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A connectivity reliability-cost approach for path selection in the maritime transportation of China's crude oil imports

Abstract: The focus of this paper is the selection of paths for the maritime transportation of crude oil. In addition to transportation cost, the nodes in a maritime transportation network are always affected by extreme events. Therefore, connectivity reliability must be considered during path selection. In this paper, uncertainty variables are introduced to describe the connectivity reliability of nodes under the influence of extreme events, and an uncertain bi-objective programming model with connectivity reliability maximization and transportation cost minimization as objectives is established for path selection. China's maritime transportation network for crude oil imports is used as a case study to validate the model, the effects of variations in the model parameters on path selection, transportation cost and connectivity reliability are discussed in the case study. The research results provide a basis on which for government decision makers to better plan crude oil transportation strategies.

Keywords: Connectivity reliability; Path selection; Maritime transportation; China's crude oil imports; Uncertainty theory

1. Introduction

Crude oil is a strategic national resource, in recent decades, strong economic growth in China has triggered a surge in crude oil imports, and maritime transportation is the primary transportation mode for the intercontinental crude oil trade. The safety of maritime transportation for crude oil plays a pivotal role in economic development and national security (Du et al. 2017; Yang et al. 2015). It is noticed that the existing transportation paths of crude oil of China are exposed to various risks. The maritime transportation network is composed of a set of port, strait and canal nodes and also a set of links between nodes. These main strait and canal nodes in this maritime transportation network such as the Strait of Hormuz, the Strait of Malacca, the Bab el Mandeb, the Suez Canal are vulnerable to military intervention from neighboring countries, piracy, terrorism, war and other extreme events (Emmerson and Stevens 2012). For example, the conflict in Yemen threats the safety of the Bab el Mandeb; the recent Jerusalem's ascription problem may cause the instability in the Middle East; the rampant piracy increases the possibility of being attacked for the tanker vessels sailing through the Strait of Malacca. If certain nodes become disconnected due to the above extreme events, the security of the crude oil supply will be affected.

The Chinese government attaches great importance to these transportation risks of the key maritime nodes. The Ministry of Transport of China is actively promoting the establishment of giant domestic tanker companies. Recently, China Merchants Group and Sinotrans & CSC Company were combined and formed the largest domestic tanker company, named China VLCC Company Limited. Because the government is the dominative stakeholder of this company, the national energy strategy and relevant policies are inevitably reflected into the strategies of this company. As for the national energy strategy, along with the transportation cost, the connectivity reliability of maritime transportation paths is also considered as a key factor, so as to guarantee the transportation safety of imported crude oil.

In this paper, a connectivity reliability-cost approach is proposed for path selection in the maritime transportation of crude oil. In this paper, the connectivity reliability of a node or path refers to the probability that the node or path will remain connected when subjected to extreme events. Here, an uncertainty variable is introduced to describe the connectivity reliability of each node in the case of extreme events, and an uncertain bi-objective programming model with connectivity reliability maximization and transportation cost minimization objectives is formulated for path selection.

The main contributions of this paper are threefold. First, previous studies regarding crude oil maritime transportation path selection mostly focused only on transportation cost or oil-spill-related costs (Hennig et al. 2012, 2015; Siddiqui and Verma 2013, 2015), failed to consider reliability. We noticed that the reliability of paths is increasing considered in other transportation modes, for example, in road networks (Chen et al. 2016; Zeng et al. 2015; Srinivasan et al. 2014). This paper is a preliminary attempt to explore the connectivity reliability of path selection for the maritime transportation of crude oil, on top of transportation cost. Second, in reliability research of road transportation, the reliability is broadly represented by random variables (Zeng et al. 2015; Srinivasan et al. 2014). In our study, consider that the historical data is insufficient to calibrate the probability distribution of node failure in maritime transportation of crude oil, we introduce the uncertainty variables to describe the imprecise nature of connectivity reliability of nodes. Third, this paper conducts a case study using real data regarding China's maritime transportation network. Based on the results, policy and strategy suggestions are made. This study can assist government policy makers and strategy planners in tanker companies to better develop crude oil transportation strategies.

The paper is organized as follows. Section 2 reviews the relevant literature. Section 3 provides an overview of the maritime transportation network, using that of China as an example, and presents our model used for path selection. In Section 4, a case study is illustrated. Section 5 describes the effects of variations in the model parameters on path selection, transportation cost and connectivity reliability. Finally, major conclusions, policy implications and directions for future research are discussed in Section 6.

2. Literature review

Crude oil is an important strategic material, there are a lot of studies addressing different areas of crude oil transportation. With regard to trade analysis, Adland, Jia and Strandenes (2017) made AIS-based estimates of crude oil trade volume. Du et al. (2017), Yang et al. (2015) and An et al. (2014) analyzed the features and evolution of international crude oil trade. Tamvakis (1995), Adland and Cullinane (2006), Kavussanos and Alizadeh-M (2002) explored the variations of freight rates in tankers markets. Shi, Yang and Li (2013), Poulakidas and Joutz (2009), Sun et al. (2014) investigated the relationship between tanker freight rates and crude oil prices. Given that the timely supply of crude oil has a great impact on the smooth operation of a national economy, there are many studies focusing on path selection for the maritime transportation of crude oil. Hennig et al. (2012, 2015) presented a model with the objective of minimizing total transportation cost for oil tanker routing and scheduling. This model considered multiple grades of crude oil, specified time windows for both pickup and delivery, and unpaired supply and demand quantities. Since the costs associated with oil spills are significant, in an effort to minimize these costs, Iakovou (2001) introduced a multi-objective programming model for oil spill risk analysis and routing for the maritime transportation of crude oil between multiple origins and destinations. The goal of the programming model was to minimize transportation cost and expected risk cost (due to oil spills) to assist regulators in assessing oil spill risk and deriving desirable routing schemes. Siddiqui and Verma (2013, 2014, 2015) presented a mixed-integer model with transportation cost and oil spill risk objectives. The model was used to determine routes and schedules for a heterogeneous fleet of crude oil tankers. The authors also summarized the methods of oil spill risk assessment and spill cost estimation that were used as the basis for solving the routing problem considering transportation cost and oil spill risk.

A maritime transportation network is subject to a number of uncertainties. Therefore, it is not sufficient to consider only oil spill risk. Transportation reliability must also be considered. Most studies of transportation reliability have focused on road networks, and several reliability measures have been proposed in the literature, including connectivity reliability, travel time reliability and capacity reliability. Connectivity reliability represents the probability that specific origin-destination (OD) pairs in a network will remain connected when some links suffer complete failure (Mine and Kawai 1982). The links are characterized by binary variables that capture two possible operating states of a link: full-capacity operation or complete failure (with zero capacity). Capacity constraints and travel time are not considered when measuring connectivity reliability. Another measure of the reliability of a transportation network is travel time reliability, which is related to the probability that a trip between a given OD pair can be completed successfully within a given acceptable time threshold (Asakura and Kashiwadani 1991). Capacity reliability was introduced by Chen et al. (1999, 2000) as a measure for evaluating the performance of a degradable road network from a planning perspective. This reliability measure is defined as the probability that the transportation network can accommodate a certain demand level at an acceptable level of service considering travelers' route choice behaviors.

Over the past decade, interest in path selection problems based on transportation reliability in transportation networks has increased. Hosseini and Wadbro (2016) employed uncertainty theory to address the problem of choosing the most reliable path in a post-disaster traffic network based on connectivity reliability, and they addressed the issue of stability analysis in the context of uncertainty programming. Wang et al. (2013) assumed that the connection probability of each edge was known and presented a reliable path selection model for the transportation of relief materials after a natural disaster, with the goal of selecting the path with the maximum connection probability between the origin and destination at a given transportation time. Zeng et al. (2015) employed a model for determining reliable paths in a stochastic transportation network with correlated link travel times. Many other studies have also focused on identifying reliable paths based on travel time reliability or capacity reliability in a stochastic transportation network (Chen et al. 2016; Zeng et al. 2016; Srinivasan et al. 2014; Xing and Zhou 2011; Ji et al. 2011; Lee et al. 2008). In most of these works, travel time reliability or capacity reliability is considered for path selection based on probability theory, with little emphasis on connectivity reliability. However, certain extreme events may greatly influence connectivity reliability by causing links to become disconnected. One reason can be explained by the insufficient historical data to calibrate the probability distribution of link failure, and it is not possible to characterize connectivity reliability using random variables. However, the imprecise nature of the connectivity reliability of links can be suitably described by uncertainty variables. Therefore, it is possible to employ the uncertainty theory to study the path selection problem considering connectivity reliability. This paper proposes an uncertain bi-objective programming model with objectives of connectivity reliability maximization and transportation cost minimization based on uncertainty theory to select paths in the maritime transportation network of crude oil.

3. Path selection in the maritime transportation network for China's imported crude oil

In this section, we first describe the path selection problem considering transportation cost and connectivity reliability, using China as an example. We then formulate this problem as an uncertain bi-objective programming model.

3.1. Problem description

The path selection model is formulated based on a country's maritime transportation network of imported crude oil. Considering the complexity and comprehensiveness of crude oil maritime transportation network, this paper uses China as an example to formulate the path selection model. In 2015, China imported 335 million tons of crude oil from 45 countries. Figure 1 shows each country's export volume to China and the associated shipping routes. These countries can be divided into five levels according to China's corresponding crude oil import volumes, as shown in the legend. The top ten crude oil exporters are Saudi Arabia, Russia, Angola, Iraq, Oman, Iran, Venezuela, Kuwait, Brazil and United Arab Emirates, whose import volumes account for 83.3% of total imports. The Middle East is still the largest source of Chinese crude oil imports, followed by Africa and Latin America. Crude oil from these countries can be transported through four transportation corridors, which are China's northeastern, northwestern, southwestern and southeastern crude oil transportation corridors. The construction of these corridors is now nearly completed. In the meanwhile, with the development of the "One Belt and One Road" proposal, China and Pakistan are considering the construction of a crude oil pipeline. If this pipeline is constructed, crude oil imports from the Middle East, Africa and other regions could be transported by sea to Gwadar Port in Pakistan and then via pipeline to China, thereby circumventing the Strait of Malacca.

The maritime transportation paths for China's imported crude oil are grouped according to the distribution of the exporters, which are shown in Figure 1.

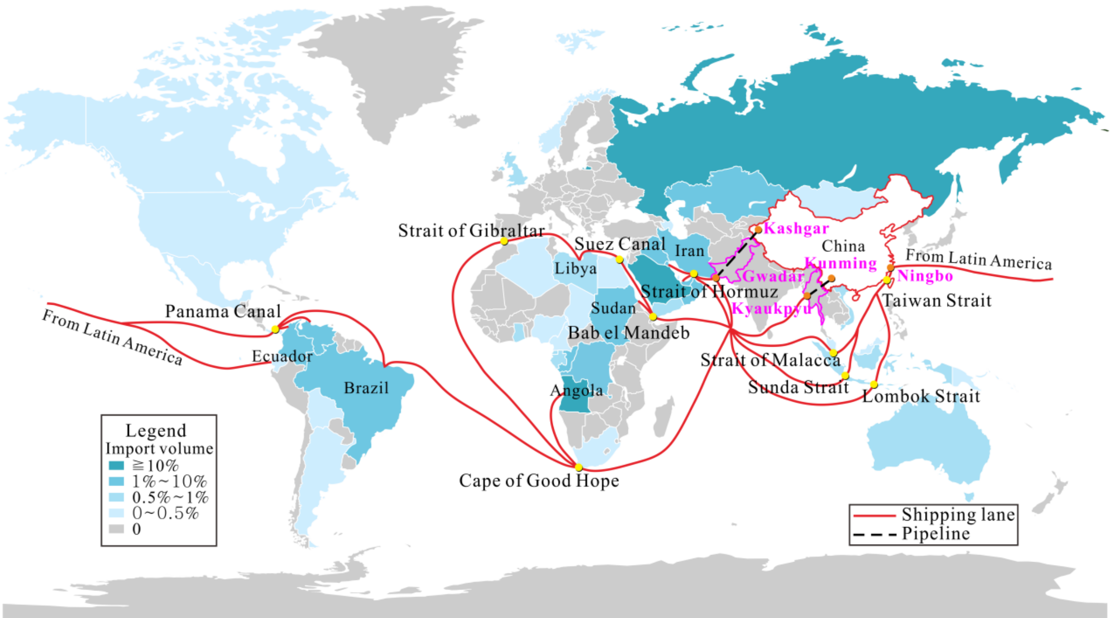

Figure 1. Maritime transportation network for China's imported crude oil

Data source: International Trade Center

We can formulate the maritime transportation network for China's imported crude oil as follows: Let $G=(V, E)$ denote the maritime transportation network for China's imported crude oil, as shown in Figure 1, where V and E represent the sets of nodes and links, respectively. In this paper, a set of uncertainty variables $\xi=(\xi_1,\xi_2,\ldots,\xi_n)$ $(0<\xi_v<1)$ is introduced to describe the connectivity reliability of each node under the influence of extreme events (Liu 2007, 2010). Each node $v\in V$ is associated with an uncertainty variable ξ_v; thus, $G=(V,E,\xi)$ represents an uncertain maritime transportation network for imported crude oil. The connectivity reliability of any path for a given OD pair in the network is the product of the reliabilities of the nodes included in that path.

3.2. Model development

The proposed issue can be defined as a bi-objective optimization problem. Because the connectivity reliability of a path is represented by an uncertainty variable, uncertain bi-objective programming is applied in this paper. Before the model is formulated, the following assumptions are made.

First, this paper assumes that there are only two possible states of each node: full-capacity operation or complete failure (with zero capacity). The links between nodes are in the normal state, and the nodes are independent of each other. The connectivity reliability of each node has a regular uncertainty distribution denoted by $\Phi_1, \Phi_2, ..., \Phi_n$. Second, the shipping companies that are responsible for the transportation of the imported crude oil are regarded as a single entity with a heterogeneous fleet of vessels of various types, including very large crude carriers (VLCCs), ultra large crude carriers (ULCCs), and Suezmax, Aframax and Panamax vessels. Vessels of each type can only operate on compatible paths. For example, a fully laden VLCC cannot pass through the Suez Canal. Third, the speed of each type of vessels is considered same on each path, and the loaded leg and ballast leg speeds are the same. Fourth, the planning horizon is one year, and the import volume from each exporter is known. Thus, the crude oil transportation demand is known for each OD pair.

The decision variable is as follows:

N_{ijk} Number of vessels of the *k*th type deployed on path *ij*

The other notations are as follows:

I Set of exporters, $i \in I$ refers to an exporter, $i=1,2,\ldots,I$

J Set of shipping lanes, $j \in J$ refers to a shipping lane, $j=1,2,\ldots,J$

J_M Set of shipping lanes passing through Gwadar Port, $J_M \subset J$

J_N Set of shipping lanes passing through Kyaukpyu Port, $J_N \subset J$

K Set of vessel types, $k \in K$ refers to a vessel type, $k=1,2,\ldots,K$

Q_i Volume of crude oil imported from exporter *i*

N_k Number of vessels of the *k*th type

C_k Average carrying capacity of a vessel of the *k*th type

H_{ij} Maximum carrying capacity of a vessel on path *ij*

c_{ijk} Operating cost for a round-trip voyage of a vessel of the *k*th type on path *ij*

c'_{ijk}	Operating cost for a one-way voyage of a vessel of the kth type on path ij from the exporter to China
$\xi_v'^{\alpha}$	α-pessimistic value of the uncertainty risk variable for node v
r_{ij}	Risk associated with path ij, which is an uncertainty variable
q_{ijk}	Cargo carrying capacity of a vessel of the kth type on path ij
T_k	Number of operating days per year for a vessel of the kth type
T_{ijk}	Transportation time for a round-trip voyage of a vessel of the kth type on path ij
A	Annual transportation capacity of the China-Pakistan crude oil pipeline
B	Annual transportation capacity of the China-Myanmar crude oil pipeline

Along with the index j, we also define the index i to indicate the exporter. This is because that we need to assign the export volume of each exporter i to the selected shipping lane j, in another word, we need to identify the trade volume from certain i on the j. For example, a shipping lane j passing through the Strait of Hormuz, the Strait of Malacca, the Taiwan Strait to China can be used by various exporters in Persian Gulf. To identify the crude oil volume from Saudi Arabia through this shipping lane, we need to name the country as i. Furthermore, the aggregated volume of crude oil transported on path ij can be obtained by adding up the number of all the kth type vessels deployed on this path. The results also indicate which paths have been selected for oil transportation.

Based on the previous analysis, an uncertain bi-objective optimization model is established as follows.

(*P*)

Minimize

$$\text{Cost:} \quad \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c_{ijk} * \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor * N_{ijk} + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c'_{ijk} * \left\lceil \left(\frac{T_k}{T_{ijk}} - \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor \right) \Big/ 0.5 \right\rceil * N_{ijk} \tag{1}$$

$$\text{Risk:} \quad \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} r_{ij} * \left(\left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor + \left\lfloor \left(\frac{T_k}{T_{ijk}} - \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor \right) \Big/ 0.5 \right\rfloor \right) * N_{ijk} \tag{2}$$

Subject to

$$\sum_{j\in J}\sum_{k\in K} \left(\left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor + \left\lfloor \left(\frac{T_k}{T_{ijk}} - \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor \right) \Big/ 0.5 \right\rfloor \right) * q_{ijk} * N_{ijk} \ge Q_i , \forall i \tag{3}$$

$$\sum_{i\in I}\sum_{j\in J} N_{ijk} \le N_k , \forall k \tag{4}$$

$$q_{ijk} = \min\{C_k, H_{ij}\}, \forall i, j, k \tag{5}$$

$$\sum_{i\in I}\sum_{j\in J_M}\sum_{k\in K}\left(\left\lfloor\frac{T_k}{T_{ijk}}\right\rfloor + \left\lfloor\left(\frac{T_k}{T_{ijk}} - \left\lfloor\frac{T_k}{T_{ijk}}\right\rfloor\right)\Big/0.5\right\rfloor\right) * q_{ijk} * N_{ijk} \leqslant A \tag{6}$$

$$\sum_{i\in I}\sum_{j\in J_N}\sum_{k\in K}\left(\left\lfloor\frac{T_k}{T_{ijk}}\right\rfloor + \left\lfloor\left(\frac{T_k}{T_{ijk}} - \left\lfloor\frac{T_k}{T_{ijk}}\right\rfloor\right)\Big/0.5\right\rfloor\right) * q_{ijk} * N_{ijk} \leqslant B \tag{7}$$

$$N_{ijk} \geq 0,\ N_{ijk} \text{ are integers}, \forall i, j, k \tag{8}$$

Here, r_{ij} in objective function (2) is the inverted variable of the connectivity reliability of path ij. In simple terms, this paper transforms the problem of maximizing the connectivity reliability into a problem of minimizing risk by inverting the reliability variables. The uncertainty risk variables are the inverted reliability variables and denote the risk levels of the nodes; thus, r_{ij} is the risk associated with path ij. It is the product of the uncertainty risk variables of the nodes included in path ij.

Objective function (1) represents the total cost of transporting crude oil from the exporters to China. This paper refers to Ng (2017) to calculate the number of round-trip voyages in equation (1). $\lfloor T_k/T_{ijk}\rfloor$ represents the number of round-trip voyages of the kth type vessels on path ij. According to Ng (2017), after the completion of all round-trip voyages, the days left before the end of the planning horizon may be sufficient for a one-way voyage, which would mean that a vessel could transport an additional amount q_{ijk} of crude oil from its exporter to China. In this function, $\lfloor(T_k/T_{ijk}-\lfloor T_k/T_{ijk}\rfloor)/0.5\rfloor$ presents whether there is a one-way voyage from the corresponding exporter to China, it is equal to either one or zero. Objective function (2) minimizes the transportation risk, which is a transformation of the maximization of the transportation reliability. Constraint (3) ensures that the total crude oil transported to China equals or exceeds the demand requirement. Constraint (4) represents the number of vessels of each type on each path, which should not exceed the total number of vessels. It is worth noting that the crude oil transportation contract can be divided into two categories. When it is a voyage charter party, the vessels for transportation have been specified in a contract (Guo 2014) for only one voyage with a prescribed loading port and path. When it is a Contract of

Affreightment (COA), the vessels have not been specified in the contract (Guo 2014). After one or several voyages, if the same type vessels deployed on different paths can roughly simultaneously arrive at the same export countries, the vessels can be swapped. q_{ijk} in constraint (5) is related to the average carrying capacity of a vessel of the kth type; it also depends on whether the vessel can pass through path ij. For example, a fully laden VLCC cannot pass through the Suez Canal. Therefore, q_{ijk} is equal to the smaller value between C_k and H_{ij}. M and N in equations (6) and (7) indicate that there are a total of M shipping lanes passing through Gwadar Port and N shipping lanes passing through Kyaukpyu Port. This means that the imported crude oil is first transported through those M shipping lanes to Gwadar Port or through N shipping lanes to Kyaukpyu Port. Then, it is further transported to China from Gwadar Port or Kyaukpyu Port by pipelines. Therefore, the total volumes of crude oil transported by sea to Gwadar Port and Kyaukpyu Port should not exceed the annual transportation capacities of the China-Pakistan and China-Myanmar pipelines, respectively. Sign restrictions and integer constraints are enforced in equation (8).

Since r_{ij} in objective function (2) is an uncertainty variable, it cannot be directly minimized. In this paper, uncertainty programming techniques are employed by introducing an α-pessimistic value based on the critical value of an uncertainty variable. The risk associated with path ij can be expressed as $r_{ij} = \Pi_{v \in ij} \xi_v'^{\alpha}$, where $\alpha \in (0,1)$. Thus, the above uncertain bi-objective programming model can be transformed into a deterministic bi-objective programming model (Liu and Chen 2015).

(P')

Minimize

$$\text{Cost: } \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c_{ijk} * \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor * N_{ijk} + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c'_{ijk} * \left\lceil \left(\frac{T_k}{T_{ijk}} - \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor \right) \Big/ 0.5 \right\rceil * N_{ijk} \quad (9)$$

$$\text{Risk: } \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} \Pi_{v\in ij} \xi_v'^{\alpha} * \left(\left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor + \left\lceil \left(\frac{T_k}{T_{ijk}} - \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor \right) \Big/ 0.5 \right\rceil \right) * N_{ijk} \quad (10)$$

Equations (9) and (10) are subject to constraints (3)-(8).

The preferences between transportation cost and transportation risk determine the paths selected for crude oil transportation. To better reflect these preferences and to enable the evaluation of the effects of different preferences on path selection, ω is introduced as the weight of the transportation risk (connectivity reliability). If tanker companies prioritize the reduction of transportation costs, the value of ω will be small. By contrast, in case the transportation reliability is prioritized per the suggestion of government, the value of ω tends to be large. In this way, the tradeoff between the two conflicting objectives can be explicitly captured, and the bi-objective programming model can be transformed into a single-objective programming model. Thus, the path selection problem for the maritime transportation of imported crude oil can be solved.

Minimize

$$
\begin{aligned}
&(1-\omega)*\left(\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c_{ijk}^{\wedge} * \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor * N_{ijk} + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c_{ijk}^{\prime\wedge} * \left\lfloor \left(\frac{T_k}{T_{ijk}} - \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor \right) \Big/ 0.5 \right\rfloor * N_{ijk} \right) + \\
&\omega * \left(\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} (\Pi_{v\in ij}\, \xi_v^{\prime\alpha})^{\wedge} * \left(\left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor + \left\lfloor \left(\frac{T_k}{T_{ijk}} - \left\lfloor \frac{T_k}{T_{ijk}} \right\rfloor \right) \Big/ 0.5 \right\rfloor \right) * N_{ijk} \right)
\end{aligned}
\tag{11}
$$

Expression (11) is subject to constraints (3)-(8), $c_{ijk}^{\wedge}$, $c_{ijk}^{\prime\wedge}$ and $(\Pi_{v\in ij}\, \xi_v^{\prime\alpha})^{\wedge}$ are the values of min-max normalization processing (Jain and Bhandare 2011). The values after min-max normalization processing are in the range [0, 1], and the dimension effect is eliminated. Expression (11) is an integer optimization model, which can be solved using the branch and bound method (Held and Karp 1971).

4. Case study

In this section, thirteen countries are recognized as the main crude oil exporters of China. We use the proposed uncertain bi-objective programming model to choose the maritime transportation paths from these exporters. The branch and bound algorithm is adopted to solve the model. It is implemented in MATLAB R2014a and executed on a computer with an i5-760 CPU and 4 GB of memory. With this configuration, an optimization result could be obtained within two hours.

4.1. Problem setting

The crude oil exporters selected in this paper include Saudi Arabia, Oman, Iraq, Iran, the United Arab Emirates and Kuwait in the Middle East; Angola, Congo, Sudan and Libya in Africa; and Venezuela, Colombia and Brazil in Latin America. Since the volume of crude oil imported from west coast countries of Latin America is very small, which only accounts for 0.6% of China's total imports, the paths from west coast countries of Latin America to China are not considered in our case study. The combined import volume from the above exporters accounts for 78% of China's total imported crude oil. The import volumes of crude oil from these exporters are listed in Table 1.

Table 1. Import volumes of crude oil from exporters

Region	Crude oil exporter	Import volume (tons)
Middle East	Saudi Arabia	50544045
	Oman	32064336
	Iraq	32112551
	Iran	26615930
	United Arab Emirates	12568874
	Kuwait	14427930
West Africa	Angola	38705959
	Congo	5862038
North Africa	Sudan	7999994
	Libya	2145312
Latin America	Venezuela	16008873
	Colombia	8866704
	Brazil	13921920

Data source: International Trade Center

Ports in the same country are assumed to have similar external environments and reactions to extreme events. Therefore, in this paper, only one port in each crude oil exporter is selected to represent all loading ports in that country. Since the selection of the unloading port will have no impact on the choice of straits and canals, in China, we choose Ningbo Port as the only port to represent the domestic unloading ports. Additionally, the handling capacities of all chosen ports are assumed to be enough to satisfy the demand in our study. The connectivity reliability of each node, except Ningbo Port, in the maritime transportation network for China's imported crude oil is assumed to be represented by an uncertainty variable with a zigzag uncertainty distribution. This uncertainty variable, $\xi \sim Z(a,b,c)$, is called a zigzag variable with parameters a, b, and c, where $a < b < c$.

The zigzag distribution is regular, and the corresponding inverse distribution is as follows.

$$\Phi^{-1}(\alpha) = \begin{cases} (1-2\alpha)a + 2\alpha b & if \quad \alpha < 0.5 \\ 2(1-\alpha)b + (2\alpha - 1)c & if \quad \alpha \geq 0.5 \end{cases} \tag{12}$$

The parameters of the uncertainty distribution of the connectivity reliability for each strait and canal node are determined according to the results of a previous safety evaluation of key straits and canals in China's maritime transportation network (lv and Wang 2015). The parameters for the port nodes in the crude oil exporters refer to the Ease of Doing Business Ranking released by the World Bank, as shown in Table 2. In addition, it is assumed that the connectivity reliabilities of Ningbo Port, the China-Myanmar and China-Pakistan crude oil transportation pipelines are all equal to 1. The transportation capacities of the China-Pakistan and China-Myanmar crude oil pipelines are 22 and 20 million tons, respectively.

Table 2. Parameters of the uncertainty distribution of the connectivity reliability for each node

Node	*a*	*b*	*c*
Saudi Arabia	0.70	0.75	0.85
Iraq	0.65	0.73	0.78
Iran	0.68	0.78	0.80
United Arab Emirates	0.80	0.88	0.95
Kuwait	0.70	0.73	0.82
Oman	0.72	0.75	0.78
Angola	0.65	0.71	0.82
Congo	0.65	0.68	0.82
Sudan	0.60	0.70	0.75
Libya	0.60	0.68	0.75
Venezuela	0.62	0.75	0.82
Colombia	0.80	0.82	0.90
Brazil	0.68	0.75	0.80
Gwadar Port	0.66	0.75	0.78
Kyaukpyu Port	0.64	0.73	0.80
Strait of Hormuz	0.60	0.78	0.88
Strait of Malacca	0.60	0.70	0.75
Sunda Strait	0.65	0.80	0.85
Lombok Strait	0.70	0.75	0.85
Strait of Gibraltar	0.70	0.80	0.85
Taiwan Strait	0.78	0.80	0.83
Bab el Mandeb	0.60	0.75	0.80
Suez Canal	0.68	0.75	0.83
Panama Canal	0.75	0.82	0.85

Note: The port node for each crude oil exporter is represented by the name of that country.

To estimate the shipping capacity of crude oil transportation (number of each vessel type) for China, we multiply the number of vessels of each type in the global fleet by the market share of seaborne crude oil import of China, which is 16.4% according to the Clarkson database. The daily operating cost for each vessel type is 4% of the vessel capacity for the loaded leg; for the ballast leg, the cost is 80% of the daily amount for the loaded leg (Siddiqui and Verma 2015). The information for each vessel type is shown in Table 3. The number of operating days per year for each vessel type is assumed to be 345 days.

Table 3. Information for each vessel type

Vessel type	Average carrying capacity (DWT)	Speed (knots)	Number	Cost ($/day)
VL/ULCC	307,539	15.7	104	22142.808
Suezmax	155,196	15.1	80	11174.112
Aframax	107,934	14.9	146	7771.248
Panamax	72,648	14.9	67	5230.656

Data source: Clarkson Research Services

4.2. Results

A confidence level of α=0.9 is adopted in this paper. To investigate the effects of different connectivity reliability weights on path selection, we set the weight of the connectivity reliability to values of ω=0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0 respectively. Since the number of paths considered in this paper is large, the numbers of vessels deployed on each path are represented by the numbers of vessels passing through each strait and canal. Table 4 shows the results obtained with connectivity reliability weights of 0.1, 0.5 and 0.9.

Table 4 shows the variations in vessel numbers deployed on paths under different connectivity reliability weights. When the connectivity reliability weight is 0.1, there are only 6 Suezmax, 3 Aframax and 3 Panamax vessels deployed on paths through the Strait of Malacca. When connectivity reliability weights are 0.5 and 0.9, no vessels are deployed on paths through the Strait of Malacca. Instead, most vessels are deployed on paths through the Sunda Strait and the Lombok Strait.

As for the Bab el Mandeb, the Suez Canal and the Strait of Gibraltar, when the connectivity reliability weight is 0.1, there are 2 Suezmax vessels deployed on paths through the Suez Canal and 5 vessels deployed on paths through the Bab el Mandeb. When connectivity reliability weights are 0.5 and 0.9, no vessels are deployed on paths through the Suez Canal. Instead, vessels are deployed on paths through the Strait of Gibraltar. The numbers of vessels deployed on paths through the Strait of Hormuz and the Taiwan Strait show minimal changes.

Table 4. Numbers of vessels deployed on paths passing through each strait and canal under different connectivity reliability weights

Node	Connectivity reliability weight											
	0.1				0.5				0.9			
	VL/ULCC	SUEZMAX	AFRAMAX	PANAMAX	VL/ULCC	SUEZMAX	AFRAMAX	PANAMAX	VL/ULCC	SUEZMAX	AFRAMAX	PANAMAX
Strait of Hormuz	44	4	1	1	48	0	0	0	57	0	0	0
Bab el Mandeb	2	2	1	0	3	0	1	0	4	0	0	0
Strait of Gibraltar	0	0	0	0	2	0	0	0	2	0	0	0
Strait of Malacca	0	6	3	3	0	0	0	0	0	0	0	0
Sunda Strait	77	1	0	1	77	0	0	0	30	0	0	0
Lombok Strait	0	1	0	1	8	0	1	0	69	0	0	0
Taiwan Strait	77	8	3	5	85	0	1	0	99	0	0	0
Suez Canal	0	2	0	0	0	0	0	0	0	0	0	0
Panama Canal	0	0	0	57	0	0	0	61	0	0	22	67

5. Discussion

In this section, we firstly discuss the effects of different connectivity reliability weights and confidence levels on path selection, then we discuss the effects of variations in import volume on transportation cost and connectivity reliability.

5.1. Effects of different connectivity reliability weights on path selection

Based on the numbers of vessels deployed on each path, the shipping path selection results for China's imported crude oil for different connectivity reliability weights were obtained. Similar to the vessel numbers, the path selection results are expressed in terms of the volume of imported crude oil transported through each strait and canal, as shown in Figure 2. In Figure 2, the values of the Panama Canal, the Suez Canal, the Bab el Mandeb and the Strait of Gibraltar are indicated on the right-hand vertical axis, and those for the other straits and canals are indicated on the left-hand vertical axis.

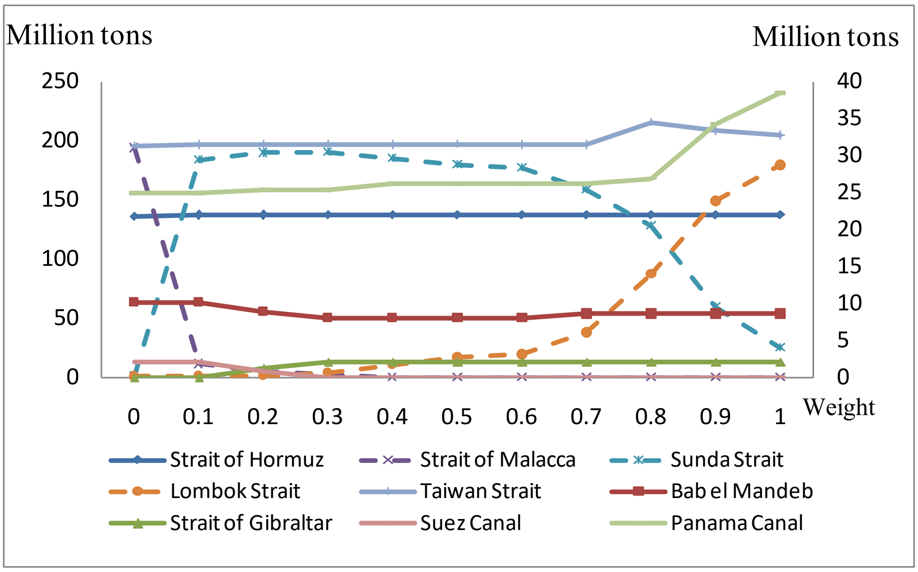

Figure 2. Path selection results under different connectivity reliability weights

The effects of different connectivity reliability weights on the volumes of imported crude oil transported through the Strait of Malacca, the Sunda Strait and the Lombok Strait are particularly notable. As shown in Figure 2, when paths are selected solely based on minimizing transportation cost (connectivity reliability weight is 0), the imported crude oil is mainly transported via paths through the Strait of Malacca. Specifically, 194 million tons of crude oil is transported through the Strait of Malacca, because the transportation costs of paths through the Strait of Malacca are much lower than those of paths through the Sunda Strait or the Lombok Strait. When the transportation risk is emphasized (connectivity reliability weight is greater than 0.4), paths through the Strait of Malacca are not selected. This result reflects a different strategy from the current one, under which approximately 80% of China's imported crude oil traverses the Strait of Malacca (U.S. Energy Information Administration, 2015). Alternatively, most of the imported crude oil is transported via paths through the Sunda Strait and the Lombok Strait. When minimizing transportation risk has higher priority (connectivity reliability weight is greater than 0.6), more crude oil is transported via paths through the Lombok Strait than that through the Sunda Strait. This is because the risk associated with the Lombok Strait is lower than that of the Sunda Strait.

With regard to the Bab el Mandeb, the Suez Canal and the Strait of Gibraltar, when paths are selected based on minimizing transportation cost (connectivity reliability weights is 0 and 0.1), the crude oil imported from Libya is transported via paths through the Suez Canal and the Bab el Mandeb. When the transportation risk is prioritized (connectivity reliability weight is greater than 0.3), paths through the Suez Canal are not selected, the crude oil transportation volume shifts to the paths through the Strait of Gibraltar. But the crude oil imported from Sudan can only be transported through the Bab el Mandeb to China. Thus, the paths through the Strait of Gibraltar cannot replace all the paths through the Bab el Mandeb.

As for the Panama Canal, when paths are selected based on improving transportation reliability (connectivity reliability weight is greater than 0.8), there is a remarkable growth in volume of imported crude oil transported through the Panama Canal. With regard to the Strait of Hormuz and the Taiwan Strait, since the crude oil imported from the Middle East, except for that from Oman, must be transported through the Strait of Hormuz, and the majority of the imported crude oil is transported through the Taiwan Strait, the imported crude oil volumes transported through these two straits barely change.

5.2. Effects of different connectivity reliability weights on the volume of imported crude oil transported via paths through Gwadar Port

With the construction of Gwadar Port in Pakistan, Chinese crude oil imports from the Middle East, Africa and Latin America could be transported by sea to Gwadar Port and then via pipeline to China, thereby circumventing the Strait of Malacca, the Sunda Strait and the Lombok Strait. This paper also investigates the impacts of different connectivity reliability weights on the volume change of imported crude oil transported via paths through Gwadar Port, as shown in Figure 3.

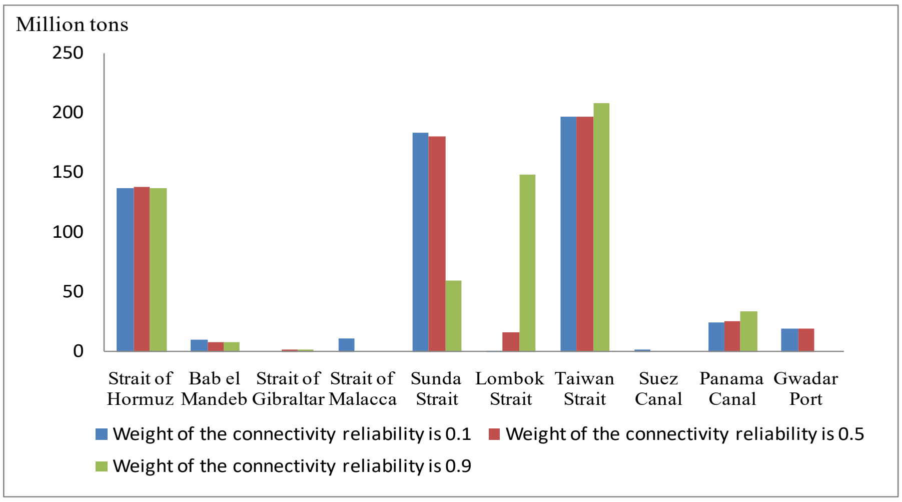

Figure 3. Variations in the volume of imported crude oil transported via paths through Gwadar Port

As shown in Figure 3, when transportation cost has higher priority or is equally important as transportation risk (connectivity reliability weight is 0.1 or 0.5), the volume of imported crude oil transported via paths through Gwadar Port nearly increases to the upper capacity limit of the China-Pakistan crude oil pipeline. Under this situation, part of the imported crude oil previously transported through the Strait of Malacca, the Sunda Strait and other key nodes shifts to via paths through Gwadar Port.

Practically, due to the complex racial and religious tensions, as well as the prevalence of terrorism and other risk factors in Pakistan, the risk associated with paths passing through Gwadar Port is high. When paths are selected based on minimizing transportation risk (connectivity reliability weight is 0.9), paths through Gwadar Port are not chosen. Alternatively, more crude oil is transported via paths through the Sunda Strait and the Lombok Strait. This is different from our previous expectation that the paths through Gwadar Port would be selected to circumvent the Strait of Malacca, the Sunda Strait and the Lombok Strait.

5.3. Influence of changes in the confidence level on path selection

The international environment is full of complexity and changes rapidly. When an extreme event occurs, the current transportation strategy should be adjusted and a new optimal strategy considering the changed international environment should be recognized. In this paper, the adjustment of the transportation strategy can be achieved by changing the value of a confidence level α. α is used to indicate the risk level of each node and, consequently, will affect the path selection. When the international environment changes, the optimal transportation strategy can be determined by our model through adjusting the value of the confidence level α. To reflect the effects of different risk levels of straits and canals on path selection, we discuss the changes in the total volumes transported through these straits and canals, considering different connectivity reliability weights. Confidence levels of 0.1, 0.5 and 0.9 and connectivity reliability weights of 0.1, 0.5 and 0.9 were chosen to illustrate these effects. Path selection was performed for the nine combinations of cases, as shown in Figure 4. In Figure 4, the values of the Panama Canal, the Suez Canal, the Strait of Malacca, the Bab el Mandeb and the Strait of Gibraltar are indicated on the right-hand vertical axis, and the values for the other straits and canals are indicated on the left-hand vertical axis.

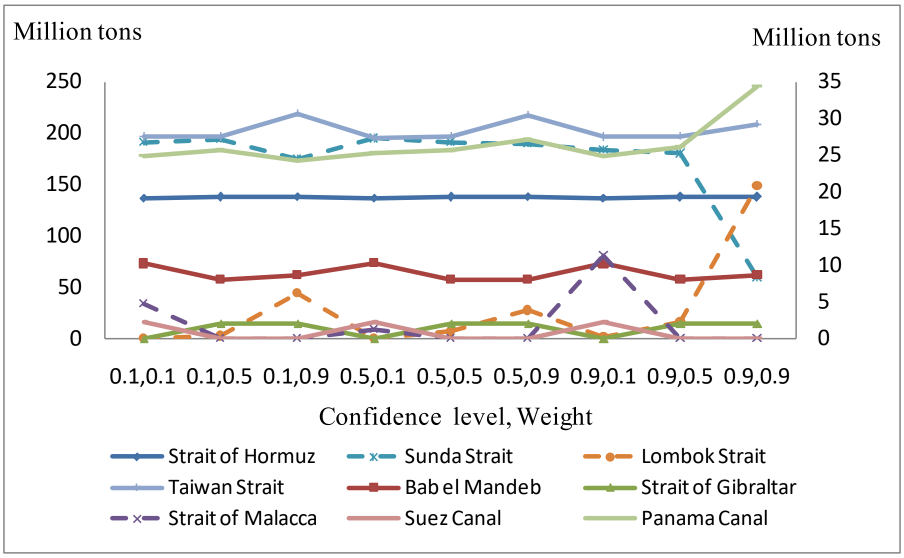

Figure 4. Influence of the confidence level on path selection

As shown in Figure 4, changes in the confidence level exert significant effects on the volumes of imported crude oil transported through the Strait of Malacca, the Sunda Strait and the Lombok Strait. As for the Sunda Strait and the Lombok Strait, when the risks associated with the two straits are either low or moderate (confidence level is 0.1 or 0.5), given the same connectivity reliability weight, more imported crude oil is transported via paths through the Sunda Strait than that through the Lombok Strait. However, when the risks associated with the two straits are high (confidence level is 0.9) and paths are selected based on minimizing transportation risk (connectivity reliability weight is 0.9), there is an increase in the volume of imported crude oil transported via paths through the Lombok Strait, accompanied by a decrease in the volume transported through the Sunda Strait. This is because the risk associated with the Sunda Strait is higher than that associated with the Lombok Strait. In terms of the Strait of Malacca, when paths are selected based on minimizing transportation cost (connectivity reliability weight is 0.1), the volume of imported crude oil transported through the Strait of Malacca is 4.8 million tons when the risk is low and it is 1.3 million tons when the risk is moderate. They are both smaller than the 11 million tons when the risk is high.

By contrast, changes in the confidence level for the same connectivity reliability weight have little effect on the volumes of imported crude oil transported via paths through other straits and canals.

5.4. Influence of changes in import volume on transportation cost and risk

The volume of crude oil imported from each exporter is treated as a parameter in the model. Changing these volumes will also affect path selection, and, in turn, transportation cost and risk. To investigate this, the confidence level was set to α=0.9, and connectivity reliability weights of 0.1 and 0.9 were chosen. Then, we varied the import volumes to compare the resulting changes in transportation cost and risk.

In this paper, we consider two cases of changes in import volume, namely, the transference of 10% of the current import supply from the Middle East to other regions and the transference of 10% of the current import supply from Latin America to other regions. We do not consider the transference of 10% of the current import supply from the North Africa and West Africa to other regions. This is because the crude oil imported from North Africa and West Africa is not much, small changes in the import volumes from these regions will have minor influence on the import volumes from the Middle East and Latin America and, consequently, only result in neglectable change to the transportation cost and risk.

First, we assume that 10% of the import volume currently supplied by the Middle East is instead obtained from North Africa, West Africa or Latin America. The resulting changes in transportation cost and risk are shown in Table 5.

Table 5. Changes in transportation cost and risk when 10% of the import supply from the Middle East is transferred to other regions

Connectivity	Scenario	Risk	Cost (one hundred

reliability weight			million dollars)
0.1	import volumes remain unchanged	4157.38	3.7009
	10% of import supply transferred to North Africa	4467.48	3.7703
	10% of import supply transferred to West Africa	4166.79	3.8346
	10% of import supply transferred to Latin America	4218.87	3.9125
0.9	import volumes remain unchanged	3524.86	4.4869
	10% of import supply transferred to North Africa	3628.84	4.6597
	10% of import supply transferred to West Africa	3488.63	4.6064
	10% of import supply transferred to Latin America	3481.15	4.8068

Note: Risk and cost refer to the total transportation risk and the total cost of transporting crude oil from the exporters to China.

When paths are selected based on minimizing transportation cost (connectivity reliability weight is 0.1), a significant increase in transportation risk is observed when 10% of the import supply from the Middle East is transferred to North Africa. This increase occurs because such a transfer of imports will significantly increase the import volumes from Sudan and Libya, by factors of 1.05 and 3.92, respectively. The crude oil imported from Sudan and Libya may be transported via paths through the Suez Canal and the Bab el Mandeb, which are high-risk bottlenecks. Similarly, when 10% of the import supply from the Middle East is transferred to West Africa or Latin America, the transportation risk is also witnessed an increase. Since the transportation distances of paths from North Africa, West Africa and Latin America to China are longer than those from the Middle East to China, the transportation cost increases accordingly when 10% of the import supply from the Middle East is transferred to the three regions.

When paths are selected based on minimizing transportation risk (connectivity reliability weight is 0.9), the transportation risk also increases when 10% of the import supply shifts from the Middle East to North Africa, but the magnitude of this increase is lower compared with that in the previous scenario. When 10% of the import supply shifts from the Middle East to West Africa or Latin America, the transportation risk decreases, and an upward trend in the transportation cost is still observed. Besides, the improvement in the transportation reliability associated with the transference to West

Africa is similar to that associated with the transference to Latin America. The increase in the cost of transportation from West Africa is less than that from Latin America. Therefore, an appropriate reduction in the volume of crude oil imports from the Middle East and an increase in those from West Africa could be considered.

When we assume that 10% of the import volume currently supplied by Latin America is replaced by from North Africa, West Africa or the Middle East, the resulting changes in transportation cost and risk are shown in Table 6.

Table 6. Changes in transportation cost and risk when 10% of the import supply from Latin America is transferred to other regions

Connectivity reliability weight	Scenario	Risk	Cost (one hundred million dollars)
0.1	import volumes remain unchanged	4157.38	3.7009
	10% of import supply transferred to North Africa	4451.60	3.6826
	10% of import supply transferred to West Africa	4231.75	3.6972
	10% of import supply transferred to the Middle East	4218.87	3.6608
0.9	import volumes remain unchanged	3524.86	4.4869
	10% of import supply transferred to North Africa	3653.25	4.5398
	10% of import supply transferred to West Africa	3511.37	4.4921
	10% of import supply transferred to the Middle East	3555.96	4.3925

Note: Risk and cost refer to the total transportation risk and the total cost of transporting crude oil from the exporters to China.

When paths are selected based on minimizing transportation cost (connectivity reliability weight is 0.1), the transportation risk increases significantly when 10% of the import supply from Latin America is transferred to North Africa. When 10% of the import supply from Latin America is transferred to West Africa, the transportation risk increases because paths with low transportation costs are selected. When paths are selected based on minimizing transportation risk (connectivity reliability weight is 0.9), the transportation risk still increases when 10% of the import supply from Latin America is transferred to North Africa, but the magnitude of the increase is smaller than that observed for the low connectivity reliability weight. The selection of more reliable paths, such as paths through the Strait of Gibraltar, will increase the transportation cost. When 10% of the import supply from Latin America is transferred to West Africa, the transportation risk does not change considerably, and the transportation cost increases only slightly. When 10% of the import supply from Latin America is transferred to the Middle East, an increase in transportation risk and a decrease in transportation cost are observed.

6. Conclusions, policy implications and future research

In this paper, we introduced a connectivity reliability-cost approach for path selection and applied it in the maritime transportation of China's imported crude oil. The results show that the effects of different connectivity reliability weights on the volumes of imported crude oil transported through the Strait of Malacca, the Sunda Strait, the Lombok Strait, the Suez Canal, the Strait of Gibraltar, the Bab el Mandeb and Gwadar Port are particularly notable. While the effects on the Strait of Hormuz and the Taiwan Strait are small. The discussion regarding effects of the confidence level changes on path selection shows that changes in the confidence level exert significant effects on the import volumes transported via paths through the Strait of Malacca, the Sunda Strait and the Lombok Strait, but have little effect on other straits and canals. Besides, variations in import volume greatly affect transportation cost and risk.

We can extract several implications for the relevant policy maker and strategy planner, as discussed below.

First, under different weights of connectivity reliability, different straits and canals are recognized as important, thus leads to different strategies on the choice of trade partners. For example, given that the objective is to minimize the total transportation cost, government policy makers may consider to guide to increase the volume of crude oil imports from the Middle East and reduce the volumes from West Africa and Latin America. By contrast, if the objective is to improve the reliability of transportation, an appropriate reduction in the volume of crude oil imports from the Middle East and an increase in the import volume from West Africa could be considered. Therefore, the policy maker and strategy planner in tanker companies should measure the risk of straits and canals under different international situation and adopt appropriate strategy to balance the national and enterprise benefit.

Second, Gwadar Port is recognized as a strategic node by the government policy maker, but we notice that it cannot handling tankers with carrying capacities of more than 100,000 tons because of capacity limitation of the port. As a result, given a certain amount of imported crude oil to be transported via paths through Gwadar Port, more vessels on those paths are needed. This leads to higher transportation risks associated with those paths according to our model. Therefore, when paths are selected based on minimizing transportation risk (connectivity reliability weight is high), paths through Gwadar Port have less chance to be chosen. To better perform the function of a strategic node for Gwadar Port, the improvement of the infrastructure at Gwadar Port should be taken into consideration for the government policy maker so as to overcome this issue.

Finally, in the future, we could seek to improve upon the work presented in this paper in the following respects. First, the import volume from each crude oil exporter can be treated as a decision variable and optimized based on path selection. It would enable the simultaneous optimization of the crude oil import strategy and the transportation strategy. However, this would make the problem more complicated and would require the incorporation of the relationships between China and the crude oil exporters, the relevant security situations, the oil prices and the maximum possible export volumes of the exporters into the objective functions and constraints. Second, we can consider to develop a new method of calculating the transportation cost by treating the numbers of voyages for specific vessel types on different paths as decision variables. This might make the model more concise.

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