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Port Recommendation System for Alternative Container Port Destinations Using a Novel Neural Language-Based Algorithm

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ABSTRACT Shipping containers are tokens of multimodal international transportation and rapid logistics. Container deliveries are scheduled to satisfy rapidly changing requirements. Unpredictable increases in costs and unforeseeable events such as pandemics compel ship owners and managers to adopt risk minimization measures. This study addresses one issue: how to determine an alternative port of call from massive data to offer a realistic destination change recommendation for a container vessel. Recommendation algorithms have become ubiquitous and are used effectively in other fields, but there is no such model for the port of call selection or recommendation. Large scale automatic identification system (AIS) data are readily available. We developed a computational framework based on a novel natural language programming algorithm that was tailored to support port recommendation rather than use a conventional adjacency matrix method. We mined large scale AIS data to construct sequential berth records for container vessels and mapped each port onto a vector in an embedded space. The natural language neural programming algorithm can suggest ports similar to the scheduled ports of call that were unable to offer service. The recommendations were validated with geo-analysis of sailing distance and could offer viable alternative ports to shipping managers.

INDEX TERMS Container shipping, neural natural language programming algorithm, AIS, network embedding, port2vec, port recommendation.

I. INTRODUCTION

Shipping containers are a consequence of the modernization of transportation and logistics that began when the shipping industry entered the megaship era in 2007. In that year, Maersk Line companies began to use container ships with a carrying capacity of more than 10,000 twenty-foot equivalent units (TEUs) to benefit from economies of scale. Today, to meet the demands of efficiency and environmental protection, even coal and grain shipments, which have always been shipped by bulk cargo vessels, are gradually becoming a part of the global logistics chain of container ships and rail transportation [1]. These trends, together with the retirement and laying up of smaller older deep sea vessels, ensure that the proportion of megaships in the global container ship fleet will continue to increase.

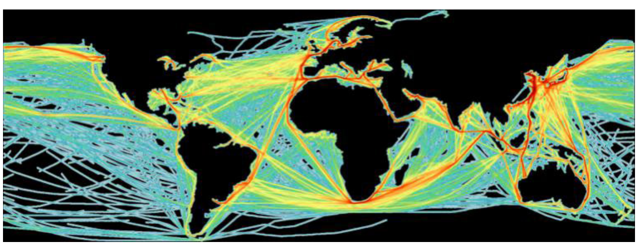

FIGURE 1. Network of global ship passages in 2018.

Container ship routes constitute a maritime network (Figure 1). Scholars have conducted in-depth research into

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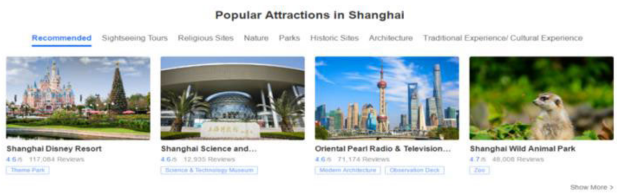

FIGURE 2. Personalized recommendations on a trip website.

many aspects of container ship services. The spoke–hub transportation model for container ships has been optimized to ensure efficient shipping operation and management [2], [3]. Reference [4] examined how to maximize a company's benefit, in terms of profit and safety, from ship berth capacity and allocation in response to ship movement. Optimal routes were determined for cases of sailing time uncertainty [5] and inefficient fleet shipping practices [6]. Global warming has forced researchers to pay attention to the environmental effects of container ship emissions [7], [8]. Reference [9] proposed innovative design alternatives for marine container terminals to facilitate efficient ship handling and container processing. Reference [10] modeled container operations to predict optimal cargo throughput for each docked ship. Reference [11] investigated container scanning systems to improve cargo monitoring.

There are still unexplored areas of research into improving container ship services. The large proportion of megaships in the global container ship fleet poses challenges to maritime administration. If there is a shipping disruption [12], perhaps due to a pandemic in some port [13], how can a good recommendation for alternative port berths for a vessel be created? How can we design and create a quantization index from big data for the destination berth of a vessel that will ensure the safety of shipping and the integrity of the logistics chain?

Many optimization models of maritime networks have been proposed that use the complex network theory and origin–destination adjacency matrices to parameterize vessel size, sailing frequency, port berths and other characteristics. The nodes and adjacent links comprise spatial networks, or graphs, that reveal shipping patterns [14], [15], robustness [16], and even economic trends [17]. Thus port–port relations derived from origin–destination shipping data can be constructed to facilitate the mining of the inherent law.

Personalized recommendation systems have developed rapidly since the 1990s; many recommendation systems are used in various business environments [18]. For example, e-shopping companies personalize online stores to direct customers to products (such as books, cameras, computers, points of interest) that are likely to be attractive (Figure 2). Recommendations are created using collaborative filtering algorithms and machine learning [19], [20].

As things stand, the choice of an alternative port depends primarily on the experience and knowledge of the captain of a ship, and there may in practice be little prior data analysis to inform the decision.

In this article, we describe our research into providing alternative port recommendations using big data. A perfect recommendation results from reliable correlation analysis that determines a spatial relationship, similar to the approach of spatially correlating road use in a traffic study [21], [22]. Berth records are strong preference indicators that are useful for targeting an acceptable choice and provide accurate information that matches the needs of a vessel and its relationship with a port. This article describes how we determined similarities between ports to obtain the perfect recommendation.

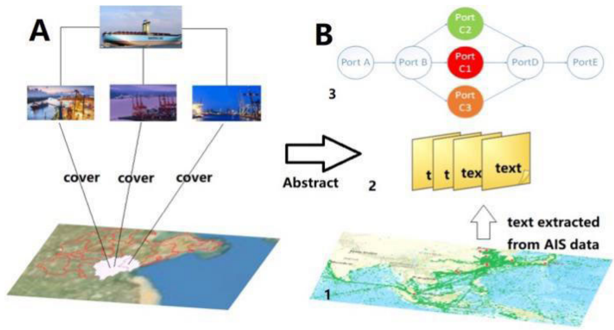

FIGURE 3. Mining synonyms for container ship's shipping law.

Reference [23] proposed a novel approach to quantifying vehicle interactions at road intersections that used natural language processing of large scale long distance route data. Shipping has similar semantic rules and the selection of a destination port for a container vessel depends on the nature of the port hinterland infrastructure. Shipping lines can always choose one or more ports from a number of ports having the same hinterland. Containers can then be distributed into this zone by land transportation (train and truck) or vessels of local shipping lines. These ports thus have many similarities, and one may be substituted for another. If port C1 is not fully operational for socioeconomic, weather or pandemic reasons, port C2 or port C3 could be a suitable alternative. A container shipping line schedule can be read semantically as a regular and fixed document. Text that forms berth records is a sequence of words, with synonyms identified from the context of the central word (Figure 3). We used Port2vec, derived from word2vec, to transform interactions between ports, obtained from berth records, into vectors and used a high degree of similarity between port vectors to suggest one or more appropriate recommendations for an alternative port.

The research consisted of the following major steps.

1) STEP 1

We used the automatic identification system (AIS) data, which were obtained from raw messages received by base stations throughout the world. The algorithm we created searched for detailed information, including time of arrival, time of departure, port name, ship type, and suchlike. The record was constructed from the basic AIS data, leveraging berth data. The text documents contained sequential berth records (Figure 4), which we then merged with the port of call records of all container ships throughout the world to form a training data set.

FIGURE 4. Sequential berth records to training text.

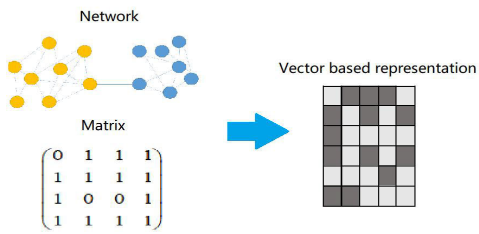

FIGURE 5. Embedding representation.

2) STEP 2

In a shipping graph $G = (V, E)$, V is a set of vertex points (nodes) representing ports, and E is a set of directed edges (links) representing shipping routes, which are relationships between nodes [24]. International ports create a large network with thousands of nodes containing many berths (Figure 1). Conventional maritime network analysis constructs adjacency matrices that identify bottlenecks. However, high computational complexity, low parallelizability and the inapplicability of machine learning methods lead to redundancy and noise [25]. In contrast to network relation representation, the use of embedding allows a port to be represented by a vector, and the similarity of vectors in a low dimensional vector space can form the basis of a port recommendation algorithm (Figure 5) [26].

Ports with similar contexts were mapped to neighboring vectors in the embedding space. The port recommendation model was trained using a large scale dataset. We implemented an approach that embedded ports in sequence into a low dimensional vector space using a neural natural language processing model applied to a berthing time series. Thus, ports with similar contexts (i.e., ports at which vessels of the same type had previously berthed or were scheduled to berth) were mapped onto neighboring vectors in the embedding space and were identified as potential recommendations using geo-analysis.

In our work, 200,000 berth records of container ships for 2018 were extracted from the data provided by AIS-equipped vessels throughout the world. Each berth port was considered to be a word and berth records were assembled as documents. The vector representation of each port was calculated from documents. The algorithm was trained by embedding technology.

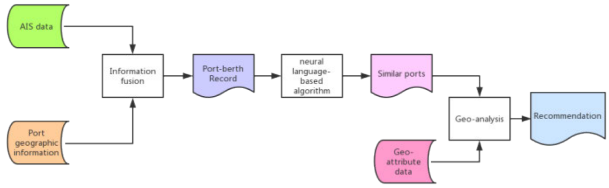

FIGURE 6. The workflow for computing recommendation results.

The real number vectors for each port in the database were created from textual geographic information by Port2vec. The port and text datasets were combined to form port–berth records. Relationships between ports were mined to identify similarities between vectors. The algorithm then presented similar vectors, which had been calculated using the geographical factors, as final recommendation results. A flowchart of the entire process is given in Figure 6.

This article is structured as follows. Section I has given an overview of research into recommendation methods and a summary of our research method. Section II describes how we obtained vectors of ports and calculated similarities using the model. Section III describes how we mined the sequential data as training data from the AIS dataset. Section IV describes our data experiment and presents a discussion of the results. Our conclusions are presented for future research, in Section V.

II. RESEARCH METHODOLOGY

A. OVERVIEW

This section outlines the principal tasks that must be completed to identify a substitute port. From a macro perspective, container vessels follow routes and have berth allocations that are fixed and published as a part of their business contract, in contrast to the navigation rules for bulk cargo ships and tankers, and ports of call are related to each other in a sailing sequence.

We can transform the linear programming transportation problem of container shipping into a natural language processing problem by mining words with high similarity and high relatedness from the published text. ImageNet object recognition and switchboard speech recognition have been extremely successful in neural network learning since 2012, and these learning methods have been introduced into natural language processing (NLP) [27], and we used it in this application. Word2vec has been used in many NLP applications. It is a template for a statistical language model that learns the probability functions of word sequences and calculates statistical properties of the words. In this study, each word in a text was represented by a single vector in a low dimensional space, and distances between words were calculated to indicate semantic relatedness in estimating similarity [28].

Researchers now have access to different areas of perception to capture correlation information that is represented by this embedded language model. A novel method, the visually supervised word2vec model, has been developed to merge visual modality with natural language to obtain important relation words in knowledge acquisition [29]. The sound–word2vec model was developed to learn specialized word embedding in order to capture interest in sounds [30]; word2vec has also been used to capture meaningful relationships in natural music [31]. Linguistic cues from video clips with spatiotemporal features were used to capture discriminative visual features using action–word2vec [32]. The methods have improved to the extent that we find it practical to identify internal relationships by mining semantic associations.

We used similar techniques to find human behaviors that influenced port selection, and used mining to develop port recommendations for ships. Figs. 3 and 5 give an outline of the method we used. We can include data for the hinterland because the behavior of a container ship captain in choosing a port is similar to the semantic search of synonyms in natural language. The use of an adjacency matrix is computationally intensive and not conducive to measuring the node similarity in conventional port–relation expression, hence in the embedding approach, we associated each port with a vector representation. Thus, similarities can be measured using a vector cosine calculation.

B. STATISTICAL LANGUAGE MODEL COMPUTATION

An NLP approach leverages the word order in text documents, explicitly modeling the assumption that nearby words in a word sequence are statistically more likely to be interrelated than distant words. Vocabulary size may become immense in practical applications, and recently developed NLP models evaluate the statistical properties of words and the relations between them.

NLP tasks such as machine translation and information extraction require that a probability be assigned to individual words in a sequence. Conventional n-gram methods use sentences that consist of words $w_1, w_2, \ldots, w_{n-1}$ in a sequence and create an n-gram Markov model of order $n-1$ that determines the probability of a word appearing based on the previous $n-1$ words [33]. The advantage of an n-gram model is that it contains all the information provided by the first $n-1$ words. These words strongly constrain the nth word. The disadvantage of this model is that it needs a considerable amount of training text to determine the parameters of the model. As we know, there are plenty of ports available for training. When n is large, the parameter space of the model becomes large. We introduced a method of learning distributed representation for words to avoid high dimensionality and to obtain semantic neighbors in a low dimension [34].

NLP modeling in this study included low dimensional distributed embedding of words using a neural network. We constructed the objective function $F(w, Context(w))$, which consists of a word w and its context $Context(w)$. In contrast to the n-gram model, this method does not retain all probability values. We used a continuous bag-of-words model (CBOW) to construct $F(w, Context(w))$. A CBOW model works well and requires less computing time since it has only three layers: input layer, hidden layer, and output layer (Figure 7) [35].

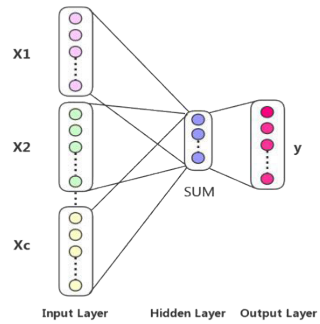

FIGURE 7. Continuous bag-of-words model.

The one-hot representation we used associates all words of the port with a single vector expression. Natural language models usually represent each word as a feature vector of the same length as the word count of the dictionary. The vector contains a single 1, corresponding to the position of the word in the dictionary, and all other entries are 0. One-hot representation of the large number of ports and berths across the world would require vectors of great length and introduce severe data sparsity [36]. However, using only this method isolates words and prevents the expression of words that play no part in representing the relationship.

The input consisted of each context word vector with one-hot representation. The transposition of output vector was $y = (y_{w,1}, y_{w,2}, \ldots, y_{w,N})$, and each element was the predicted probability of each word from the corpus appearing as the central word. Then the final probability of the central word w_i, given surrounding words $Context(w_i)$, was given by the Softmax function:

$$p(w_i|Context(w_i)) = \frac{e^{y_{w,i_w}}}{\sum_{i=1}^{N} e^{y_{w,i}}} \tag{1}$$

where i_w is word i in the dictionary [37].

C. TRAINING PORT VECTORS AND CALCULATING SIMILARITIES BETWEEN VECTORS

The model samples phrases (groups of words) depending on the size of the window by using a sliding window. The following diagram illustrates the process. The purple box contains the central word, and the words in the yellow box are context words.

Data are sampled through the sliding window until the training data have been completely parsed and the final training of the model is completed. When a set of context words was input, the vector produced in the output layer contained the prediction probabilities for all words in the corpus. We expect that the probability of the occurrence of the middle word is the highest and that the probability of the occurrence of other words is as small as possible. When we construct the objective function, we expect that the probability of the occurrence of positive samples is the greatest and that of negative samples is the least. The objective function is:

$$F(w, Context(w)) = \sigma(x_w^\top \theta^\omega) \prod_{u \in NEG(w)} [1 - \sigma(x_w^\top \theta^u)] \tag{2}$$

where x_w is the word vector sum of $Context(w)$, $NEG(w)$ is the set of negative central words in the sample w, θ^i is the coefficient vector for any word of i which is w or belongs to $NEG(w)$ in the corpus, $\sigma(\varphi)$ is the Sigmoid function that is the activation function of the model coefficient vector:

$$y_i = \sigma(\varphi) = \frac{1}{1+e^{-\varphi}} \tag{3}$$

and $\sigma(x_w^\top \theta^i)$ is the probability of word i calculated.

The training was accelerated, using negative sampling by stochastic gradient descent. In order to facilitate derivative calculation, the logarithm of the objective function was taken:

$$\mathcal{L} = \sum_{w\in C} \sum_{i\in\{w\}\cup NEG(w)} \{L^w(i)\cdot \log[\sigma(x_w^\top \theta^i)] + [1-L^w(i)]\log[\sigma(x_w^\top \theta^i)]\} \tag{4}$$

where

$$L^w(i) = \begin{cases} 1 & where\ word\_i \leftarrow w \\ 0 & where\ word\_i \leftarrow NEG(w) \end{cases} \tag{5}$$

Both θ^i and $v(\tilde{w})$ are constantly updated by the gradient descent calculation:

$$\frac{\partial \mathcal{L}}{\partial \theta^i} = L^w(i)[1-\sigma(x_w^\top \theta^i)]x_w - [1-L^w(i)]\sigma(x_w^\top \theta^i)x_w = [L^w(x) - \sigma(x_w^\top \theta^i)]x_w \tag{6}$$

$$\theta^i := \theta^i + \eta \cdot \frac{\partial \mathcal{L}}{\partial \theta^i} \cdot x_w \tag{7}$$

$$\frac{\partial \mathcal{L}}{\partial x_w} = [L^w(i) - \sigma(x_w^\top \theta^i)]\theta^i \tag{8}$$

$$v(\tilde{w}) := v(\tilde{w}) + \eta \sum_{i\in\{w\}\cup NEG(w)} \frac{\partial \mathcal{L}}{\partial x_w}, \quad \tilde{w} \in Context(w) \tag{9}$$

When the optimal parameter set θ^* of θ^i has been determined by optimization, $p(w|Context(w))$ is given by $F(w, Context(w))$; η is the default learning rate, 0.025; $v(\tilde{w})$ is updated constantly; and L is calculated by gradient descent. Each vector $v(\tilde{w})$ becomes stable in the hidden layer which will be input cosine similarity calculation [38].

In summary, embedded representations of words in a vector space are used to give a measure of the similarity of words in text sentences, based on the assumption that words that appear frequently in a document and co-occurring words within the same context are semantically similar.

The similarity between ports in terms of berths was measured by the cosine similarity $cos(\theta)$ of vectors calculated in the hidden layer; two vectors for port a and port b are similar when:

$$Cos\ Sim(a,b) = \cos(\theta) = \frac{\sum_{i=1}^n a_i b_i}{\sqrt{\sum_{i=1}^n a_i^2}\sqrt{\sum_{i=1}^n b_i^2}} \tag{10}$$

where a_i and b_i are the elements of port vectors a and b. Vectors with similar contexts have larger cosine values when ports have similar neighboring contexts.

TABLE 1. Description of automatic information system parameters.

Parameter	Entity represented
Mmsi	Ship ID
Time	Time AIS signal was received
Location	Latitude and longitude
Speed	Speed of vessel under way
Course	Course of vessel
Vessel_name	Name of ship
Flag state	Country of vessel registration
Destination	Port of destination
Type	Type of vessel

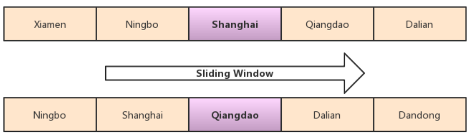

FIGURE 8. Choosing central words with the sliding window.

Our Port2vec model was trained by the Python package gensim of word2vec. The model was:

$$\text{Model} = \text{gensim.models.Word2Vec}(documents, dimension, window)$$

where *documents* are text sentences that contain the berth port sequences used to determine the similarity; *dimension* is the vector length, with the value set to 200; and *window* is the set of words surrounding the central word that form the context of the central word for training, with the value set to 5 [23].

III. CONVERTING SEQUENTIAL TRAINING DATA FROM AIS DATA

The berth records of container ships that were used as input data for the Port2vec model originated from AIS. AIS uses transponders and GPS receivers to transmit and receive static and dynamic vessel and voyage data between other vessels and ground stations. There is a wealth of AIS data, which is used for collision avoidance, marine traffic management, and trade analysis of the maritime business. AIS parameters used in this study are given in Table 1.

In this section, we describe how we used port information to provide data based recommendations, including the neural NLP models that are fundamental to our port recommendation system. AIS vessel data tuples and port–berth tuples were the basis of shipping characteristic representation (Figure 8). Data derived from AIS constituted the ship data tuples (Table 1). The port–berth tuples contained information about ports and berths. Each port was artificially delimited by an irregular polygonal boundary.

The relevant procedure was as follows.

1) STEP 1

AIS data tuples, which contain static vessel information and dynamic data such as position, velocity, and heading, were obtained from navigation information. Port–berth tuples contain port attributes. Tuples were defined as follows.

The AIS vessel data tuple was defined as:

$$A_i^t = (m_i, l_i, w_i, v_i^t, p_i^t, c_i^t, d_i^t) \tag{11}$$

where A_i^t is the tuple for vessel i at time t, m_i is the unique identification of vessel i, l_i is the length of the vessel, w_i is the beam of the vessel, v_i^t is the vessel speed at location p_i^t, c_i^t is the heading, and d_i^t is the vessel draft.

The port–berth tuple was defined as:

$$T_{\mathrm{i}} = (f_i, b_i, n_i) \tag{12}$$

where T_i is the tuple of port i; f_i is the database key for port i; b_i is an irregular polygon representing the boundary of port; and n_i is the name of port i.

2) STEP 2

In a large port, ship speed is only 9–15 km/h in the fairway, and arrival or departure takes nearly one hour. We set 30 minutes as the interval for the observation window of a vessel position in the AIS data to moderate computer resource use during queries. For data recorded within the interval, we compared ports and berths, screened out vessels that had latitude and longitude values located within the port boundary, and compared vessel characteristics to derive the specific characteristics of the destination port of call.

3) STEP 3

We created a description of the characteristics of arrivals, departures, and berthing for a port using the following process.

Define the boundary of port y as b_y in the sampling period t. The function $contains(b_y, p_x)$ shows that vessel x was located within the polygonal port boundary b_y. The set of all ships in port y at time t, R_y^t, was defined as:

$$R_y^t = \{Mmsi_x | contains(b_y, p_x) \wedge t_x > t - \Delta t \wedge t_x \leq t \wedge v_x \leq \Delta v\} \tag{13}$$

At time $t + \Delta t$, the set of all vessels in port y was defined as:

$$R_y^{t+\Delta t} = \{Mmsi_x | contains(b_y, p_x) \wedge t_x > t \wedge t_x \leq t + \Delta t \wedge v_x \leq \Delta v\} \tag{14}$$

Two other conditions for deriving characteristics were defined. The timestep Δt was the sampling time of 30 min and an increment Δv of 1 km/h was used for vessel speed, which may be affected by wind and current when the vessel is moored in a harbor.

The *heading rate* can be used as a reference point because it does not vary when vessels are moored. The sampling time for this parameter was set to 30 minutes.

If the set of vessels that reach or leave port y during the interval from time t to time $t + \Delta t$ is $D_y^{t+\Delta t}$, then $D_y^{t+\Delta t} = R_y^{t+\Delta t} - R_y^t$ shows the arrival or departure of one or more vessels.

(a) sailing vessel (b) vessels at berth (c) moored container ship

FIGURE 9. Sailing and berthing of container ships.

The arrival time of a vessel allows us to quickly extract data for ships that arrive at a port or berth, such as arrival frequency, docking records, and similar information. The extremely large quantity of AIS data makes it impossible to monitor the positional information of every ship at any time. Thus, data snapshots were used to extract the arrival and departure time and berth details of ships by sampling historical AIS data at intervals and combining snapshot data with AIS data tuples and port–berth tuples.

We obtained ship position information from AIS data, deriving port and port boundaries and screening out vessels that were outside port boundaries by latitude and longitude. The remaining data were compared with the characteristics of vessels arriving at the port to obtain the characteristics of vessels departing from the port. The characteristics of all berthing behavior were extracted and assembled to form a sequential berth record for our training data:

$$Portberth\_seq = \{Port_1, Port_2, Port_3, \ldots, Port_n\} \tag{15}$$

The sequential words were extracted as the training text in Figure 4 and input to the gesim package.

IV. EXPERIMENTAL RESULTS AND RECOMMENDATION EXPLANATION

This section demonstrates the operation of the Port2Vec recommendation model. The experimental AIS data were obtained from hifleet.com. The proportion of ships with deadweight >50,000 tonnes was 43.56%, showing that port facilities are very adaptable in terms of ship size (Figure 10).

We chose Shanghai, the largest container ship port in the world in terms of throughput, and a typical regional port in China; Singapore, a global hub port in the Malacca Strait; and Hamburg, the third largest container ship hub in Europe, to test our method of determining the similarity between ports and creating recommendations for alternative destination ports for vessels. The geographical factor we set was the sailing distance from the chosen port to backup ports based on sailing cost. The function for a recommendation of port i was calculated as:

$$R_{\mathrm{i}} = \frac{S_{\mathrm{i}}}{\delta_{\mathrm{i}}} \tag{16}$$

where S_i is the similarity calculated by the Port2vec algorithm and δ_i is the attenuation coefficient of sailing distance. The recommendation value of the backup port is R_i.

The ports of Zhangjiagang, Nantong, Ningbo, and Zhoushan are located in the Yangtze River delta along the

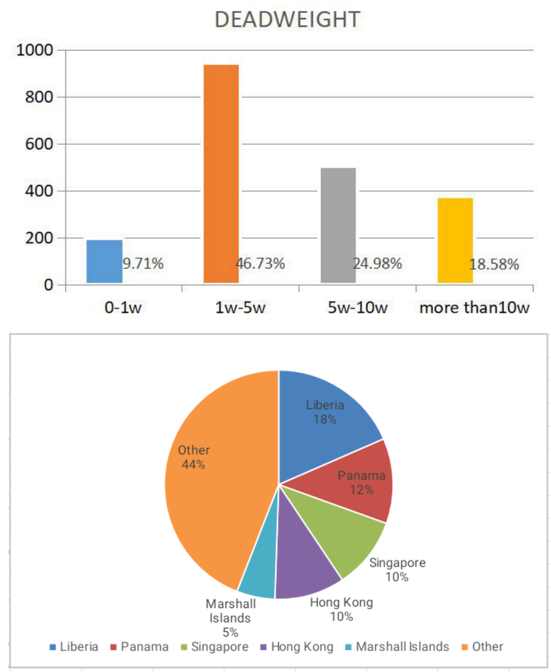

FIGURE 10. **Registration and deadweight distributions of data.**

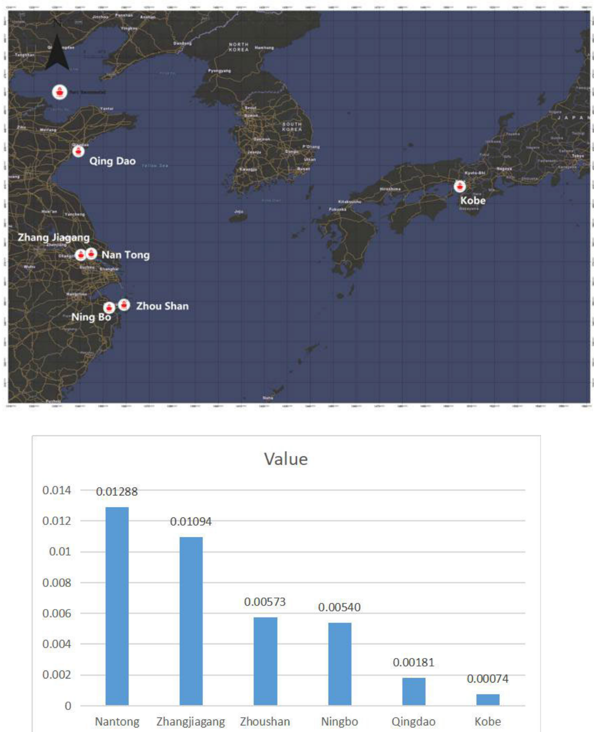

FIGURE 11. **Location and recommendation values to Shanghai of alternative ports.**

economic belt on China's mainland coastline. Zhangjiagang has 16 berths, with an annual throughput capacity of more than 60 million tonnes. Nantong has 24 public berths above 1000 tonnes, with a maximum berthing capacity of 200,000 tonnes. These two river ports can be used by any vessel as alternatives to Shanghai (Figure 11).

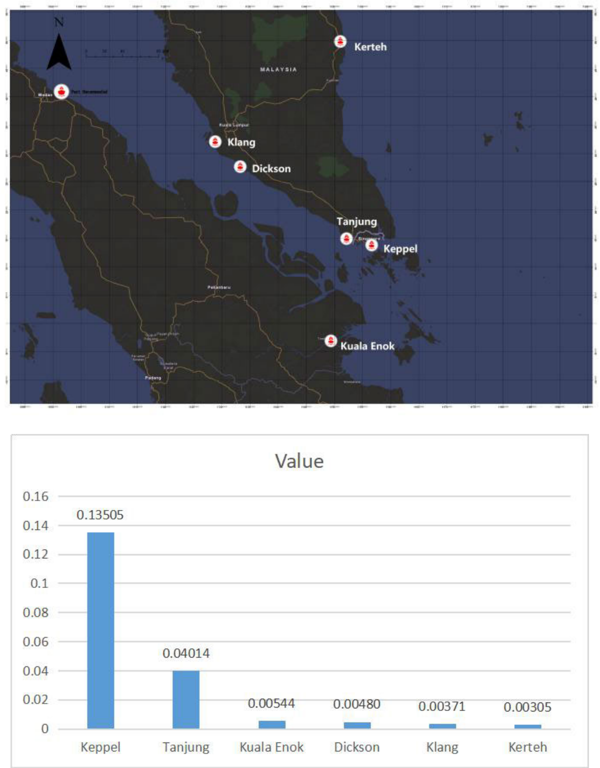

FIGURE 12. **Location and recommendation values to Singapore of alternative ports.**

Ningbo and Zhoushan are the top two recommended ports for the period 1995–2015. Chinese hub ports associated with the Silk Road have grown from two (Hongkong and Shanghai) to four (Shanghai, Shenzhen, Ningbo, and Hongkong) due to their relative centrality in the complex port network [39]. The set of shipping lines using Ningbo overlaps greatly with the set of those using Shanghai. Qingdao and Kobe are determined to be similar ports because they both handle megaships and both are hubs of international land freight networks.

Likewise, Singapore and Hamburg (Figure 12 and Figure 13) are similar, benefiting from the volume of shipping that passes through the Malacca Strait or the North Sea by an ability to forward containers across a continent. Our analysis also supports the view that China's investment in developing Melaka Gateway as a backup port for Singapore is a reasonable assurance of trade security.

Melaka Gateway as a backup port for Singapore is a reasonable assurance of trade security.

Our Port2vec analysis and related geographical analysis enabled us to select six container ship ports, most of which are in the top 20 ports of world, to offer data based recommendations to maritime management: Lianyungang, Xiamen, Hongkong, and Tianjin in China, Los Angeles in the United States and Inchon in South Korea. As we acknowledge, if theses ports were inactive due to a pandemic, there would be great financial losses. The top five recommendations of alternatives to each of these ports are given in Table 2.

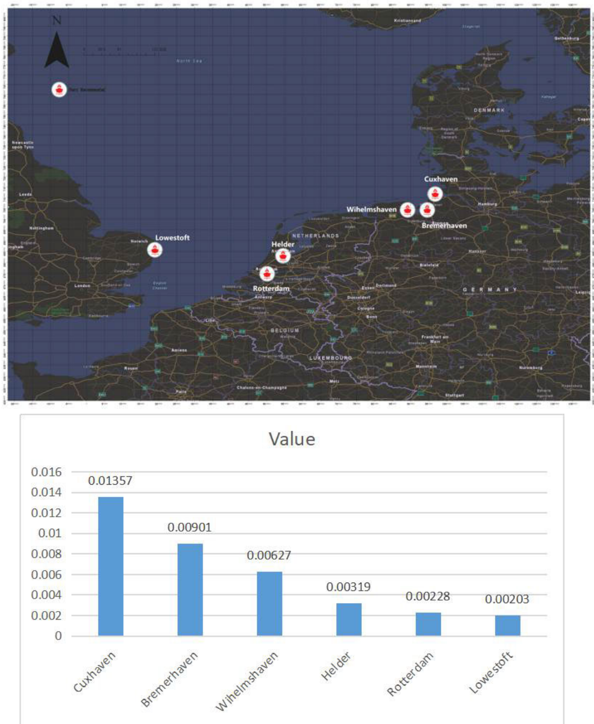

FIGURE 13. Location and recommendation values to Hamburg of alternative ports.

TABLE 2. Top five recommendations for selected main spots.

Main Port	Top Five Recommendations				
Lianyungang	Lanshan	Shidao	Weihai	Kunsan	Pyeongtaek
Inchon	Daesan	Pyeongtaek	Samcheon	Penglai	Yantai
Xiamen	Zhangzhou	Gulei	Mailiao	Songxia	Luoyuan
Hongkong	Da Chan Bay	Chiwan	Zhongshan	Yangpu	Dung Quat
Los Angeles	Long Beach	El Segundo	Richmond	Oakland	Antioch
Tianjin	Caofeidian	Qinhuangdao	Dalian	Yantai	Shidao

The results presented in Table 2 show that the ports with a high recommendation value have similar connections to internal transportation networks and are export-focused. The computational framework we developed will help shipping managers to choose alternative destination ports effectively, especially in a period of epidemic. This work can also help us to detect communities of port clusters in the future.

V. CONCLUSION

We used a novel approach to calculate the similarity using word embedding. This study demonstrates for the first time that Port2vec technology, derived from word2vec, can be used effectively to provide port recommendations in shipping and maritime applications. The key points in our research are summarized as follows: Port2vec can identify relevant similarities between container ship ports; and geographical analysis supports the effectiveness of the methodology.

This recommendation technology can be used only for container ports because it leverages sequences of berth records by treating them as textual sentences. In subsequent research, we intend to improve the approach to provide recommendations for other types of shipping.

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