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Optimising the climate resilience of shipping networks

Abstract

Climate catastrophes (e.g. hurricane, flooding and heat waves) are generating increasing impact on port operations and hence configuration of shipping networks. This paper formulates the routing problem to optimise the resilience of shipping networks, by taking into account the disruptions due to climate risks to port operations. It first describes a literature review with the emphasis on environmental sustainability, port disruptions due to climate extremes and routing optimisation in shipping operations. Second, a centrality assessment of port cities by a novel multi-centrality-based indicator is implemented. Third, a climate resilience model is developed by incorporating the port disruption days by climate risks into shipping route optimisation. Its main contribution is constructing a novel methodology to connect climate risk indices, centrality assessment, and shipping routing to observe the changes of global shipping network by climate change impacts.

Keywords: *Climate resilience; Shipping network; Optimisation; Artificial Bee Colony Algorithm; Maritime transport*

1. Introduction

Seaports are in vulnerable areas to climate change impacts: on coasts susceptible to sea-level rise and storms or at mouths of rivers susceptible to flooding (Becker et al., 2012). In the past decades, there has been much effort from researchers and practitioners to reduce the carbon footprint of maritime transport for mitigating climate change effect by adopting operations management practices. These include operational decisions such as speed reduction, berth scheduling and route re-engineering to rationalise fuel consumptions and to reduce greenhouse gases (GHG) emissions. On the adaptation direction, there are growing interests but mainly focusing on climate vulnerability assessments and risk assessments (Poo et al., 2018) and yet to implement operations management practices. Such studies are conducted in different regions in isolation and yet to investigate the local port-level impact of climate change to global shipping network configuration.

The stability in port operations is the key factor in facilitating international trade (Zhang and Lam, 2015), and the operation of a seaport is highly dependent on the ocean climate (Du et al., 2015). Climate extreme, which leads to port disruptions, is a significant and much serious issue that must be taken into consideration. Storminess, heavy wind, heavy precipitation, sea-level rise, storm surge and heat wave are all affecting port operations (Associated British Ports, 2011, Felixstowe Dock and Railway Company, 2011, Field et al., 2014, Intergovernmental Panel on Climate Change, 2014, Mersey Docks and Harbour Company Ltd, 2011, PD Teesport Ltd, 2011, Peel Ports Group, 2011, Port of Dover, 2011) including berthing, loading and unloading areas, storages, and transportation (Gou and Lam, 2018).

Beside physical damages and financial loss during the climate extremes, disruptions can have a long-term negative impact on an organisation's future performance (Tang, 2006). Disruptions may affect customer relationship and the impact is irreversible (Sheffi and Rice Jr, 2005). From the lessons of 1995 Kobe earthquake, there are three types of loss: loss related to regional economy, loss related to other Japanese ports and loss related to other ports in the world (Chang, 2010). As global warming is still unstoppable, and it brings more extreme climate events, the relevant risks become serious. Moreover, economic losses due to fatalities become more severe and long lasting (Lurie, 2015). Port strategic alliance is important to reduce such losses (Chen et al., 2015) by developing climate resilient route options to vessels for transhipments.

To address this research need, the paper aims to formulate the routing problem to optimise the resilience of shipping networks, by considering the disruptions due to climate risks to port operations. It is structured as follows. Section 2 is the literature review about port disruptions due to climate extreme, multiple-objective decision support for environmental sustainability in the maritime industry, and the Artificial Bee Colony (ABC) algorithm for transportation routing problems. Section 3 describes the two-step methodology. Finally, Section 4 presents the computation results and Section 5 concludes the paper with the implications of the findings.

2. Literature review

The literature review is divided into three parts, port disruptions due to climate extreme, multiple-objective decision support for environmental sustainability in the maritime industry, and the Artificial Bee Colony algorithm for a vehicle routing problem and supply chain management.

2.1 Port disruptions due to climate extreme

Considering a full coverage of risks, Chopra and Sodhi (2004) classify supply chain risks into nine categories: Disruptions, delays, systems, forecast inaccuracies, intellectual property breaches, procurement failures, system breakdown, inventory, and capacity issues. Hurricane Lorenzo, the most potent eastern Atlantic storm ever recorded, hit the UK and Ireland in October 2019 and sunken tugboat carrying fourteen crew members (Fedschun, 2019). Seaports are vulnerable to climate change impacts such as sea level rise and flooding. On the other hand, extreme and continuous heat can also damage road surfaces and distort rail lines that link seaports and hinterland transport (Sieber, 2013), and affects the connectivity of seaports. Climate extremes present an important factor influencing port operation disruptions (Lam and Su, 2015).

Hubbert and Mclnnes (1999) develop a storm surge inundation model to assess coastal flooding resistance. Then, Ronza et al. (2009) evaluate the economic damages originated by major accidents in port areas. In 2011, Hanson et al. (2011) provide a comprehensive study to compare the performance of large port cities when facing sea-level rise risks, and Hallegatte et al. (2011) assess climate impacts, sea-level, and storm surge risk in Copenhagen. In 2014, Genovese and Green (2014) assess the storm surge damage to coastal settlements in Southeast Florida. Akukwe and Ogbodo (2015) propose a spatial analysis of vulnerability to flooding in Port Harcourt Metropolis, Nigeria. In 2016, Vitor Baccarin et al. (2016) present a climate change vulnerability index and case study in a Brazilian coastal city, and Hoshino et al. (2016) estimate the increase in storm surge damage due to climate change and sea-level rise in the Greater Tokyo area. Alsahli and Alhasem (2016) assess the sea-level rise vulnerability of Kuwait coast, and Zhang and Lam (2015) estimate the economic losses of port disruption by extreme wind events. Djouder and Boutiba (2017) set up a vulnerability assessment of coastal areas to sea-level rise from the physical and socioeconomic parameters at Gulf of Bejaia, Algeria, and Abou Samra (2017) uses cartographic modelling to assess the impacts of coastal flooding, with a case study of Port Said Governorate, Egypt. Then, Cortès et al. (2018) implement the flood risk in Mediterranean urban areas, with the case of Barcelona.

It is evident that all previous studies focus on the climate impact to a local coast/port region or an area. The disruptions due to climate impacts on port operations will certainly affect shipping traffic; however, upon the best knowledge of the authors, there is little research on how the climate impact on port operations will be transmitted to shipping network configuration for resilience-based shipping operation optimisation. Therefore, a shipping network resilience model is developed by analysis of vessel routing selection under different climate risk scenarios, considering the port disruption days in the future. The mechanism is to add the distribution days on different transhipment ports and use the optimisation model to search better alternative routes.

2.2 Multiple-objective decision support for environmental sustainability in the maritime industry

Sustainability has become an essential concern in designing the organisational business models (Sarkis et al., 2013) of many industries, including shipping and ports. A literature review is conducted to examine the potential of multi-objective optimisation (MOO) as a decision support system (DSS). There are fifty-two journal papers collected from by Mansouri et al. (2015), which are presented in three categories relating to shipping such as Environmental sustainability, DSS and MOO. Environmental sustainability in shipping is a vital attribute of the literature review. DSS is commonly considered to be implemented for maritime business (Fagerholt et al., 2009, Lam, 2010). MOO is the common optimisation in maritime shipping (Finkelstein et al., 2009, Kollat and Reed, 2007). There are forty studies in the environmental sustainability category, twelve in DSS, and fourteen in MOO, including overlaps (see Figure 1). 14 overlapped studies, providing useful insights on the newly proposed MOO-based DSS for sustainability in shipping, are in-depth analysed in the ensuing section. Mansouri et al. provide an pioneering insight that MOO-based DSS for sustainability in maritime shipping is a possible new reseach direction.

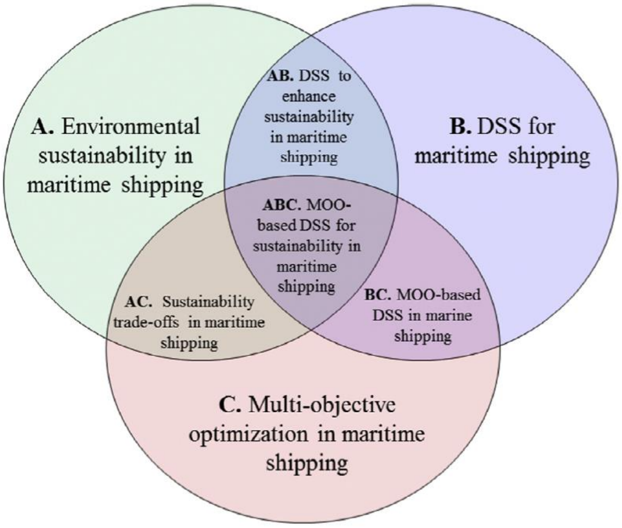


Figure 1. The scope of the literature review for multiple-objective decision support for environmental sustainability in the maritime industry

There are five studies for inventing DSSs to enhance sustainability in shipping and eight studies on sustainability trade-offs in the maritime sector. There is only one study on MOO-based DSS in shipping. Ballou et al. (2008) develop a DSS to support optimised ship operation including the vessel's hull design, propulsion system, seakeeping models and a safe operating limit for reducing fuel consumption and GHG emissions. Balmat et al. (2011) implement a risk assessment in shipping regarding safety at sea with a focus on pollution prevention at open sea. Windeck and Stadtler (2011) develop a DSS for designing liner shipping networks by considering environmental factors and minimising cost and CO2 emissions. Bruzzone et al. (2010) present a simulator for assessing the environmental impact on port operations. A fuzzy framework for maritime risk assessment for safety and oil pollution prevention at sea is designed (Balmat et al., 2009, Balmat et al., 2011). Palacio et al. (2016) determine container depots for minimising the total cost of the network and the environmental impact of the depots and their associated delivery operations. Chen et al. (2013) propose a model for optimising truck arrival patterns at marine container terminals to reduce emissions from idling truck engines by minimising both trucks waiting times and arrival pattern changes. Qi and Song (2012) optimise vessel scheduling considering uncertainty in port availability and frequency requirements on the liner schedule, considering service level and fuel consumption. Brouer et al. (2013) analyse a vessel schedule recovery problem (VSRP) to evaluate a given disruption scenario and to select a recovery action that balances the trade-off between increased bunker consumptions and the impact on service levels. Hu et al. (2014) establish a model for allocating the berth and quay-cranes to vessels by minimising fuel consumption and emissions of vessels. Song and Xu (2012a) compare CO2 emissions from direct and feeder liner services in the case of Asia–Europe Services and they develop an operational activity-based method for estimating CO2 emissions from shipping networks (Song and Xu, 2012b) . Corbett et al. (2009) analyse the impacts of a fuel tax policy and a speed reduction mandate on CO2 emissions by applying a profit-maximising equation to estimate route-specific speeds which are economically efficient. Grabowski and Hendrick (1993) assess the trade-offs between shipboard safety and crew size.

2.3 The Artificial Bee Colony algorithm for vehicle routing problems and supply chain management

The ABC algorithm simulating the foraging behaviour of honey bees was invented by Karaboga (Karaboga, 2005). Among different swarm intelligence (SI) algorithms mentioned, the ABC is one of the algorithms based on bee swarms which have been most widely studied and applied to solve real-world problems, so far (Karaboga et al., 2014). One of the primary applications is the vehicle routing problem (VRP) with different constraints, including vehicle capacities and carbon emissions. For instance, three studies were working on the capacitated vehicle routing problems (CVPR) by the ABC algorithm (Brajevic, 2011, Szeto et al., 2011, Gomez and Salhi, 2014). Then, three enhanced versions of the ABC heuristic are also proposed to improve the solution qualities of the original version. Afterwards, time constraint is imparted to the CVPR (Ji and Wu, 2011, Shi et al., 2012, Yao et al., 2013), and there are case studies on public bike repositioning (Shui and Szeto, 2015) and green vehicle routing with cross-docking (Yin and Chuang, 2016).

SCM is being adopted as the most efficient way of managing operations in an enterprise, and organisations deploying supply chain systems are globally on the rise. The main objective of SCM is to establish the highest coordination between all the entities of the network. Swarm Intelligence (SI) techniques have been applied to the realm of SCM in the following significant areas (Soni et al., 2019):

- Distribution network design;
- Supplier management;
- Inventory optimisation;
- Vehicle routing; and
- Resource allocation.

Except for VRP, ABC has been applied to different sectors in SCM. By the summary from Soni et al., eleven studies are imparting the ABC algorithm on shipping logistic problems after 2010. Kumar et al. (2010) minimise the supply chain cost with embedded risk using computational intelligence approaches. Pal et al. (2011) use the ABC algorithm to solve an aggregated procurement, production, and shipment planning decision problem for a three-echelon supply chain. Taleizadeh et al. (2013) propose a hybrid method of ABC fuzzy simulation to optimise constrained inventory control systems with stochastic replenishments and fuzzy demand. Then, Zhang et al. (2016) develop a mixed-integer nonlinear programming (MINLP) model to design supply chains. Kefer et al. (2016) use a fuzzy multi-criteria-based ABC classification method. Gökkus and Yildirim (2017) compute a container traffic forecasting model by using the ABC. Zeng et al. (2017) present a metaheuristic model for gantry crane scheduling and the storage space allocation problem in railway container terminals. Zhu et al. (2017) optimise a shipping model by the ABC. Sumner and Rudan (2018) propose a hybrid MCDM approach to transhipment port selection. Zhang et al. (2018) develop a mixed-integer linear programming model to obtain the optimal repositioning of empty containers through an intermodal transportation network. Poo and Yip (2019) propose an optimisation model for container inventory management. Wang et al. (2019) construct a three-level marine logistics network site-distribution model based on a low-carbon scenario.

By understanding the use of ABC in VPR and SCM, ABC can solve routing problems at a global scale. An advanced ABC model is applied to integrate the climate change impacts to assess the impacts of port disruptions and incorporate climate resilience into shipping network configuration. For assessing the impacts of port disruptions due to climate extremes on global shipping networks, an ABC algorithm is favourable for imparting into a MOO model to find a heuristic solution as the global shipping network is always vast with many solutions.

3 Solution methodology

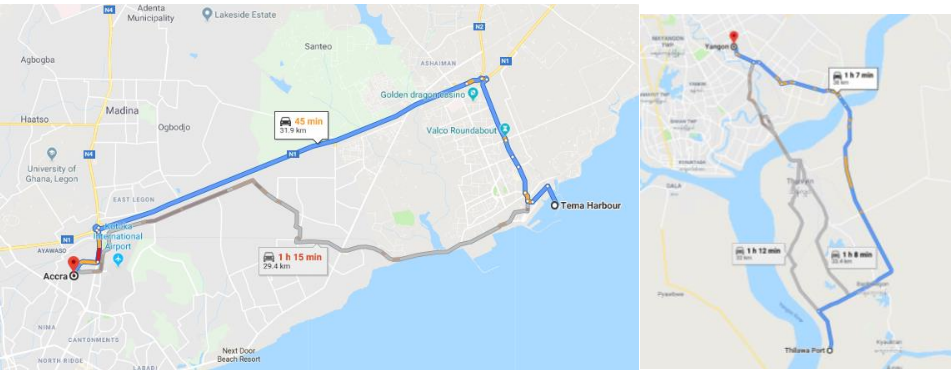
For optimising the climate resilience on a global shipping network from climate risk indicators, a two-step methodology is introduced to assess the climate vulnerabilities of the network. First, a multi-centrality assessment is done for measuring the importance of seaports in the worldwide network. This is a crucial step to sort out the hubs, as known as the important port, for case study on route changes. Second, a shipping route optimisation model is designed to estimate the climate change impacts on shipping routes. The program formulations have been set up and can be used to solve shipping routing problems (Poo and Yip, 2019). For optimising the performance, an ABC based heuristics method is suitable to sorting out the solution within many possible answers. For constructing a notable global shipping network for assessing climate resilience, a suitable dataset with independent climate risk indices on different ports is needed. The centrality assessment 136 large port cities, population exceeding one million inhabitants in 2005, are chosen to form the global shipping network in this study (Hanson et al., 2011). Briguglio (2010) has defined a framework to assess the risk of being harmed by climate change. The vulnerability and adaptability are both assessed for each port and then the risks of territories being affected by climate change (CR) are ranked as shown in Annex 1. The mechanism of the experiment is to compose a total travel time by summarising voyage times and port service time. Voyage time is referred to the information from Maersk website, and port service time is referenced by an index, basic service time, and CR. CR is associated with the possible disruption by climate change on port cities, which results in different extra basic service time.

3.1. Multi-centrality assessments

3.1.1. Structuring the global shipping network and data collection

Structuring the global shipping network is an crucial step to undergo vulnerability assessment as some seaports that are not in the city centres (Pape, 2017). So, a criterion is set up before further investigation: The seaports within 2-hour circle and 200km travelling distance can be used to represent a traffic flow of the city. The required information is collected from Google map, as shown in Figures 2 and 3 (Google Maps, 2019). For examples, Tema Harbour is chosen to represent Accra, and Thilawa Port is chosen to represent Yangon. After grouping some sub-urban ports to cities, there are two cities mismatched, Hangzhou and Rabat. By the first criteria, Hangzhou and Rabat can be referenced to Ningbo and Casablanca.

The data of service route sourced in our research is from the Maersk shipping line from 12th July 2019 to 31st July 2019 from Maersk website (http://www.maerskline.com). July is assessed by Baltic Dry Index (BDI) to best represent the average traffic volume comparing to other months, and it is the typhoon season for most of port cities in the northern hemisphere, including Pacific Ocean, Atlantic Ocean, and Indian Ocean. BDI in July proves that the activities of the shipping market are ordinary in July. The port cities are chosen for data collection (see Annex 1), and twenty transit ports are found between the shipping routes as shown in Annex 2, and six agglomerations cannot locate any routes related to them, they are Dhaka, Belem, Maceio, Natal, Nampo, and Sapporo. Therefore, 2397 attributes are found between all chosen port cities and transit port cities. Thus, 154-node shipping network is formed and modelled.



Figures 2 & 3. Google map recommended travel routes in Ghana and Myanmar

3.1.2. Modelling of the global shipping network

UCINET 6 for Windows is a software package for the analysis of social network data, and it is chosen for the data analysis in this study (Borgatti et al., 2002). To present a network into the tool, an adjacency 154 x 154 matrix $A_{154\times154}$ is created, a_{ij} is the attribute or route from i to j. $a_{ij}=0$ means the service does not exist, and $a_{ij}=1$ means otherwise. After inputting the data for all values between two nodes, the network can be visualised by the software.

3.1.3. Modelling of the global shipping network

The analyses are conducted on degree centrality, closeness centrality, and betweenness centrality independently. Degree centrality is defined as the number of links directly connected to it, which represents the association and importance of that node with other nodes. Closeness centrality represents the sum of the shortest distances from all nodes to a fixed node, which indicates the central location of the node in the network. Betweenness centrality measures the extent to which a node is in the "middle" of other "point pairs" in the graph, reflecting the role of the node in the network. Degree centrality and closeness centrality are directional, and then the two rank sets are based on accumulative values of two directions. Also, transit port cities are not included in any ranks. The top 20 ports with these three centralities are listed in Table 1.

Table 1. Top 20 agglomerations in Relation to Centralities

Rank	**ID**	**Seaport**	**Degree centrality**	**ID**	**Seaport**	**Closeness centrality**	**ID**	**Seaport**	**Betweenness centrality**
1	31	Shanghai	151	31	Shanghai	1.302	99	Singapore	8.919

2	29	Ningbo	141	29	Ningbo	1.268	31	Shanghai	8.629
3	99	Singapore	133	99	Singapore	1.218	29	Ningbo	7.806
4	93	Busan	114	93	Busan	1.162	86	Panama City	6.341
5	27	Guangzhou	107	27	Guangzhou	1.152	93	Busan	6.041
6	28	Shenzhen	101	28	Shenzhen	1.142	84	Rotterdam	5.063
7	38	Hong Kong	99	38	Hong Kong	1.114	49	Hamburg	4.758
8	30	Qingdao	85	82	Rotterdam	1.103	38	Hong Kong	4.542
9	86	Panama City	83	30	Qingdao	1.095	27	Guangzhou	3.687
10	82	Rotterdam	81	112	London	1.082	120	New York	3.479
11	120	New York	72	86	Panama City	1.079	28	Shenzhen	2.661
12	112	London	67	120	New York	1.078	110	Dubai	2.623
13	48	Hamburg	65	49	Hamburg	1.060	30	Qingdao	2.101
14	110	Dubai	65	57	Mumbai	1.042	112	London	1.974
15	39	Barranquilla	62	12	Santos	1.041	39	Barranquilla	1.855
16	57	Mumbai	62	110	Dubai	1.040	114	Baltimore	1.640
17	12	Santos	61	39	Barranquilla	1.032	33	Tianjin	1.598
18	72	Tokyo	60	129	Virginia Beach	1.031	62	Surabaya	1.351
19	35	Xiamen	59	118	Miami	1.024	116	Houston	1.341
20	33	Tianjin	55	116	Houston	1.016	97	Jeddah	1.332
20	116	Houston	55						
20	118	Miami	55						
20	129	Virginia Beach	55						

If some seaports have the same values, they will be assigned the highest rank to the set of duplicates. For example, Hamburg and Dubai rank the same for degree centrality. Shanghai has the highest degree centrality and closeness centrality. Ningbo and Singapore rank second and third places. Singapore scores the highest on betweenness centrality table and follow closely by Shanghai and Ningbo. Busan, Guangzhou, Hong Kong, and Rotterdam are top 10 in both three ranks, and these show their contributions to the global shipping network too. Moreover, the six exempted agglomerations are ranked the lowest. To obtain a final rank for chosen agglomerations, multi-centrality indicator is implemented, and the ranking is visualised in Table 2.

Table 2. Top 20 agglomerations of multi-centrality ranking

Rank	**ID**	**Final score**	**Agglomeration**
1	31	461	Shanghai
2	29	458	Ningbo
2	99	458	Singapore
4	93	452	Busan
5	27	444	Guangzhou
6	38	440	Hong Kong
7	28	439	Shenzhen
8	86	437	Panama City
8	82	436	Rotterdam

10	30	426	Qingdao
11	49	425	Hamburg
11	120	425	New York
13	112	418	London
14	110	414	Dubai
15	39	403	Barranquilla
16	57	397	Mumbai
17	12	394	Santos
18	33	390	Tianjin
19	116	389	Houston
20	35	382	Xiamen

More than half of the top 20 agglomerations are from Asia. Then, the other remaining agglomerations are from Europe, Northern America, South America, and Middle East. Global vulnerabilities of all chosen agglomerations are found, and the data set is going to be analysed with local vulnerability data set.

3.2. Shipping route optimisation model

Shipping route optimisation model is designed to choose the best route from a starting port to the ending port. There are possibly different numbers of transhipment ports for the whole route. Program formulations have been set up and can be used to solve the shipping routing problems (Poo and Yip, 2019).

3.2.1. The ABC algorithm

In the ABC algorithm, it is population-based, and the position of a food source is a possible solution with a corresponding fitness. The “bees” are going to find out a food source as fit as possible in a scope. There are three key steps or types of “bee” in the whole algorithm: employed bees, onlooker bees and scout bees (Karaboga, 2005).

The value, or say the quality, of a food source, depends on two factors, which are travel time and service time. For the sake of simplicity, a single quality is used to represent a food source. Employed bees are associated with a food source which they are recently exploiting. They grab the information of the source and share the information with the probability of profit. Onlooker bees are waiting in the nest and establishing food sources by receiving the information shared by the employed bees. Scout bees are searching for the whole search area for new food sources randomly.

The part of the colony consists of “employees”, and the other part consists of “onlookers”. For every food source, there is only one employed bee. The employed bees whose food sources have been exhausted will convert to be a scout. Based on the basic idea of ABC, the steps of the ABC algorithm are summarized as follows:

1. Generate a set of solutions randomly as initial food sources w_i, $i = 1,\dots,\pi$. Assign each employed bee to a food source
2. Evaluate the fitness $f(x_i)$ of each of the randomized food sources w_i, $i = 1,\dots,\pi$
3. Set a counter, $z = 0$ and limitation of food sources (solution), $w_1 = w_2 = \dots = w_\pi = 0$
4. REPEAT
   a. Employed Bee Phase
      i. For each food source x_i, enforce a neighbourhood operator, $x_i \rightarrow x^*$
      ii. If $f(x_i) > f(x^*)$, x_i is substituted by x_i^* and $w_i = 0$. Otherwise, $w_i = w_i + 1$
   b. Onlooker Bee Phase
      i. For each food source x_i, undergo the fitness-based roulette wheel selection method.
      ii. For each food source x_i, enforce a neighbourhood operator, $x_i \rightarrow x^\#$
      iii. If $f(x_i) > f(x^\#)$, x_i is substituted by $x^\#$ and $w_i = 0$. Otherwise $w_i = w_i + 1$
   c. Scout Bee Phase
      i. For each food source x_i, w_i = Limit, x_i is substituted by a randomly generated food source
   d. $z = z + 1$
5. UNTIL (Reaching Operation Cycle)

After figuring out the idea of ABC, the solution representation and neighbourhood operators have to be introduced to make the shipping route problem fitted to the ABC algorithm.

3.2.2. Solution representation

In order to apply the ABC in shipping route problems, identifying the food sources as the route solutions, is essential for the bees throughout the whole algorithm. z(x) is set up as the cost function of the whole delivery process. First, the solution is represented in the form of a vector with a length of (starting port + transhipments + ending port). A sequence denotes the starting point in the beginning and ending node at the end. The list of ports is shown in Annex 1 and Annex 2. Figure 2 presents a delivery route with 6 transshipment ports, starting at Port 13 and ending at Port 44. The port number is referenced from Annex 1, and the details of port are further explained in Section 4.

13	15	24	46	38	7	91	116	34

Figure 4. Solution Representation

The ship passes through 13→15→24→46→38→7→91→116→34. Then, an initial solution is generated by putting the ports into the solution vector accordingly. Then the sequence will be shuffled several times. The shuffling time equals to half of the number of ports. A total of τ solutions are generated during initialization. Then, a neighbourhood operator is used to find out new solution from the current solution. A neighbourhood operator will be further explained in the next part.

3.3.3. Neighbourhood operators

A neighbourhood operator is used to find out new solution $X^{\#}$ from the current solution X_i. A neighbourhood operator will be chosen between three neighbourhood operators and applied for one time.

Three neighbourhood operators, which are widely used in VRP (Kıran et al., 2013, Poo and Yip, 2019), are chosen to put in the program for random selection:

- Random swaps: The operator randomly chooses two positions, i and j with $i \neq j$ and exchanges the positions.

Before:

13	15	24	46	38	7	91	116	34

After:

13	15	91	46	38	7	24	116	34

Figure 5. Example of Random Swap

- Reversing a subsequence: The operator randomly chooses a subsequence and reverses it.

Before:

13	15	24	46	38	7	91	116	34

After:

13	15	24	46	38	116	91	7	34

Figure 6. Example of Reversing a subsequence

- Random swaps of reversed subsequence: The operator randomly chooses two sub-sequences and swaps them. Then each of the swapped subsequence has a chance to be reversed with a 50% probability.

Before:

13	15	24	46	38	7	91	116	34

After:

13	15	91	116	38	7	24	46	34

Figure 7. Example of Random swaps of reversed subsequence

The length of sequence has been limited to 3. For exploring the whole solution sets, scout bee takes places to rearrange the sequence. A new node is created by shuffling the sequence.

Before:

13	4	24	46	38	7	91	116	34

After:

13	97	3	113	23	9	98	117	34

Figure 8. Example of shuffling subsequence

3.3.4. Fitness evaluation

In every period, each onlooker chooses a food source randomly. In order to drive the choosing process towards a better solution, a roulette-wheel selection method is implemented for randomly choosing a solution by setting the fitness value of each bee is inversely proportional to the cost function value. Higher fitness value of each bee gives a higher chance to be selected. The probability of choosing the solution X_i is then calculated as:

$$p(X_i) = \frac{z(X_i)}{\sum_{j=1}^{\tau} z(X_j)}, i = 1,2, \dots, \tau$$

3.3.5. Numerical Experiment

In terms of parameter setting, the bee colony size is set to be 50, which is a reasonable amount commonly used by other experiment (Diwold et al., 2011). Then, the numbers of employed bees and onlooker bees are equal to half of the bee colony size (i.e., 25 for each). It can help reduce parameters when conducting the program including the algorithm without a heavy drop of accuracy (Karaboga and Basturk, 2007). 25 employed bees represent that 25 routes are recently exploited, and 25 onlooker bees represent that 25 routes are established by receiving information from “employed bees”. All experiments were performed on a computer equipped with Windows 10, an Intel(R) Core(TM)2 Quad CPU Q9550 @ 2.83GHz 2.83 GHz, and a 8.00GB of RAM, and the program was coded by using Dev-C++ 4.9.9.2.

4. Computation result

There are two parameters for measuring the performance of modelling: (1) The best route between starting port and ending port, and (2) Accumulated minimum times of all the best routes between starting port and ending port with different transshipment times (MinTimes). The best route between starting port and ending port is used to observe the global climate change impact, each origin-destination pair’s best route is found to observe the importance of each port upon different levels of climate change impact. MinTimes is the parameter used to observe the performance of the model, and the minimum of transshipment times is zero and that of maximum is eight. 20 numerical runs have been done for each test and each transhipment time. The length of the solution representation is fixed from two ports to ten ports for the ECR problem.

A 10-node benchmark model has been designed to validate the experiment result and explain two parameters. The heuristic model and a Dijkstra’s shortest path model (Gass and Fu,

2013) implemented by Excel solver are both run to compare the accuracy of the heuristic model and access the possibility of performing experiments for a larger network. Then, they have given the same results and it is possible to examine the 154-node global shipping network.

Table 3. Result of 10-node model with origin port 4 and destination port 5

Transhipment time	Route	Average objective value (days)	Minimum objective value (days)
0	4 -> 5	9	9
1	4 -> 6 -> 5	8	8
2	4 -> 6 -> 8 -> 5	11	11
3	4 -> 8 -> 7 -> 6 -> 5	22	22
4	4 -> 6 -> 8 -> 7 -> 1 -> 5	2012	2012
5	4 -> 6 -> 8 -> 7 -> 1 -> 2 -> 5	3014	3014
6	4 -> 6 -> 8 -> 7 -> 2 -> 3 -> 1 -> 5	4017	4017
7	4 -> 6 -> 8 -> 7 -> 1 -> 2 -> 9 -> 10 -> 5	5020	5020
8	4 -> 6 -> 8 -> 7 -> 2 -> 9 -> 10 -> 1 -> 3 -> 5	6023	6023
(1) The best route between starting port and ending port		8	8
(2) Accumulated minimum times of all the best routes between starting port and ending port with different transshipment times (MinTimes)		20136	20136

Four sets of computational experiments have been further conducted. Three pairs of starting ports and ending ports are used for the experiment (Starting port/ Ending port): Benghazi/ Zhanjiang (75/37), Luanda/ Wenzhou (2/34), Copenhagen/ Visakhapatnam (43/59). Three pairs, rather than only one pair, are chosen as there will be variations for on performance. The first set of experiments is to test the performance of the heuristic optimisation programme with the ABC algorithm for assessing the climate resilience of the global shipping network. Afterwards, the neighbourhood operator combinations are tested, and the best values of limit and maximum operation cycle are found to optimise the programme performance. Therefore, combination of neighbourhood operator, values of limit and maximum operation cycle are fixed for global shipping network assessment and Top 20 port cities assessment. Two assessments provide two different insights. One is the overview, and the other one is the case study on hubs.

4.1. Global shipping network assessment

Different basic service days are assigned to run the model to forecast the shipping routing in the future with more extreme weather and port disruption days. Changes on route selection by the increase of service days can imply changes in the nature of the global shipping network and the importance of each port. The best routes with different basic service days and port pairs are shown in Table 3. The route from Benghazi (75) to Zhanjiang (37) is going across Krishnapatnam (140), Tanjung Pelepas (148), and Hong Kong (38). The route from Luanda (2) to Denmark (34) is going across Cape Town (101), London (112), and Hamburg (49). The route from Wenzhou (34) to Visakhapatnam (59) varies if basic service time increases. If basic service time is one day, it goes across Hong Kong (38), Cape Town (148), and Colombo (137). If basic service time is more than one day, it just passes through Hong Kong (38), and Colombo (137).

Table 4. Climate change impact assessment on route selection

Basic service time	**Route for 75/37**	**Route for 2/43**	**Route for 34/59**
1 day	75 -> 140 -> 148 -> 38 -> 37	2 -> 101 -> 112 -> 49 -> 43	34 -> 38 -> 148 -> 137 -> 59
2 days	75 -> 140 -> 148 -> 38 -> 37	2 -> 101 -> 112 -> 49 -> 43	34 -> 38 -> 137 -> 59
3 days	75 -> 140 -> 148 -> 38 -> 37	2 -> 101 -> 112 -> 49 -> 43	34 -> 38 -> 137 -> 59
4 days	75 -> 140 -> 148 -> 38 -> 37	2 -> 101 -> 112 -> 49 -> 43	34 -> 38 -> 137 -> 59
5 days	75 -> 140 -> 148 -> 38 -> 37	2 -> 101 -> 112 -> 49 -> 43	34 -> 38 -> 137 -> 59

It can prove that the model can observe the route changes and the service time affects the shipping route selection. Therefore, a global whole network assessment is necessary as the importance of each agglomeration needs to be assessed. The mechanism of the assessments is assigning three basic service time, one day, three days, and five days. One day is assumed as the present situation, and three days and five days represent the near future and the long future situation. Then, CR of each port city, an index between one to four, is assigned to multiply the basic service time to be the service time of each port.

11,935 OD pairs between 154 port cities are assessed, and their routes are all evaluated by the program. The highest 10 positive and negative changes from the present to the near future and long future are recorded to show the changes among all seaports. Then, the changes of total transhipments are also counted to observe the changing natures of routing. Kuala Lumpur (77) is ranked number 1 on both changes. Then, Shenzhen (28), Busan (93), Santos (12), Dubai (110), Shanghai (31), Barranquilla (39), Hamburg (49), and Miami (18) are listed twice in the Table 4. Finally, Ningbo (29) and Panama City (86) are on the table once. For the higher influence side, Singapore (99) is ranked number 1 twice, and Tokyo (72) and Barcelona (103) are both in the top 3 twice. Then, Lisbon (90), Hong Kong (38), Yangon (80), Jeddah (97), and Naples (66) are ranked twice in Table 5 while Montreal (23), Vancouver (24), Athens (51), and Tel Aviv (65) are only ranked once. Furthermore, the total number of transhipments on each agglomeration is counted by the three cases again, and it drops as -14.22% in the near future and -19.12% in the long future.

Table 5. Rank of agglomerations having a lower influence on global shipping network by climate change

	Changes in the near future			**Changes in the long future**		
Rank	**ID**	**Agglomerations**	**Changes**	**ID**	**Agglomerations**	**Changes**
1	77	Kuala Lumpur	-530	77	Kuala Lumpur	-686
2	28	Shenzhen	-354	93	Busan	-420
3	93	Busan	-292	12	Santos	-379
4	12	Santos	-230	28	Shenzhen	-318
5	110	Dubai	-209	49	Hamburg	-310
6	31	Shanghai	-204	110	Dubai	-277
7	39	Barranquilla	-200	31	Shanghai	-258
8	49	Hamburg	-190	86	Panama City	-232
9	29	Ningbo	-184	118	Miami	-229
10	118	Miami	-184	39	Barranquilla	-214

Table 6. Rank of agglomerations having higher influence on global shipping network by climate change

	Changes in the near future			**Changes in the long future**		
Rank	**ID**	**Agglomerations**	**Changes**	**ID**	**Agglomerations**	**Changes**
1	99	Singapore	378	99	Singapore	739
2	72	Tokyo	185	103	Barcelona	257
3	103	Barcelona	138	72	Tokyo	225
4	90	Lisbon	63	97	Jeddah	112
5	38	Hong Kong	56	90	Lisbon	93
6	80	Yangon	50	66	Naples	54
7	97	Jeddah	46	80	Yangon	28
8	66	Naples	15	51	Athens	25
9	23	Montreal	5	65	Tel Aviv	19
10	24	Vancouver	4	38	Hong Kong	11

4.2. Top 20 port cities assessment

The top 20 port cities shown in Table 2, which are the hubs of global shipping network, are assigned as five regions as Table 7. Then, the changes of 190 origin-destination (OD) pairs between them are recorded, and the OD pairs between the same region are exempted. Then, Hong Kong (38), Rotterdam (82), Singapore (99), and London (112) become more important to the global shipping network as they are shown in Table 6 more than 3 times. On the other hand, Shenzhen (28), Qingdao (30), Shanghai (31), Panama City (86), Busan (93), and New York (120) are listed in Table 8 more than 3 times.

Table 7. Summary of top 20 agglomerations having lower influence on global shipping network by climate change

		From				
		North America	South America	Europe	West Asia	East Asia
To	North America	N/A	Shenzhen (28), Barranquilla (39), Busan (93), Philadelphia (121)	No change	New York (120)	Melbourne (6) Shenzhen (28) Shanghai (31) Guayaquil (45) Los Angeles (117), San Diego (124)
	South America	Santo Domingo (44), Panama City (86), Miami (118), New Orleans (119)	N/A	Panama City (86)	New York (120)	Qingdao (30), Shanghai (31), Hong Kong (38) Tokyo (72), Kuala Lumpur (77), Panama City (86)
	Europe	London (112) Miami (118) New York (120)	No change	N/A	No change	Shenzhen (28), Kuala Lumpur (108)
	West Asia	No change	No change	Rotterdam (82)	N/A	Guangzhou (27), Wenzhou (34), Mumbai (57), Busan (93)
	East Asia	Shenzhen (28), Qingdao (30), Shanghai (31), Hamburg (49), Busan (93), Inchon (95), Miami (118)	Shenzhen (28), Ningbo (29), Qingdao (30), Hamburg (40), Busan (93)	Rio de Janeiro (12), Shenzhen (28), Shanghai (31), Hamburg (49), Busan (93)	Shenzhen (28), Bangkok (105)	N/A

Table 8. Summary of top 20 agglomerations having higher influence on global shipping network by climate change

	From				
	North America	South America	Europe	West Asia	East Asia

	North America	N/A	Singapore (99)	No change	London (112)	Brisbane (5), Tokyo (72), Auckland (83), Lisbon (90), Busan (93)
	South America	No change	N/A	London (112)	Singapore (99), London (112)	Santos (12), Auckland (83), Los Angeles (117)
To	Europe	Lisbon (90)	No change	N/A	London (112)	Jeddah (97), Singapore (99)
	West Asia	No change	Singapore (99)	No change	N/A	Melbourne (6), Hong Kong (38), Singapore (99)
	East Asia	Tokyo (72), Rotterdam (82), San Francisco (125), San Jose (126) Seattle (127)	Hong Kong (38), Rotterdam (82), Singapore (99), Miami (118)	Jeddah (97), Singapore (99)	Hong Kong (38), Singapore (99)	N/A

5. Conclusion

This section presents a methodology for assessing the climate resilience on global shipping network, by integrating climate risk indices, centrality assessment, and shipping route modeling together. it gives a new direction for multiple-objective decision support for environmental sustainability in the maritime industry. From the results, it shows the possible changes in shipping routing in the future which cannot be reflected by the independent local climate vulnerability assessment in different regions. As port disruption due to climate change likely takes place more frequently and it is inevitable, it is necessary to provide more routes as the total number of transhipments is decreased. The new routes can be added to bear the risks of port disruption in any location, and it can be known as decentralization.

Further improvement on climate risk indicators can be done to present the global and local climate vulnerabilities more rationally First, climate sensitivity and adaptive capacity can be included. Also, more climate threats, such as snow storming and heatwave, can be included in the indicator framework. A more comprehensive and worldwide climate risk and resilience assessments are necessary for an in-depth global shipping network evaluation. On the other hand, the methodology can be implied to different perspectives, including comparing the performance of shipping companies, and assessing other transportation networks.

Annex 1. List of the 136 port cities analysed by United Nations

ID	Region	CR	Agglomeration	ID	Region	CR	Agglomeration
1	AFRICA	3	Algiers	68	SE ASIA	2	Hiroshima
2	AFRICA	3	Luanda	69	SE ASIA	2	Nagoya
3	S. AMERICA	4	Buenos Aires	70	SE ASIA	2	Osaka
4	AUSTRALASIA	1	Adelaide	71	SE ASIA	1	Sapporo
5	AUSTRALASIA	1	Brisbane	72	SE ASIA	1	Tokyo
6	AUSTRALASIA	1	Melbourne	73	ASIA	1	Kuwait City
7	AUSTRALASIA	1	Perth	74	EUROPE	1	Beirut
8	AUSTRALASIA	1	Sydney	75	AFRICA	1	Benghazi
9	ASIA	4	Chittagong	76	AFRICA	3	Tripoli
10	ASIA	4	Dhaka	77	SE ASIA	3	Kuala Lumpur
11	ASIA	4	Khulna	78	AFRICA	3	Casablanca/ Rabat
12	S. AMERICA	3	Santos	79	AFRICA	4	Maputo
13	S. AMERICA	3	Belem	80	ASIA	2	Yangon
14	S. AMERICA	3	Fortaleza	81	EUROPE	2	Amsterdam
15	S. AMERICA	4	Vitoria	82	EUROPE	1	Rotterdam
16	S. AMERICA	3	Maceio	83	AUSTRALASIA	4	Auckland
17	S. AMERICA	3	Natal	84	AFRICA	3	Lagos
18	S. AMERICA	3	Recife	85	ASIA	3	Karachi
19	S. AMERICA	3	Porto Alegre	86	S. AMERICA	3	Panama City
20	S. AMERICA	4	Rio de Janeiro	87	S. AMERICA	3	Lima
21	S. AMERICA	3	Salvador	88	SE ASIA	4	Davao
22	AFRICA	3	Douala	89	SE ASIA	1	Manila
23	N. AMERICA	1	Montreal	90	EUROPE	1	Lisbon
24	N. AMERICA	2	Vancouver	91	EUROPE	2	Porto
25	ASIA	4	Dalian	92	S. AMERICA	2	San Juan
26	ASIA	4	Fuzhou	93	ASIA	1	Busan
27	ASIA	4	Guangzhou	94	ASIA	2	Ulsan
28	ASIA	4	Shenzhen	95	ASIA	4	Inchon
29	ASIA	4	Hangzhou/ Ningbo	96	EUROPE	1	St Petersburg
30	ASIA	4	Qingdao	97	ASIA	3	Jeddah
31	ASIA	4	Shanghai	98	AFRICA	1	Dakar
32	ASIA	4	Taipei	99	SE ASIA	3	Singapore
33	ASIA	4	Tianjin	100	AFRICA	3	Mogadishu
34	ASIA	4	Wenzhou	101	AFRICA	3	Cape Town
35	ASIA	4	Xiamen	102	AFRICA	1	Durban
36	ASIA	3	Yantai	103	EUROPE	1	Barcelona
37	ASIA	4	Zhanjiang	104	EUROPE	4	Stockholm
38	ASIA	2	Hong Kong	105	SE ASIA	4	Bangkok
39	S. AMERICA	3	Barranquilla	106	AFRICA	4	Lome
40	AFRICA	4	Abidjan	107	EUROPE	3	Istanbul
41	N. AMERICA	3	Havana	108	EUROPE	4	Izmir

42	ASIA	3	Nampo	109	ASIA	2	Odessa
43	EUROPE	1	Copenhagen	110	ASIA	1	Dubai
44	N. AMERICA	3	Santo Domingo	111	EUROPE	2	Glasow
45	S. AMERICA	4	Guayaquil	112	EUROPE	3	London
46	AFRICA	4	Alexandria	113	AFRICA	2	Dar es Salaam
47	EUROPE	1	Helsinki	114	N. AMERICA	2	Baltimore
48	EUROPE	1	Marseille	115	N. AMERICA	2	Boston
49	EUROPE	2	Hamburg	116	N. AMERICA	2	Houston
50	AFRICA	3	Accra	117	N. AMERICA	2	Los Angeles
51	EUROPE	1	Athens	118	N. AMERICA	2	Miami
52	AFRICA	3	Conakry	119	N. AMERICA	2	New Orleans
53	N. AMERICA	3	Port-au-Prince	120	N. AMERICA	2	New York
54	ASIA	4	Chennai	121	N. AMERICA	1	Philadelphia
55	ASIA	4	Cochin	122	N. AMERICA	2	Portland
56	ASIA	4	Kolkata	123	N. AMERICA	1	Providence
57	ASIA	4	Mumbai	124	N. AMERICA	2	San Diego
58	ASIA	4	Surat	125	N. AMERICA	1	San Francisco
59	ASIA	3	Visakhapatnam	126	N. AMERICA	1	San Jose
60	SE ASIA	4	Jakarta	127	N. AMERICA	2	Seattle
61	SE ASIA	4	Palembang	128	N. AMERICA	2	Tampa
62	SE ASIA	3	Surabaya	129	N. AMERICA	1	Virginia Beach
63	SE ASIA	3	Ujung Pandang	130	N. AMERICA	3	Washington
64	EUROPE	1	Dublin	131	S. AMERICA	3	Montevideo
65	EUROPE	1	Tel Aviv	132	S. AMERICA	4	Maracaibo
66	EUROPE	1	Naples	133	ASIA	4	Haiphong
67	SE ASIA	2	Fukuoka	134	ASIA	2	Ho Chi Minh City

Note: "CR" means risk of a territory being affected by climate change, and the definition of CR groups: "1" = Lowest risk scenario, "2" = Managed-risk scenario, "3" = Mismanaged-risk scenario, and "4" = Highest risk scenario

Annex 2. List of the 20 transit port cities

ID	Region	Agglomeration	ID	Region	Agglomeration
135	AFRICA	Tangier	145	N. AMERICA	Freeport
136	ASIA	Salalah	146	AFRICA	Port Elizabeth
137	SE ASIA	Colombo	147	EUROPE	Gdansk
138	EUROPE	Algeciras	148	ASIA	Tanjung Pelepas
139	EUROPE	Valencia	149	AFRICA	Pointe Noire
140	ASIA	Krishnapatnam	150	ASIA	Kaohsiung
141	EUROPE	Marsaxlokk	151	S. AMERICA	Buenaventura
142	S. AMERICA	Navegantes	152	N. AMERICA	Charleston
143	AFRICA	Port Said East	153	ASIA	Pipavav
144	AUSTRALASIA	Tauranga	154	AFRICA	Port Reunion

References

ABOU SAMRA, R. 2017. The use of cartographic modeling to assess the impacts of coastal flooding: a case study of Port Said Governorate, Egypt. *An International Journal Devoted to Progress in the Use of Monitoring Data in Assessing Environmental Risks to Man and the Environment,* 189**,** 1-12.
AKUKWE, T. I. & OGBODO, C. 2015. Spatial Analysis of Vulnerability to Flooding in Port Harcourt Metropolis, Nigeria. *SAGE Open*, 5.
ALSAHLI, M. M. M. & ALHASEM, A. M. 2016. Vulnerability of Kuwait coast to sea level rise. *Geografisk Tidsskrift-Danish Journal of Geography,* 116**,** 56-70.
ASSOCIATED BRITISH PORTS 2011. Climate Change Adaptation Report. Associated British Ports (ABP).
BALLOU, P., CHEN, H. & HORNER, J. D. Advanced methods of optimizing ship operations to reduce emissions detrimental to climate change. OCEANS, 2008. 1-12.
BALMAT, J.-F., LAFONT, F., MAIFRET, R. & PESSEL, N. 2009. MAritime RISk Assessment (MARISA), a fuzzy approach to define an individual ship risk factor. *Ocean Engineering,* 36**,** 1278-1286.
BALMAT, J.-F., LAFONT, F., MAIFRET, R. & PESSEL, N. 2011. A decision-making system to maritime risk assessment. *Ocean Engineering,* 38**,** 171-176.
BECKER, A., INOUE, S., FISCHER, M. & SCHWEGLER, B. 2012. Climate change impacts on international seaports: knowledge, perceptions, and planning efforts among port administrators. *An Interdisciplinary, International Journal Devoted to the Description, Causes and Implications of Climatic Change,* 110**,** 5-29.
BORGATTI, S. P., EVERETT, M. G. & FREEMAN, L. C. 2002. Ucinet for Windows: Software for social network analysis. *Harvard, MA: analytic technologies,* 6.
BRAJEVIC, I. Artificial bee colony algorithm for the capacitated vehicle routing problem. Proceedings of the European computing conference (ECC'11), 2011. 239-244.
BRIGUGLIO, L. P. 2010. Defining and assessing the risk of being harmed by climate change. *International Journal of Climate Change Strategies and Management,* 2**,** 23-34.
BROUER, B. D., DIRKSEN, J., PISINGER, D., PLUM, C. E. M. & VAABEN, B. 2013. The Vessel Schedule Recovery Problem (VSRP) – A MIP model for handling disruptions in liner shipping. *European Journal of Operational Research,* 224**,** 362-374.
BRUZZONE, A., MASSEI, M., MADEO, F. & TARONE, F. 2010. Modeling environmental impact and efficiency in maritime logistics. *Proceedings of the 2010 Summer Computer Simulation Conference.* Ottawa, Ontario, Canada: Society for Computer Simulation International.
CHANG, S. E. 2010. Urban disaster recovery: a measurement framework and its application to the 1995 Kobe earthquake. *Disasters,* 34**,** 303-327.
CHEN, G., GOVINDAN, K. & GOLIAS, M. M. 2013. Reducing truck emissions at container terminals in a low carbon economy: Proposal of a queueing-based bi-objective model for optimizing truck arrival pattern. *Transportation Research Part E,* 55**,** 3-22.
CHEN, W., YANG, Z. & PAN, W. 2015. Port strategic alliance partner selection using grey target model based on error propagation and vertical projection distance. *Journal of Coastal Research,* 73**,** 797-804.
CHOPRA, S. & SODHI, M. S. 2004. Managing risk to avoid supply-chain breakdown: by understanding the variety and interconnectedness of supply-chain risks, managers can tailor

balanced, effective risk-reduction strategies for their companies. *MIT Sloan Management Review,* 46**,** 53.
CORBETT, J. J., WANG, H. & WINEBRAKE, J. J. 2009. The effectiveness and costs of speed reductions on emissions from international shipping. *Transportation Research Part D,* 14**,** 593-598.
CORTÈS, M., LLASAT, M., GILABERT, J., LLASAT-BOTIJA, M., TURCO, M., MARCOS, R., MARTÍN VIDE, J. & FALCÓN, L. 2018. Towards a better understanding of the evolution of the flood risk in Mediterranean urban areas: the case of Barcelona. *Journal of the International Society for the Prevention and Mitigation of Natural Hazards,* 93**,** 39-60.
DIWOLD, K., ADERHOLD, A., SCHEIDLER, A. & MIDDENDORF, M. 2011. Performance Evaluation of Artificial Bee Colony Optimization and New Selection Schemes. *Memetic Computing,* 3**,** 149-162.
DJOUDER, F. & BOUTIBA, M. 2017. Vulnerability assessment of coastal areas to sea level rise from the physical and socioeconomic parameters: case of the Gulf Coast of Bejaia, Algeria. *Arabian Journal of Geosciences,* 10**,** 1-20.
DU, Y., CHEN, Q., LAM, J. S. L., XU, Y. & CAO, J. X. 2015. Modeling the impacts of tides and the virtual arrival policy in berth allocation. *Transportation Science,* 49**,** 939-956.
FAGERHOLT, K., JOHNSEN, T. A. V. & LINDSTAD, H. 2009. Fleet deployment in liner shipping: a case study. *Maritime Policy & Management,* 36**,** 397-409.
FEDSCHUN, T. 2019. Hurricane Lorenzo sinks tugboat carrying 14 crew members; at least 1 found dead at sea, 3 rescued. *Fox News*, September 30.
FELIXSTOWE DOCK AND RAILWAY COMPANY 2011. Climate change adaptation report. Felizstowe dock and railway company.
FIELD, C. B., BARROS, V. R., DOKKEN, D. J., MACH, K. J. & MASTRANDREA, M. D. 2014. *Climate Change 2014 Impacts, Adaptation, and Vulnerability : Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change,* Cambridge, Cambridge : Cambridge University Press.
FINKELSTEIN, A., HARMAN, M., MANSOURI, S., REN, J. & ZHANG, Y. 2009. A search based approach to fairness analysis in requirement assignments to aid negotiation, mediation and decision making. *Requirements Engineering,* 14**,** 231-245.
GENOVESE, E. & GREEN, C. 2014. Assessment of storm surge damage to coastal settlements in Southeast Florida. *Journal of Risk Research,* 18**,** 1-21.
GÖKKUS, Ü. & YILDIRIM, M. 2017. Estimation of Container Traffic at Seaports by Using Several Soft Computing Methods: A Case of Turkish Seaports. *Discrete Dynamics in Nature and Society,* 2017.
GOMEZ, A. & SALHI, S. Solving capacitated vehicle routing problem by artificial bee colony algorithm. 2014 IEEE Symposium on Computational Intelligence in Production and Logistics Systems (CIPLS), 2014. IEEE, 48-52.
GOOGLE MAPS. 2019. *Google Maps* [Online]. Google Maps. Available: https://www.google.co.uk/maps/dir/accra/tema+harbour/@5.6434247,-0.1548833,12z/data=!3m1!4b1!4m13!4m12!1m5!1m1!1s0xfdf9084b2b7a773:0xbed14ed8650e2dd3!2m2!1d-0.1869644!2d5.6037168!1m5!1m1!1s0x102078b84e1be8eb:0x51be0a7fbca0d94a!2m2!1d0.0166667!2d5.6333333?hl=en [Accessed 26 August 2019].
GOU, X. & LAM, J. S. L. 2018. Risk analysis of marine cargoes and major port disruptions. *Maritime Economics & Logistics***,** 1-27.

GRABOWSKI, M. & HENDRICK, H. 1993. How low can we go?: validation and verification of a decision support system for safe shipboard manning. *IEEE Transactions on Engineering Management,* 40**,** 41-53.
HALLEGATTE, S., RANGER, N., MESTRE, O., DUMAS, P., CORFEE-MORLOT, J., HERWEIJER, C. & WOOD, R. 2011. Assessing climate change impacts, sea level rise and storm surge risk in port cities: a case study on Copenhagen. *An Interdisciplinary, International Journal Devoted to the Description, Causes and Implications of Climatic Change,* 104**,** 113-137.
HANSON, S., NICHOLLS, R., RANGER, N., HALLEGATTE, S., CORFEE-MORLOT, J., HERWEIJER, C. & CHATEAU, J. 2011. A global ranking of port cities with high exposure to climate extremes. *An Interdisciplinary, International Journal Devoted to the Description, Causes and Implications of Climatic Change,* 104**,** 89-111.
HOSHINO, S., ESTEBAN, M., MIKAMI, T., TAKAGI, H. & SHIBAYAMA, T. 2016. Estimation of increase in storm surge damage due to climate change and sea level rise in the Greater Tokyo area. 80**,** 539.
HU, Q.-M., HU, Z.-H. & DU, Y. 2014. Berth and quay-crane allocation problem considering fuel consumption and emissions from vessels. *Computers & Industrial Engineering,* 70**,** 1-10.
HUBBERT, G. D. & MCLNNES, K. L. 1999. A storm surge inundation model for coastal planning and impact studies. *Journal of Coastal Research***,** 168-185.
INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability.Part A: Global and Sectoral Aspects. Cambridge: Cambridge University Press.
JI, P. & WU, Y. An improved artificial bee colony algorithm for the capacitated vehicle routing problem with time-dependent travel times. Tenth international symposium on operations research and its applications (ISORA 2011), 2011. Citeseer, 75-82.
KARABOGA, D. 2005. An idea based on honey bee swarm for numerical optimization. Technical report-tr06, Erciyes university, engineering faculty, computer ….
KARABOGA, D. & BASTURK, B. 2007. A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *Journal of global optimization,* 39**,** 459-471.
KARABOGA, D., GORKEMLI, B., OZTURK, C. & KARABOGA, N. 2014. A comprehensive survey: artificial bee colony (ABC) algorithm and applications. *Artificial Intelligence Review,* 42**,** 21.
KEFER, P., MILANOVIC, D. D., MISITA, M. & ZUNJIC, A. 2016. Fuzzy Multicriteria ABC Supplier Classification in Global Supply Chain. *Mathematical Problems in Engineering,* 2016.
KıRAN, M. S., İŞCAN, H. & GÜNDÜZ, M. 2013. The analysis of discrete artificial bee colony algorithm with neighborhood operator on traveling salesman problem. *Neural computing and applications,* 23**,** 9-21.
KOLLAT, J. & REED, P. 2007. A framework for Visually Interactive Decision-making and Design using Evolutionary Multi-objective Optimization (VIDEO). *Environmental Modelling & Software,* 22**,** 1691-1704.
KUMAR, S. K., TIWARI, M. K. & BABICEANU, R. F. 2010. Minimisation of supply chain cost with embedded risk using computational intelligence approaches. *International Journal of Production Research,* 48**,** 3717-3739.
LAM, J. 2010. An integrated approach for port selection, ship scheduling and financial analysis. *NETNOMICS: Economic Research and Electronic Networking,* 11**,** 33-46.

LAM, J. S. L. & SU, S. 2015. Disruption risks and mitigation strategies: an analysis of Asian ports. *Maritime Policy & Management,* 42**,** 415-435.
LURIE, C. 2015. Taking flight in a climate of change: Logan airport addresses severe weather events, climate change. *Boston Business Journal,* 35**,** 16.
MANSOURI, S. A., LEE, H. & ALUKO, O. 2015. Multi-objective decision support to enhance environmental sustainability in maritime shipping: A review and future directions. *Transportation Research Part E,* 78**,** 3-18.
MERSEY DOCKS AND HARBOUR COMPANY LTD 2011. Climate Change Adaptation Report Report to Defra under the Adaptation Reporting Powers. Peel Ports Group.
PAL, A., CHAN, F. T. S., MAHANTY, B. & TIWARI, M. K. 2011. Aggregate procurement, production, and shipment planning decision problem for a three-echelon supply chain using swarm-based heuristics. *International Journal of Production Research,* 49**,** 2873-2905.
PALACIO, A., ADENSO-DÍAZ, B., LOZANO, S. & FURIÓ, S. 2016. Bicriteria Optimization Model for Locating Maritime Container Depots: Application to the Port of Valencia. *A Journal of Infrastructure Modeling and Computation,* 16**,** 331-348.
PAPE, M. 2017. EU port cities and port area regeneration. *In:* TANK, E. P. T. (ed.).
PD TEESPORT LTD 2011. PD Teesport (Ports of Teesport and Hartlepool) Climate Adaptation Assessment Report to Defra under the Adaptation Reporting Powers. PD Teesport Ltd.
PEEL PORTS GROUP 2011. Port of Sheerness Ltd Climate Adaptation Assessment, Report to Defra under the Adaptation Reporting Powers. Peel Ports Group.
POO, M. C.-P., YANG, Z., DIMITRIU, D. & QU, Z. 2018. Review on seaport and airport adaptation to climate change: a case on sea level rise and flooding. *Marine Technology Society Journal,* 52**,** 23-33.
POO, M. C.-P. & YIP, T. L. 2019. An optimization model for container inventory management. *Annals of Operations Research,* 273**,** 433-453.
PORT OF DOVER 2011. Climate change adaptation report. Dover: Port of Dover.
QI, X. & SONG, D.-P. 2012. Minimizing fuel emissions by optimizing vessel schedules in liner shipping with uncertain port times. *Transportation Research Part E,* 48**,** 863-880.
RONZA, A., LÁZARO-TOUZA, L., CAROL, S. & CASAL, J. 2009. Economic valuation of damages originated by major accidents in port areas. *Journal of Loss Prevention in the Process Industries,* 22**,** 639-648.
SARKIS, J., DE BRUIJN, T. & ZHU, Q. 2013. Guest Editorial: Sustainability in Engineering Management-Setting the Foundation for the Path Forward. *IEEE Transactions on Engineering Management,* 60**,** 301-314.
SHEFFI, Y. & RICE JR, J. B. 2005. A supply chain view of the resilient enterprise. *MIT Sloan management review,* 47**,** 41.
SHI, Y.-J., MENG, F.-W. & SHEN, G.-J. 2012. A modified artificial bee colony algorithm for vehicle routing problems with time windows. *Information Technology Journal,* 11**,** 1490-1495.
SHUI, C. & SZETO, W. An artificial bee colony algorithm for public bike repositioning. 2015 Sydney. The 37th Australasian Transport Research Forum (ATRF 2015).
SIEBER, J. 2013. Impacts of, and adaptation options to, extreme weather events and climate change concerning thermal power plants.(Report). *Climatic Change,* 121**,** 55.
SONG, D.-P. & XU, J. 2012a. CO2 Emission Comparison Between Direct and Feeder Liner Services: A Case Study of Asia-Europe Services Interfacing with the UK. *International Journal of Sustainable Transportation,* 6**,** 214-237.

SONG, D.-P. & XU, J. 2012b. An operational activity-based method to estimate CO 2 emissions from container shipping considering empty container repositioning. *Transportation Research Part D,* 17**,** 91-96.
SONI, G., JAIN, V., CHAN, F. T. S., NIU, B. & PRAKASH, S. 2019. Swarm intelligence approaches in supply chain management: potentials, challenges and future research directions. *Supply Chain Management: An International Journal,* 24**,** 107-123.
SUMNER, M. & RUDAN, I. 2018. A Hybrid MCDM Approach to Transshipment Port Selection. *Pomorstvo = Maritime Affairs,* 32**,** 258.
SZETO, W. Y., WU, Y. & HO, S. C. 2011. An artificial bee colony algorithm for the capacitated vehicle routing problem. *European Journal of Operational Research,* 215**,** 126-135.
TALEIZADEH, A. A., NIAKI, S. T. A., ARYANEZHAD, M.-B. & SHAFII, N. 2013. A hybrid method of fuzzy simulation and genetic algorithm to optimize constrained inventory control systems with stochastic replenishments and fuzzy demand. *Information Sciences,* 220**,** 425-441.
TANG, C. S. 2006. Robust strategies for mitigating supply chain disruptions. *International Journal of Logistics: Research and Applications,* 9**,** 33-45.
VITOR BACCARIN, Z., WILSON CABRAL DE SOUSA, J. & DÉBORA, M. D. F. 2016. A Climate Change Vulnerability Index and Case Study in a Brazilian Coastal City. *Sustainability,* 8**,** 811.
WANG, W., REN, Y., BIAN, W. & JIA, X. 2019. Low-carbon Marine Logistics Network Design under Double Uncertainty of Market Demand and Carbon Trading Price. *Journal of Coastal Research,* si**,** 30-39.
WINDECK, V. & STADTLER, H. A Liner Shipping Network Design – Routing and Scheduling Impacted by Environmental Influences. 2011 Berlin, Heidelberg. Springer Berlin Heidelberg, 574-576.
YAO, B., HU, P., ZHANG, M. & WANG, S. 2013. Artificial bee colony algorithm with scanning strategy for the periodic vehicle routing problem. *Simulation,* 89**,** 762-770.
YIN, P.-Y. & CHUANG, Y.-L. 2016. Adaptive memory artificial bee colony algorithm for green vehicle routing with cross-docking. *Applied Mathematical Modelling,* 40**,** 9302-9315.
ZENG, M., CHENG, W. & GUO, P. 2017. Modelling and Metaheuristic for Gantry Crane Scheduling and Storage Space Allocation Problem in Railway Container Terminals. *Discrete Dynamics in Nature and Society,* 2017.
ZHANG, L. L., LEE, C. & ZHANG, S. 2016. An integrated model for strategic supply chain design: Formulation and ABC-based solution approach. *Expert Systems With Applications,* 52**,** 39-49.
ZHANG, S., RUAN, X., XIA, Y. & FENG, X. 2018. Foldable container in empty container repositioning in intermodal transportation network of Belt and Road Initiative: strengths and limitations. *Maritime Policy and Management,* 45**,** 351-369.
ZHANG, Y. & LAM, J. S. L. 2015. Estimating the economic losses of port disruption due to extreme wind events. *Ocean & Coastal Management,* 116**,** 300-310.
ZHU, M., HAHN, A., WEN, Y.-Q. & BOLLES, A. 2017. Identification-based simplified model of large container ships using support vector machines and artificial bee colony algorithm.(Report). *Applied Ocean Research,* 68**,** 249.