booking space in periods of high demand. The spot market has a fluctuating shipment price, where one can benefit from lower prices than contract rate shipment prices in the low season, but face escalating shipment prices and less certainty of being able to secure a booking on a particular vessel in peak season, as space is reserved for contracted customers. However, both the pricing strategies followed have no relationship between current shipment demand and available shipping capacity and shipment prices are quoted based on predefined price lists (hard copy). This paper addresses the research gap of optimal spot shipment price calculation based on current shipment demand and available shipping capacity. To do so, we have developed a model that utilizes historical data to calculate spot pricing for container shipments. The proposed model is capable of calculating shipment spot prices based on shipment demand and capacity. Data from various sources was gathered to generate a shipping dataset for three years (i.e. from 2016 until 2018). Regression and correlation analysis are used to quantify research outcomes. Results have shown that the proposed model significantly increases the correlation between shipment price and shipment demand from 0.33 to 0.88 and available capacity from $-0.03$ to 0.35 respectively.

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1. Introduction

The need for transportation arises due to the need to move goods from one place to another in line with consumer demand. Sea transportation is one of the cheapest and oldest modes of transportation of goods. The magnitude of sea transportation is directly connected to the economic growth of any country. It steers the economy of the country [1]. Like any other service industry, seasonal events affect the operation of the shipping industry. A container vessel follows a schedule, a set route of port calls and sailing times and departs a port on a scheduled date regardless of the cargo utilization factor. Cargo volumes are very seasonal and are driven by consumer events such as Christmas and Chinese New Year and agricultural produce harvests, and are affected by geopolitical events such as a US–China trade war. In contrast, available shipping capacity (supply) is fixed in the short run as extra capacity cannot be rapidly deployed or withdrawn to match cargo shipment demand. This mismatch in available shipping capacity (supply) and shipment demand creates shipment price volatility.

Pricing is one of the most influential factors in a service industry such as container shipping. The shipping market continues to grow but freight rates remain stagnant due to inflexible and ineffective pricing strategies [2]. This results in revenue loss and instead of increasing revenue, shipping companies end up suffering significant losses. According to a study conducted by Deloitte University [3], the shipping industry can increase its profit margin by 2% to 7% in just 12 months and can yield a 200% to 350% return on investment by setting effective pricing. Although there is much potential to expedite returns, the domain of setting optimal pricing is still under-explored. There is a lack of interest in conducting research on optimal spot pricing for container shipments in the shipping industry. There are very few studies that focus on identifying price-setting challenges and finding optimal opportunity cost for container shipment spot pricing. However, no such study investigates optimal pricing based on available shipment demand and capacity.

The primary contribution of this research study is to present an optimal spot pricing model for the container shipping industry.
This model can help shipping companies implement competitive pricing based on current shipment demand and available capacity resulting in increased revenue. To achieve this goal, we have sourced demand data from the five international Australian ports [4–7] [8] (namely Port Botany, Port of Melbourne, Port of Brisbane, Fremantle Port and Flinders Port). The available shipment capacity data was obtained from Sea Intelligence [9]. Sea intelligence provides analytics in the container shipping industry by publishing one week ahead of shipment capacity for global shipments. The shipment pricing data is gathered from Shanghai Freight Index, a global shipment pricing company [10] and Mizzen Group, an Australian owned shipment spot price provider [11]. The sourced data is integrated and cleansed followed by data analytics. Using modern data analytics techniques (details can be seen in Section 4), the existing relationship between demand, prices and capacity is studied. This multivariate analysis is then compared with the ideal statistical relationship between demand, capacity and pricing strategies in the shipping industry to design an optimal pricing model that can calculate shipment spot prices based on current demand and available capacity of the market.

The remainder of this paper is organized as follows. In Section 2, we review the existing related work. In Section 3, we explain the real-time pricing strategy currently employed in the shipping industry. Section 4 describes the research setting and proposed model for the calculated optimal shipment price followed by the results and a discussion. Section 6 concludes this paper.

2. Related work

Estimations are very important in relation to making business decisions. Researchers have shown that due to a varied number of dependencies, shipment price estimation is quite complicated in the shipping industry [12]. Hence, the key idea behind shipment price estimation for the container shipping industry is not to trust estimations for price-setting; rather it is more to do with developing future plans [13]. Modeling optimal pricing in the shipping industry is an understudied area. However, in the recent past, a few studies have been conducted to address the issue. Based on these studies, the shipment pricing methods can be classified into two major classes, Scenario-based pricing methods and Algorithmic pricing as shown in Fig. 1.

2.1. Scenario-based pricing

In this group of pricing studies, authors have made assumptions of the shipment routes, number of carriers/forwarders and have proposed the pricing strategies based on supposed specific shipping scenarios. In [14], the authors studied pricing decisions in the container industry by taking into account empty container repositioning costs and obtained some analytics properties. They worked on two port-closed systems to simplify their research problem. Xu et al. [15] developed the work in [14] by extending the research scenario to one carrier, two forwards, and one shipper. The author built a mathematical model to study the price determination method followed by carriers and forwarders. According to Chen, there exist minimum and maximum pricing thresholds and pricing is quoted within the threshold limit. The forwarder pays for the shipment price if the shipment price estimation is below the threshold. However, if the shipment price exceeds that threshold, it has to be given by the carrier. Shah et al. [16] proposed a novel price-setting model. This model determines the price of transport for a shipment and the inventory holding costs, although, a varied number of deterministic variables are considered to set shipment prices in the above studies. However, in real life, shipments are not operated under ideal scenarios. There can be a varied number of carriers, forwarder ports and shipment lines may or may not become part of any cargo transportation. Hence other approaches are also explored for price setting in the shipping industry.

2.2. Algorithmic pricing

Keeping in view the limitations of scenario-based studies, researchers have also studied algorithms for pricing. In this group of research studies, game theory has been used along with Nash equilibrium to determine the price for shipment containers keeping demand or capacity as deterministic factors. Lee et al. [17] adopted a game theory approach. The authors modeled three players who compete with each other for pricing and routing choices. The selection criteria used in this method is the Nash equilibrium. Wang et al. conducted groundbreaking research in the pricing domain in 2014. The authors used the game theory as a research setting and used freight rate, service frequency, and capacity as key price-setting criteria [18]. In 2016, a pricing method based on game theory was proposed using Nash equilibrium and ship capacity [19]. However, the aforementioned research takes shipment demand as a deterministic factor. In the research studies presented in [17,19,20], varied pricing decisions are proposed using shipment demand as a non-deterministic factor. In these studies, the authors do not use competition between shipping lines as a deterministic variable.

To the best of our knowledge, there exists no study that considers the current shipment demand and available shipping capacity and their historic relationship to determine the optimal spot price for a shipment. To fill this gap, we propose a novel model to determine container shipment price based on the bivariate analysis between shipment demand and capacity for a single trade lane. The number of forwarders, carriers and ports have no effect on pricing. The only deterministic factor for price determination is current demand, available shipment capacity and their correlational effect from past data.

3. Pricing strategy in the shipping industry

To deal with volatility in shipment pricing, there are two types of pricing strategies currently employed in the shipping sector, contract market pricing and spot pricing. The contract market offers a fixed shipment price for a known cargo task over a set period, with secured booking space in periods of high demand. The spot market has a fluctuating shipment price, where one can benefit from lower than contract rate shipment prices in the low season, but face escalating shipment prices and less certainty of
being able to secure a booking on a particular vessel in peak season, as space is reserved for contracted customers [21]. Current industry pricing practices and commercial product offerings deliver sub-optimal outcomes for the shipping lines and also for their customers.

Freight rates are set with a date validity and not by vessel voyage. Any vessel can be booked in that date range at the same price, regardless of the utilization factor. Therefore, there is a disconnect between shipment price, available shipping capacity (supply), and shipment demand. In addition, there is very little market-wide data on real-time cargo shipment demand, available shipping capacity (supply), and shipment price, which results in pricing decisions being based on a shipping line’s internal data only. Pricing is a best estimate only and not driven by broader, real-time data. Moreover, shipping lines offer limited product choice for customers. A customer can take the price flexibility of the spot market but forego booking certainty in peak season or they can trade off certainty with a contract but forego price flexibility. These factors are compounded by a lack of contractual obligation at the time of booking, enabling shipping line customers to book cargo, often the same cargo with multiple carriers, and then cancel at the last minute without penalty. To counteract this, shipping lines have adopted a practice of overbooking. In peak season, cargo cancellation does not exceed overbooked vessel cargo carrying capacity and therefore not all the cargo can be loaded on a vessel and is left behind or “rolled” until the next vessel departure [22].

The main objective of shipping line spot pricing is to maximize the profitability of each vessel voyage. Internal factors affecting spot pricing include the vessel utilization factor in the coming weeks for the service (a measure of capacity and shipment demand), port pairs, equipment deficit or surplus, global network requirements impacting the key variable cost component of equipment imbalance charge, the weight of the cargo and number of containers to be booked. External factors driving spot pricing include current market conditions and the actions of competitors. In this process, they need to manage seasonality and fluctuating cargo shipment demand in the operating year and ensure they have a base load of contract business and fill the remaining allocation with the spot market.

This cargo mix will vary from shipping line to shipping line and trade lane to trade lane, based on each line’s strategy and the inherent characteristics of a market’s structure. However, regardless of the cargo mix, in the short run, the spot market is the only way for a shipping line to improve its profitability because the rate has not been fixed for a time like the contract market [23]. The process flow diagram of the shipment price setting in the shipping industry is shown in Fig. 2.

4. Research design

In this research, the aim is to find an optimal spot shipment price based on current shipment demand and available shipping capacity for a cargo container. In order to do so, we have limited the scope of this research for the Asia Oceania trade lane in the Australian shipping industry. Additionally, we do not consider any competition between shipping lines and carriers. Moreover, the shipping prices must lie between the maximum and minimum threshold already set by the Australian shipping industry carriers. This is because clients are not willing to pay shipment prices above a particular value [11]. Hence, we aim to develop a pricing model that will keep the minimum and maximum thresholds in the loop and will provide a shipment price that can maximize the profit within those thresholds. We consider the price-setting process as explained in Section 3. The first step is data collection and cleansing followed by relationship modeling of the key variables (i.e. shipment demand, capacity, and price). Finally, the design of the optimal spot pricing model is implemented.

4.1. Data sourcing

In order to source real-time data, the first step is to limit the scope of the data. We have selected Asia-Oceania trade lane data for the application of our research design. The horizon of data collection is of three years i.e. 2016 to 2018. The shipment demand, available shipping capacity (supply), and pricing data are collected from four different sources and aggregated together to form a single dataset. The available shipping capacity (supply) dataset is sourced from Sea-Intelligence. Sea-Intelligence is an analytical reporting company that publishes weekly available shipping capacity (supply) trade summaries. The weekly outlook is based on published schedules provided by ocean carriers. This data contains weekly total capacity (in TEUs) along with the vessel names [9]. Fig. 3 shows a snapshot of the dataset sourced from Sea-Intelligence for the Asia Oceania trade lane.

The pricing data for the Asia Oceania trade lane is gathered from two different sources: (1) Shanghai Freight Index (SCFI) [10] and (2) Mizzen group propriety database [11]. The SCFI publishes weekly shipment prices per TEU for different trade lanes. However, Mizzen records weekly shipment prices quoted in real-time for shipments. Hence, we have expected and actual pricing information for an individual week. In order to get real-time shipment prices, we have selected Mizzen prices where SCFI and Mizzen prices are not the same. Fig. 4(a) and (b) shows snapshots of SCFI and Mizzen price lists.

The shipment demand dataset is collected by sourcing data from five international Australian ports. These ports include Port Botany [4], Port of Melbourne [5], Fremantle Port [7], Flinders Port [8] and the Port of Brisbane [6]. The detailed trade summary from Port Botany is shown in Fig. 5. It consists of monthly trade summaries in TEUs for both empty and full containers (see Fig. 5(a)), region-based trade summaries (see Fig. 5(b)) and top ten shipped commodities (see Fig. 5(c)). Fremantle Port and Port of Melbourne provide monthly trade summaries of all empty and full containers (see Fig. 6(a) and (b) respectively). However, the Flinders Port provides a region-wise break down for cargo shipment demand (see Fig. 6(c)) similar to Port Botany. On the other hand, the Port of Brisbane provides a commodity-based trade summary (see Fig. 6(d)). From the trade summaries, it is evident that Port Botany has the maximum transparency in its trade summary. Using the available statistic from Port Botany and Flinders Port, the total shipment demand for imports can be calculated using Eq. (1).

\[ D^t(I) = C_E(I) + C_F(I) \] (1)
where $D_t(I)$ represents total import shipment demand, $C_{F}(I)$ and $C_{E}(I)$ represents a total of full and empty containers for imports.

In order to calculate the total import shipment demand for the Asia Oceania trade lane, total demand from all the participating regional ports in the trade lane (i.e. East Asia, North Asia, South Asia and South-East Asia) are added. Subtracting the sum of total demand of all the participating ports from the total import shipment demand for all the trade lanes ($D_t(I)$) gives the total import shipment demand for the Asia Oceania Trade lane. This can be expressed in Eq. (2).

$$D_{Asia-Oceania}(I) = D_t(I) - \{D_{EastAsia}(I) + D_{SouthAsia}(I) + D_{SouthEastAsia}(I)\} \quad (2)$$

In Eq. (2), $D_{EastAsia}(I)$ presents the total shipment imports demand of East Asia. $D_{SouthAsia}(I)$ presents the total shipment imports demand of South Asia and $D_{SouthEastAsia}(I)$ presents total shipment imports demand of South-East Asia. This segregates the import shipment demand for the Asia Oceania trade lane. However, for the other three Australian Ports (i.e. Port of Brisbane, Port of Melbourne and Fremantle Port), only total shipment demand is provided in their trade summaries. No division of shipment demand based on trade lane is available. To do so, we have calculated the ratio for Asia-Oceania trade lane shipment demand from Port Botany. Although we do have Flinders Port with the same statistics, Port Botany is a big port in comparison to Flinders Port and the ratio of import shipment demand for Asia Oceania trade lane can represent the remainder of the ports [11].

This ratio for Asia Oceania imports shipment demand can be calculated using Eq. (3) shown below.

$$R_{Asia-Oceania}(I) = \frac{D_{Asia-Oceania}(I)}{D_t(I)} \quad (3)$$

where $R_{Asia-Oceania}(I)$ represents calculated ratio discussed in the above paragraph. Thus, import shipment demand specifically for Asia Oceania trade lane for Port of Brisbane, Port of Melbourne and Fremantle Port can be calculated using Eq. (4). This shipment demand is in a monthly view as shown in Fig. 7.

$$D_{Asia-Oceania}(I) = R_{Asia-Oceania}(I) * D_t(I) \quad (4)$$

Since the dataset for shipment price and capacity are available in a weekly view, this shipment demand has to be converted into a weekly view. To do so, Eq. (5) is used.

$$D_{weekly}(I) = \frac{D_{Asia-Oceania}(I) * 12}{52} \quad (5)$$

Once the weekly shipment demand is calculated for each port, they are summed up to get total shipment demand for the Asia Oceania trade lane for Australia (see Fig. 8). The snapshot of the final dataset is shown in Fig. 9.

There were no missing values in the available shipping capacity (supply) dataset. However, the missing values in pricing data are handled using forward fill methodology and that of shipment demand data are filled by using an average from the previous or coming year at the similar timestamps (whichever is applicable) [24]. The individual variable data description is shown in Fig. 10.

### 4.2. Relationship modeling

In order to model the relationship between shipment demand, available shipping capacity (supply) and pricing in the Australian shipping industry for the Asia-Oceania trade lane, statistical analysis is performed. The results from the preliminary exploratory data analysis (EDA) depict a ‘disconnect between suppliers, shipment demand, and pricing. There exists no linear relationship

Fig. 3. Sea Intelligence weekly capacity dataset snapshot.

Fig. 4. Snapshot of Price dataset (a) SCFI price summary (b) Mizzen price summary.
between available shipping capacity (supply), shipment demand, and pricing [25]. This is further augmented using density plots (see Fig. 11(a) and (b)). From Fig. 11(a), it is evident that the relation between shipment price and shipment demand is not obvious. An increase in shipment demand does not necessarily increase the shipment price. In addition to this, the relationship between available shipping capacity (supply) and shipment price also appears to be non-binding. The density distribution between shipment demand and shipment price is bimodal showing that firstly, shipment prices increase with shipment demand but do not follow the same trend and start falling with an increase in shipment demand. On the other hand, the density distribution between available shipping capacity (supply) and shipment price is unimodal and a bit left-skewed. As available shipping capacity (supply) increases, shipment prices do not seem to have any dependency on it. Moreover, the left skewness is not very prominent. It can be concluded that shipping prices are more jumbled in the center of the distribution showing no evident positive relationship between the variables under observation.

To further the analysis, we have performed a regression analysis on the dataset (see Fig. 12). From Fig. 12, it can be seen that there exists a correlation between shipment demand and shipment price but the relationship is not obvious. However, there is no relationship between capacity and shipment price.

Thus, it can be shown from the above-presented data analytics that shipment prices are not steered by cargo shipment demand and available shipping capacity in the Australian shipping industry. An increase in shipment demand does not necessarily increase the cargo pricing. Moreover, there is no relationship between shipment demand and capacity. However, capacity and shipment prices are bound in different types of relationships. Thus, from this EDA, it can be concluded that the shipment demand, available shipment capacity, and cargo shipment price setting are not interrelated in the containershipping industry. The results from EDA depict the natural consequence of an uninformed market with material opportunity cost to shipping lines and their customers, which is what our research will address. Thus, with this study, visibility into the current operations of the container shipping available shipping capacity (supply) chain is provided and the long-held objective for industry stakeholders is proved statistically. In order to solve this long-standing issue, we have designed an optimal shipment price calculation formula using historic data.
Fig. 6. Trade Summaries (a) Fremantle Port (b) Port of Melbourne (c) Flinders Port (d) Port of Brisbane.

Fig. 7. Monthly demand for Asia-Oceania trade lane in the Australian shipping industry.
4.3. Optimal price calculation

In order to calculate the opportunity cost for shipping companies based on shipment demand and available shipment capacity, we analyzed the historical data. There are three predefined propositions for pricing decisions.

4.3.1. Proposition 1

Shipment demand is greater than the available shipping capacity (supply). In this case, ideally, the increase in shipment demand will cause an increase in shipment price provided the shipping capacity remains the same. Hence, it can be written as Eqs. (6) and (7). Thus, cargo shipment demand can be written as Eq. (8).

\[
D > S \quad (6)
\]

\[
D \propto P \quad (7)
\]

\[
D = \frac{1}{m_{\text{max}}} P \quad (8)
\]

In Eq. (3), \( m \) is a constant of proportionality. The values of \( m \) vary from the maximum shipment price limit per TEU to minimum shipment price per TEU and are derived from historic data. The constant \( m \) can be calculated using Eq. (9). The value of \( m_{\text{max}} \) and \( m_{\text{min}} \) is derived from historic data (see Eqs. (12)–(14)).

\[
m_{\text{min}} \leq m \leq m_{\text{max}} \quad (9)
\]

4.3.2. Proposition 2

Shipment demand is less than available capacity. Then the increasing shipment demand should not result in increasing the price to the maximum level. However, average pricing must be quoted so carriers avoid quoting shipment prices which are below average. This would help them earn reasonable revenue to keep their business profitable. The Eqs. (6) and (7) can be written as

\[
D \leq S \quad (10)
\]

\[
D = \frac{1}{m_{\text{av}}} P \quad (11)
\]

4.3.3. Calculating constant of proportionality

The opportunity cost calculation is highly correlated with the constant of proportionality used in Eqs. (7) and (8). Hence, it is
very important to calculate it precisely. The value of $m$ is driven by historic shipment demand and available shipping capacity (supply) data. Eqs. (12)-(14) are used in this research to calculate the respective values of $m_{\text{max}}$, $m_{\text{avg}}$ and $m_{\text{min}}$.

$$m_{\text{max}} = \frac{P_{\text{max}}}{\text{Demand}(P_{\text{max}})}$$  \hspace{1cm} (12)

$$m_{\text{avg}} = \frac{P_{\text{avg}}}{\text{Demand}(P_{\text{avg}})}$$ \hspace{1cm} (13)

$$m_{\text{min}} = \frac{P_{\text{min}}}{\text{Demand}(P_{\text{min}})}$$ \hspace{1cm} (14)

where $P_{\text{max}}$ and $P_{\text{min}}$ is the maximum and minimum threshold of the shipment price the shipping companies can quote to the customers. $P_{\text{avg}}$, is the average shipment price quoted and is calculated from the pricing presented in the dataset under observation. These shipment prices are fixed and spot pricing must lie between these price limits. Thus, the opportunity cost model must provide the cost between these set thresholds. Thus, the formal model for spot pricing opportunity cost is given in (15) given below.

$$p(D) = \begin{cases} 
Dm_{\text{max}}, & D > S \\
Dm_{\text{avg}}, & D \leq S 
\end{cases} \hspace{1cm} (15)$$

5. Results and discussion

Using Eq. (15) for optimal spot shipment price calculation, we have calculated shipment prices based on shipment demand and available shipping capacity. In order to determine the relationship between the variables, data analytics is performed (similar to Section 4.2). From the density plots, it can be seen that the correlation between the demand and shipment price is improved and has become more positive in comparison to previous values (see Fig. 13(a) in comparison with Fig. 11(a)). The same is true for capacity and shipment price (see Fig. 13(b) in comparison with Fig. 11(b)). Moreover, from the regression analysis (see Fig. 14), it can be seen that the regression line between shipment demand and shipment price becomes positive in comparison to Fig. 12 (accroding to current pricing method). However, the regression line between available shipping capacity and shipment price remains negative but seclusion is achieved.

The graph below (see Fig. 15) shows the optimal spot pricing and current pricing with respect to cargo container shipment demand. It is evident that the designed model is able to calculate spot shipment prices based on cargo shipment demand and can help carriers increase their businesses. However, the current pricing is quite low and does no good for their businesses. To further the results concluded from the aforementioned graphs, we also performed correlation analysis on both datasets.

In Fig. 16, we quantify our correlation results. In traditional pricing, there is no relationship between shipment demand, available shipping capacity (shown as supply), and spot pricing. The
correlation between shipment demand and shipment price is 0.34, showing less correlation between the two variables. Furthermore, the correlation between capacity and pricing is $-0.12$, depicting the negative relationship between capacity and shipment price. On the other hand, the designed optimal pricing formula designed to calculate shipment spot pricing based on shipment demand and available capacity increased the shipment demand-shipment price correlation up to 0.88 and that of
capacity and shipment price is improved to −0.35 respectively. Thus, the proposed model is capable of generating a positive relationship between variables that exist inherently in datasets but which have been unused due to a lack of visibility in the shipping operation.

Hence, the proposed algorithmic method to calculate shipment spot pricing based on current market demand and available shipment capacity has proved to be optimal, based on four statistical matrices. (1) density plots to explore relationship between spot prices, demand and capacity (see Figs. 11 and 13); (2) Scatter plots and regression analysis (see Figs. 12 and 14); (3) Line graph visualization for comparison of current spot prices and optimal spot prices with respect to shipment current demand (see Fig. 15); (4) In the end we have quantified our research with a correlation heat map (see Fig. 16). Results from all of the metrics indicate that the proposed model is optimal for calculating shipment spot prices based on current shipment demand and available capacity.

6. Conclusion and future work

From this research study, it can be concluded that the shipment price setting in the shipping industry is quite complicated and is highly seasonally driven. There is a disconnect between current shipment demand, available shipping capacity (supply), and shipment pricing. Hence, there is a strong need to explore the relationship between shipment demand, available shipping capacity (supply), and pricing to set optimal pricing for shipment containers. However, not much research has been done in the past to address this area. In order to fill this gap, we have conducted a research study for the Australian shipping industry. From the conducted research, it is evident that pricing is not dependent on shipment demand and available shipping capacity (supply), which is not the ideal case. There must be a positive relationship between these three factors. There is also a need to have a model to calculate spot shipment prices based on factors that affect pricing. We have proposed a novel mathematical model for setting container shipment spot pricing based on shipment demand and available shipping capacity (supply). The results have shown that the proposed model is able to set prices based on market shipment demand. Moreover, there is a need to improve the model by adding more factors that affect pricing such as oil prices, ship utilization factors, political situations such as the US–China trade lane, and environmental factors such as the outbreak of coronavirus which may affect shipping operations. Thus, this research provides a base for future research in the same area and much more sophisticated optimal shipment pricing models can be designed.

CRediT authorship contribution statement

Ayesha Ubaid: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - original draft. Farookh Hussain: Project administration, Funding acquisition, Review. Jonathan Charles: Resources, Project administration, Writing - review.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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