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Using artificial neural networks to predict container flows between the major ports of Asia

Feng-Ming Tsai* and Linda J.W. Huang

Department of Shipping and Transportation Management, National Taiwan Ocean University, Keelung, Taiwan

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Container flow information is a critical issue for port operators and liners to support their strategic planning and decision-making. This study uses artificial neural networks (ANNs) to predict container flows by considering GDP, interest rates, the value of export and import trade, the numbers of export and import containers and the number of quay cranes. ANNs are developed for data mining purposes, and the developed model can simultaneously predict container flows between the major ports of Asia. The forecasting results indicate that the prediction errors are relatively small in most selected ports, and thus shipping companies can use the container flow prediction model to make decisions concerning operations. The results can be further applied to the trend analysis of container flows among the major ports of Asia, and a community analysis of the containers was conducted for the purpose of supply chain management.

Keywords: container flows; decision-making; artificial neural networks; ports of Asia; supply chain management

1. Introduction

Today the globalisation of production has emerged a critical way to reduce the production cost, and most of the manufactures are located in Asia. A major focus in logistics is not only on the physical movement of these raw materials, components and finished products but also the network that moves the product globally. Maritime shipping plays an irreplaceable role in international trade. Overall, the cargo volume of maritime shipping accounts for up to 90% of the global trading volume. The percentage of container shipping has increased drastically from 2.75% in 1980 to 6.14% in 1990, 10.49% in 2000 and 16.02% in 2010, demonstrating the increasing importance of maritime shipping. In 2010, the number of containers shipped in Asia accounted for more than 50% of all global containers, and more than 90% of international trade in Taiwan is processed by ocean shipping.

Due to the dramatic increase in shipping demand, countries in Asia are paying increasing attention to maritime shipping. The database of containerisation is an important resource in decision-making for liner companies and port operators. Subscribed databases, which collect results from surveys, can only provide container flows in terms of country-to-country flows or the throughput at each port (Containerisation International 2012; Containerisation International Yearbook 2011). In this study, to analyse port-to-port container flows, artificial neural networks (ANNs) are used to forecast container flows for a liner shipping company to optimise its operation strategies, including shipping route adjustment and fleet allocation. Port operators can utilise the container flows to adjust marketing strategies in the face of challenges from competitors.

In recent years, Asia has become a world factory, and a large amount of transportation demand is derived from this role. Newly built ports compete with other ports, and old ports are being renovated. To further increase the competitiveness of a port, many incentives are being launched to attract shipping lines. The growth rate of container volume in Asian ports has increased in recent years. According to statistics collected by UNCTAD for 2010, the total container volume in Asia is 260,030,000 TEU, which accounts for 48.93% of the global container volume. The percentage of imports and exports of containers in Asia is higher than the global average, which highlights the importance of Asia in global marine trade. Statistics provided by UNTCAD for 2011 indicate that the total values of loaded and discharged cargo account for 37.9 and 45.9% of the global marine train, respectively. Manufacturing development in Asia and incentives offered to shipping lines have introduced many changes to container flow between regions; these changes have made the industry more complex, indicating that an in-depth understanding of the flows of maritime cargo shipping is indispensable and that these flow statistics are worthy of investigation.

*Corresponding author. Email: chucktsai@ntou.edu.tw

From the viewpoint of liner shipping companies, understanding the port-to-port container volume is essential for the arrangement of shipping routes and waypoints. Reviewing literature in the past, most previous studies (Coto-Millan, Banoe-Pino, and Castro 2005; Gosasang, Chandraprakaikul, and Kiattsin 2011; Xie et al. 2013; Xiao et al. 2014) predicted container volume in ports or countries; in contrast, only few studies have analysed container flows between origin and destination (O-D) ports. This article provides the following contributions to the existing literature on container volume prediction. First, it utilises ANNs for data mining to address the large amount of data available, including data from the International Monetary Fund (IMF), the Containerisation International Yearbook, Containerisation International Online, the IHS Global Insight Commerce & Transport online database, TRADE-VAN and official data from the websites of Asian ports. Second, a prediction model is used to predict port-to-port container flows, which were not considered in previous studies.

Methods of gathering statistics, assumptions used, predictive objects, and standards of error evaluation vary, making it difficult to determine the accuracy of these models and thus limiting their applicability in practice. While comparing ANNs and traditional forecasting methods, some previous studies (Pulido-Calvo, Montessinos, and Ruiz-Navarro 2007; Peng and Chu 2009; Sahoo, Schladow, and Reuter 2009; Dhamija and Bhalla 2010) have indicated that the prediction result of ANNs performed better than traditional forecasting. ANNs have three advantages over traditional methods such as universal approximation capabilities, recognising implicit dependencies and relationship in data learning to adapt their behaviour. Therefore, the use of ANNs in data mining provides the ready availability of large mass of data sets (Fei, Lu, and Liu 2011; Lu 2012; Lu and Zhou 2014) and the reported ability of ANNs to detect and admit relationships between a large numbers of variables.

The remainder of this article is organised as follows. Section 2 presents a review of literature regarding container estimation modelling based on export and import container volumes. The proposed procedure for predicting container flows is detailed in Section 3, and numerical examples and results are presented and discussed in Section 4. Concluding remarks are provided in Section 5.

2. Literature review

Coto-Millan, Banoe-Pino, and Castro (2005) analysed the main variables that affect the import and export trade at sea of normal cargo in Spain. The results indicated that the variables that affect imports include monetary income, import prices and domestic commodity prices, whereas the variables that affect exports include real income, relative export prices and the national production index. Chou, Chu, and Liang (2008) used data from 1989 to 2001 and additional variables, including the population, industrial production indices, GNP and GDP. The study compared the accuracy of the results from a traditional regression model and a modified regression model and determined that the modified model more accurately predicted the import container volume of Taiwan.

Xie et al. (2013) proposed three hybrid approaches based on a least-squares support vector regression (LSSVR) model for forecasting container throughput at ports, namely SARIMA–LSSVR, SD–LSSVR and CD–LSSVR. Gosasang, Chandraprakaikul, and Kiattsin (2011) predicted the future container throughput of the Bangkok Port by multilayer perception (MLP) and linear regression. The independent variables included domestic GDP, world GDP, exchange rates, population, inflation rates, interest rates and fuel prices. The results were measured using the root-mean-square error and mean absolute error and were found to have correlation coefficients greater than 75%. MLP was found to be superior to linear regression for this type of prediction.

Cho and Yang (2011) identified the potential of a national environment to increase container volume using a statistical method, robust regression. The variables applied in the regression include container volume in a single country, globalisation, information and communication technology, innovation and institutional influence, and these variables within a country's business environment were found to be significant factors leading to an increase in container volume. Nela et al. (2012) forecasted container volume at the Port of Koper by regression using data from 1997 to 2008. Using regression analysis alone did not meet the needs of the some studies, and thus they made improvements to the method or added other means of prediction.

Wang, Meng, and Bell (2013) estimated the capacity utilisation of a liner ship route with a bounded polyhedral container shipment demand pattern. In their study, maximum and minimum liner ship route capacity utilisation problems were formulated as a linear programming model and min–max model, respectively. Two e-optimal global optimisation algorithms were then proposed to solve the min–max model. The results indicated that max and min capacity utilisation provides useful information for fleet deployment and shipping route design for shipping lines.

Most previous studies focused on forecasting container volume in a single port or country, and thus the utilisation of their models has inherent limitations. Jones et al. (2011) proposed an import and export container flow model to analyse flows of US import and export of containerised freight and the potential changes in those flows under a variety of conditions. The network model, called System for Import/Export Routing and Recovery Analysis, predicts container flows between foreign countries and North American ports and the total handling volume of each port.

Santos et al. (2012) used ANNs to determine a model to predict solar still distillate production. The variables affecting solar still performance includes daily total insolation, daily average wind velocity, daily average cloud cover, daily average wind direction and daily average ambient temperature. The objective of the study was to assess the sensitivity of the ANNs predictions to different combinations of input parameters. In addition, the minimum amount of inputs necessary was determined to accurately model solar still performance.

The forecasting of container volume between two ports is essential to the planning of a shipping route or the selection of a waypoint. This research analyses port-to-port container volume and provides a functional forecasting model to fill the deficiency in models for port-to-port analysis. Previous studies attempted to predict trends for a single port or country, but this study focuses on port-to-port export-import traffic volume. Although the objective is different, the variables used in the existing literature are applicable to this study.

3. Proposed procedure for container flow prediction

3.1 *Data collection*

The throughput container volume, including export, import and transshipment, of each Asian port was collected from the Containerisation International Yearbook. The country-to-country container volume data were retrieved from the IHS Global Insight Commerce & Transport online database and Containerisation International Online, which was also used to calculate the container handling volume of the 10 ports selected by this study as a percentage of the volume of the top 500 global ports. More than one million port-to-port container flow data points were collected from TRADE-VAN, which manages Taiwanese customs clearance documents. Financial data, including GDP, the exchange rate and the industrial production index, were collected from the IMF, which can be integrated with other databases.

Cargo with the higher price level per unit and lowest volume per shipment has the greatest demand within container shipping. The three main routes of international container shipping are the Trans-Pacific route, which connects the Far East and North America, the Trans-Atlantic route, which connects North America and Europe, and the Mediterranean route, which connects Europe and the Far East. Table 1 illustrates that the container flow from the Far East to North America represented the largest volume between 1995 and 2010. Container flow from the Far East to Europe had the second largest volume, followed by North America and Europe to the Far East, Europe to North America and North America to Europe. For bilateral flow, the Mediterranean route had the greatest volume, followed by the Trans-Pacific and Trans-Atlantic routes. This allocation of volume is due to the maturity of the global economy and the conditions of individual countries. Countries with greater purchasing power are located primarily within the European Union, North America, Northeast Asia and Oceania, whereas countries with low purchasing power but abundant natural resources and an inexpensive labour market are mainly located in Eastern Europe, Southeast Asia, Africa and Central and South America. Thus, the largest one-way flow of containers is from the Far East to Europe and the Far East to North America, with the former gradually exceeding the latter. (UNCTAD 2011)

Table 1. Container flow on primary routes (Unit: million TEU).

	Route					
	Trans-Pacific		Mediterranean		Trans-Atlantic	
Time	East Bound (Far East to North America)	West Bound (North America to Far East)	East Bound (Europe to Far East)	West Bound (Far East to Europe)	East Bound (North America to Europe)	West Bound (Europe to North America)
1995–2002	9	4.4	3.6	7.3	1.9	2.8
2002–2007	11.6	5.2	4.5	10.2	2.1	3.3
2007–2010	12.8	6.6	5.3	12.8	2.5	3.2

Source: UNCTAD (2011).

Table 2. Input values for independent variables in the regression model (2011).

Country	GDP (US $ bn)	Exchange Rate (One US dollar)	Economic Growth Rate (%)	Industrial Production Index (%)	Average per Capita Gross Domestic Product (Dollar)	Import Trade Value (US. $ bn)	Export Trade Value (US $ bn)
Japan	5869.5	77.57	−0.70	−3.09	46,932.96	853.53	821.30
Hong Kong	243.32	7.78	4.89	0.70	34,907.69	482.64	427.85
China	7497	6.33	9.29	13.84	5415.79	1743.46	1898.60
Taiwan	414.2	31.09	4.10	5.00	20,574.00	141.73	155.82
South Korea	1116.4	1108.20	3.64	6.90	21,062.91	524.50	557.80
Singapore	359.82	1.26	4.90	7.61	50,086.41	365.41	409.27

Source: http://www.imf.org/external/index.htm

3.2 *Data processing*

The country-to-country export and import container flows can be distributed to each Asian port based on the percentages of export and import container volume as a function of total export and import volumes for each country. For instance, the container handling volume at the Port of Shanghai in 2010 is used as the numerator, whereas the sum of the container handling volumes at all ports in China within the top 500 global ports is used as the denominator, resulting in the percentage that Shanghai volume accounts for within all rated ports in China.

The percentages of O-D data can then be incorporated to obtain port-to-port weight distributions. For example, regarding Shanghai as the origin and Yokohama as the destination, the percentages of the container handling volume of each port within its own country can be multiplied by one another to obtain the volume weight of the Shanghai–Yokohama route.

Finally, the volume weight is multiplied by the country-to-country container volume. For example, the volume weight of Shanghai–Yokohama is multiplied by the total container handling volume traffic from China to Japan to obtain the container volume traffic from Shanghai to Yokohama. A 10 × 10 assignment matrix can be produced for all ports considered (Table 2). The sum of the import volumes of each port can be incorporated into the regression model as explained variables to represent the port's features. The other variables in the ANNs model are as follows:

- GDP – the market value of all officially recognised final goods and services produced within a country in a given period of time.
- Exchange Rate – the rate at which one currency may be converted into another. The exchange rate is used when simply converting one currency to another or for engaging in speculation or trading in the foreign exchange market.
- Economic Growth Rate – a measure of economic growth from one period to another as a percentage. This measure does not adjust for inflation; instead, it is expressed in nominal terms.
- Industrial Production Index – an economic indicator that is released monthly by the Federal Reserve Board that measures the output from the manufacturing, mining and electric and gas industries. The reference year for the index is 2002, which has a value of 100.
- Per Capita GDP – a measure of the total output of a country; it is calculated as the GDP divided by the number of people in the country. The per capita GDP is particularly useful when comparing one country to another because it shows the relative performance of the countries. An increase in per capita GDP signals growth in the economy and tends to translate into increased productivity.
- Import Trade Value – the total value based on the release date and calculated by CIF price.
- Export Trade Value – the total value based on ship departure date and calculated by the FOB price.

3.3 *Development of the ANNs model*

In computational process, ANNs are mathematic models aroused by animal central nervous systems to process machine learning and pattern recognition. The models are represented as systems of interconnected neurons that can compute values by providing information from inputs through the network. ANNs can be divided into network applications, associative learning networks, unsupervised learning networks, etc. The basic levels of neurons layers include an input layer, a hidden layer and an output layer as shown in Figure 1.

In an ANN model, the artificial neurons are interconnected between different layers in each system. Each layer contains a number of processing units, including the input layer for processing external environment messages and the output layer for processing messages to the external environment. The first layer, input layer, processes input neurons to the second layer by synapses. The number of neurons considered in the second layer, hidden layer, is calculated by the arithmetic mean of input neurons and output neurons. The training mode data are subdivided into two sub-data sets to avoid overfitting/overtraining situation through early-stop training rules.

In a neural network, a set of input neurons may be activated by the pixels of an input image representing a letter or digit. The related activation takes the following settings: first, the number of hidden layer is the arithmetic mean of input and output neurons; second, the non-linear conversion function of hidden and output layers adopt Sigmoid function; third, the network weights uses backpropagation learning algorithm to strike the network; fourth, the network uses early-stop rule to avoid overfitting/ overtraining learning situation. In this study, the feed forward multilayer perceptron neural networks (MLPNN) model is developed in the system with three layers and the backpropagation learning algorithm is used to train the MLPNN.

The following assumptions are made to establish an ANN prediction model for container flows within the major ports of Asia and obtain the critical variables for the prediction model:

(1) The data of the top 500 global ports, as provided by CI-Online, and the sum of the container throughput of each country are used to calculate the total container throughput.
(2) The percentage of container throughput is calculated to obtain the gross container volume, and the percentages of exports and imports are assumed to be identical.
(3) The percentages of container handling volumes are used to estimate container traffic flow.

In artificial neuron model, the processing units of each artificial neuron can be indicated as input or output number of processing elements as shown in Figure 2. The equation used to calculate the input and output values, the relationship between respond output processing elements and variable input processing elements can be formulated in Equation (1) by multiplying input values and weights of the interconnections. The value of weighting function is manipulated by the strength of signal connecting between processing units. The activation function is used to convert the weighted input of neurons to its activated output in Equation (1).

$$Yj = f\left(\sum_i XiWij - \theta j\right). \tag{1}$$

where Yi is the output variable
Xi is the input signal
Wij is the weighted link
θj is the threshold correction
f is the conversion function

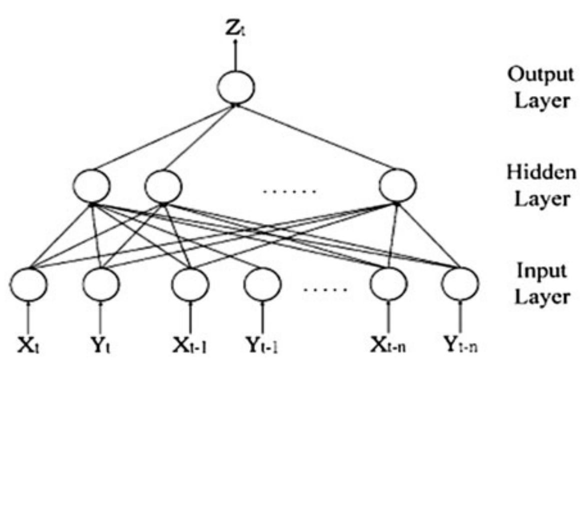

Figure 1. Training architecture.

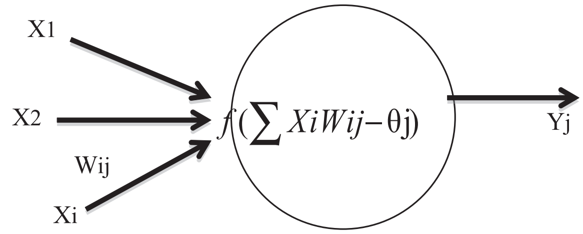

Figure 2. Model of an artificial neuron.

4. Experiments

Due to the insufficient amount of port-to-port container volume flow data on the market, this research provides estimates based on currently existing data to analyse and further understand the container flows between the major ports of Asia. To predict the OD pairs of containers at the main ports in Asia, several major ports were selected for this research, including Shanghai, Hong Kong and Shenzhen in China, Singapore and Busan, South Korea, which were rated the top 5 Asian ports by Containerisation International in 2010. Thus, this research focused on 5 countries and 10 ports.

The export and import container data provided by Hong Kong Shipping Statistics, Yokohama Harbour Bureau, and the TRADE-VAN do not include information on transit containers. Furthermore, whether containers were laden or empty is unknown. However, data from the Kobe Port Official and Nagoya Port Authority include information on whether containers were laden or empty containers. According to the ANN prediction model, a proportional distribution of container volume can be calculated for the 10 ports without considering domestic container volume. The results are shown in Table 3, and they will be incorporated into the regression model as reference variables to estimate the port-to-port export and import container volumes.

The export and import container volume flow data provided by the officials of Yokohama, Hong Kong, Kobe, Nagoya and the TRADE-VAN can be used together with the independent variables of GDP (X1), exchange rate (X2), economic growth rate (X3), industrial production index (X4), per capita GDP (X5), export trade value (X6) and import trade value (X7) from 2008 to 2011, the results from the Proportional Distribution of Container Volume at Ports (Table 3), the total annual export and import container volumes and gantry cranes. Thus, a total of 243 data points will be acquired. The prediction results of the six research ports are shown in Table 4. This research also used data from other ports in Asia, including Yokohama, Kobe and Nagoya in Japan and Keelung and Kaohsiung in Taiwan, due to the comprehensiveness of the available data.

A comparison of the results of this research and the official data provided by Hong Kong, Kobe, Yokohama, Nagoya, Kaohsiung and Keelung (shown on Table 5) illustrate that the model can accurately forecast the import volumes of Hong Kong, Nagoya and Keelung and the export volumes of Kobe, Yokohama, Nagoya and Hong Kong. The errors of the estimated container volumes of each port to Shenzhen Port is large, as Shenzhen Port is an emerging port that has a gradually increasing container volume but a low total volume of exports and imports. To reduce this error, the variables considered in the estimation were those for China as a whole, not for Shenzhen Port alone.

The business in the Port of Yokohama focuses on exporting, which comprises two-thirds of its trade value. The import volume is relatively small, and thus the error of the estimated volume of import containers is large. The error in the export volume from Busan to the 3 ports in Japan is the migration of Incheon Port and Gwangyang Port, which began to gradually trade directly with ports in Japan starting in 2011 rather than transshipping via Busan, which caused a decrease in the container volume from Busan to ports in Japan. The large error of Keelung and Kaohsiung to Yokohama, Nagoya and Kobe was caused by two factors. One factor is the small container volume from or to Taiwan and Japan despite the large number of transit containers, which was not considered in this research. The other factor is the earthquake that struck Japan on 11 March 2011, which resulted in a huge tsunami and thus paralysed city functions and economic activities.

Table 3. Results of the container volumes distribution (Units: TEU).

	Shanghai	Singapore	Hong Kong	Shenzhen	Busan	Kaohsiung	Yokohama	Kobe	Nagoya	Keelung	Total
Shanghai	–	43,111	164,127	–	212,895	186,510	47,755	37,207	37,098	39,875	768,578
Singapore	63,219	–	14,410	48,954	40,326	72,212	28,090	21,885	21,822	15,439	326,356
Hong Kong	116,523	56,628	–	90,230	83,385	126,229	50,722	39,518	39,403	26,987	629,624
Shenzhen	–	33,383	127,092	–	164,856	144,425	36,980	28,811	28,727	30,877	595,152
Busan	313,519	22,865	12,522	242,774	–	40,224	88,129	68,662	68,462	8600	865,757
Kaohsiung	103,199	30,584	30,998	79,913	89,094	–	54,451	42,423	42,300	–	472,962
Yokohama	94,816	8692	671	73,421	48,020	25,747	–	–	–	5505	256,871
Kobe	73,872	6772	523	57,203	37,413	20,060	–	–	–	4289	200,130
Nagoya	73,657	6752	521	57,036	37,304	20,001	–	–	–	4276	199,548
Keelung	22,063	6539	6627	17,085	19,048	–	11,641	9070	9043	–	101,117
Total	860,868	215,324	357,492	666,617	732,340	635,408	317,769	247,576	246,855	135,847	4416,096

Note: '–' Represents domestic container volume, which is not discussed in this study.

Table 4. Forecasting results of the ANNs (Units: TEU).

	Yokohama		Hong Kong		Kobe		Nagoya		Kaohsiung		Keelung	
	Import	Export	Import	Export	Import	Export	Import	Export	Import	Export	Import	Export
Shanghai	133,826	151,724	418,900	201,561	141,382	169,321	141,460	189,894	55,053	55,144	100,445	61,802
Singapore	57,590	138,699	257,657	187,612	64,332	25,727	64,477	25,315	66,501	113,462	73,045	11,931
Hong Kong	100,157	609,993	–	–	593,629	84,435	593,656	71,090	77,559	97,589	91,894	4503
Shenzhen	55,572	19,747	597,001	394,567	59,377	19,747	–	–	–	–	–	–
Busan	48,592	78,108	189,445	151,724	51,134	78,108	51,159	68,225	73,492	68,076	67,902	6969
Kaohsiung	27,603	53,288	278,168	138,699	29,460	53,288	29,483	48,361	–	–	–	–
Yokohama	–	–	42,718	609,993	–	–	–	–	60,807	22,350	42,983	6108
Kobe	–	–	–	–	–	–	–	–	86,718	7572	43,203	4082
Nagoya	–	–	–	–	–	–	–	–	49,740	27,149	41,096	7010
Keelung	6277	42,983	154,900	394,567	6277	42,983	6279	41,477	–	–	–	–

Note: '—' Represents domestic container volume, which is not discussed in this study.

Table 5. Errors in the forecasting results.

	Yokohama		Hong Kong		Kobe		Nagoya		Kaohsiung		Keelung	
	Import (%)	Export (%)	Import (%)	Export (%)	Import (%)	Export (%)	Import (%)	Export (%)	Import (%)	Export (%)	Import (%)	Export (%)
Shanghai	7	6	32	4	46	6	−32	−1	−8	−9	11	2
Singapore	151	21	−2	−5	8	21	58	2	−48	7	584	−32
Hong Kong	174	−17	–	–	707	−17	101	21	−10	−7	−15	−93
Shenzhen	18	13	−4	0	63	13	–	–	–	129	–	−33
Busan	−1	1	4	13	−9	1	−21	60	−5	10	107	−27
Kaohsiung	149	51	−1	−12	−24	51	137	71	–	–	–	–
Yokohama	–	–	−73	153	–	–	–	–	−41	−28	36	77
Kobe	–	–	–	–	–	–	–	–	−6	−71	58	−22
Nagoya	–	–	–	–	–	–	–	–	−7	0	92	16
Keelung	−3	38	0	1	−4	38	−21	72	–	–	–	–

Note: '—' Represents domestic container volume, which is not discussed in this study.

5. Conclusions and recommendations

This research collected data from the IMF, the Containerisation International Yearbook, Containerisation International Online, IHS Global Insight Commerce & Transport online database, TRADE-VAN and official data from the website of Asian ports to predict container flows in the major ports of Asia. The estimates for export and import containers in Hong Kong exhibited the smallest errors and are closest to the actual container volumes. Thus, this forecasting model is suitable for estimating container volumes in Hong Kong. The prediction errors of importing to Shenzhen, Kaohsiung and Keelung from Japan were relatively large, as were prediction errors of importing to Singapore from the two ports in Taiwan. The largest errors for exports were from Shenzhen to ports in Japan.

The reasons for such errors may be the small port-to-port volumes and the small amount of national data incorporated into the regression model. Methods of calculating export and import container volume are different for each port, which also inevitably results in errors. Therefore, when collecting data in the future, it is necessary to refer to unified websites or data that provide detailed information on the calculation methods used. This research estimates port-to-port container volume by a proportional distribution from the total export and import container volume of the countries and assumes that the percentages of exports and imports are identical. These assumptions result in errors when compared to the actual data. Such errors could be avoided if direct and actual export and import values for each port were acquired and incorporated into the regression model.

Predicting port container volume plays an important role in port planning and provides liner shipping companies with a useful resource in their decision-making, including operating fleet size, itinerary planning and container adjustment planning. Factors that affect shipping lines include the import and export volumes, port facility operations and port development and improvement. However, the establishment of a port requires significant investments of time and assets, which is a permanent cost for the lifetime of the port. When a prediction of container volume is found to be significantly in error, resources will have been wasted and are difficult to recover. The numbers of containers processed is the main source of profit for a port, and thus container volume prediction provides the foundation for the planning, establishment and management of a port. Through an accurate prediction, one can easily predict the traffic volume for future time periods to determine whether existing port facilities are sufficient. Such data can also be provided to port authorities and shipping lines for optimisation purposes. Container volume prediction is important for cost-benefit analyses. Long-term predictions are critical in planning an integrated strategy for maritime shipping.

Each port has unique features, assets and liabilities that impact different forecasting methods. Thus, the best method of forecasting and the necessary variables to consider are not the same for different ports. If compatible variables and forecasting methods are found, the estimating result can more closely reflect reality. Different data distributions can affect the precision of the model, and thus, future studies should establish compatible models and variables that match port features. Moreover, the traffic volume of each route of the shipping lines can be incorporated into the analysis in future research to obtain a more precise result. In addition, different methods of forecasting or estimating might be related to the forecasting datum. Long-term forecasting would benefit from a new model based on precise short-term models.

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