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Maritime Cargo Prioritisation during a Prolonged Pandemic Lockdown Using an Integrated TOPSIS-Knapsack Technique: A Case Study on Small Island Developing States—The Rodrigues Island

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Abstract: Many remote areas, such as island states, are highly dependent on the transportation of cargo, and any disruptions similar to the 2020 pandemic lockdowns can negatively affect their respective supply chains. These disruptions could lead to a severe humanitarian crisis. It is therefore imperative to develop a cargo prioritisation process to ensure that essential commodities are transported. We propose a decision-aid tool that integrates two methods: (a) the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and (b) the knapsack problem. Containers are prioritised based on attributes such as their importance and their economic value. TOPSIS is used to calculate a score for each container and the knapsack problem determines the containers to be imported respecting the transportation capacity constraints. The practical applicability of the model is demonstrated by a case study on a Small Island Developing State. The proposed decision-aid tool could also be extended to be used in disaster relief situations.

Keywords: import prioritisation; maritime transportation; TOPSIS-knapsack methodology; SIDS

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1. Introduction

In early 2020, the leagility, resilience and sustainability of global supply chains faced an unprecedented series of shocks caused by the COVID-19 virus outbreak and global pandemic leading to unparalleled disruptions [1,2]. The first epicentre of the pandemic was identified in China, where it was successfully contained via strict lockdown rules [3,4]. Eventually, with the global propagation of the virus, most nations adopted various lockdown strategies in order to keep the number of cases under some kind of control [5]. However, these lockdowns lead to an inevitable cascading economic meltdown of world economies. There is also no doubt that the COVID-19 pandemic (in addition to other recent events such as Brexit and US-China sanctions) will have a huge impact on the design of future global supply chains [2,6]. The post-COVID-19 social and financial crisis will probably affect every country and most notably Small Island Developing States (SIDS) [7]. SIDS are naturally limited in land area and population, with highly vulnerable reliance on cargo imports, tourism and natural resources [8]. Furthermore, most of the SIDS archipelagos have complex and costly domestic interisland maritime transport systems. Likewise, several British Overseas Territories (BOT) and other small island dependencies might face similar problems [9,10].

With the advent of the COVID-19 pandemic, most SIDS and BOT archipelagos have adopted various lockdown strategies, which disrupted both the airline flights schedules and the ship sailing schedules. A reduction or interruption of the cargo services would not only create a cargo backlog but also considerably reduce the essential supplies in a period of crisis. Hence, the main purpose of this study is to respond to the following research question: Is it possible to develop a cargo prioritisation process to ensure that essential commodities are transported based on a fair decision-support system?

The problem is, thus, given a set of available containers, how to select the ones that will be transported. Our methodology (see Section 3 for more) is the following: We prioritise the containers based on a number of factors, such as their economic value, their cargo, etc. One way to take all these parameters into account—when ranking the available containers—is through the use of a multi-criteria decision analysis method. In this study, we use the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), a very well-studied and widely used method. Other methods can also be used; see Section 4 for more. TOPSIS scores each container, taking into account the set of attributes/criteria and their weights; both are based on expert judgement. One approach to solve this problem would be to rank all available containers based on their score and load them in this order until the available capacity is reached. This is not the best approach though, as it does not maximize the total score of the containers that are transported and, in most cases, not even the total weight of the containers transported; see Section 3.3, Step 8, for more. The latter can be achieved by solving the so-called 'knapsack problem', which maximises the total score of the containers to be transported under the constraint that their total weight is less than or equal to the available ship capacity.

In brief, our decision-aid tool is integrating two methods: (a) the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and (b) the knapsack problem. TOPSIS is a multi-criteria decision analysis method (MCDA), which was originally developed by Hwang and Yoon [11] and modified by Hwang et al. [12]. It ranks alternatives based on the concept that the best alternative should have the shortest distance from the 'positive ideal solution' (PIS) and the longest distance from the 'negative ideal solution' (NIS). The knapsack problem is a well-studied problem in combinatorial optimisation [13], which refers to the common problem of packing the most 'useful' without overloading the luggage. Our problem, also referred to as the 0–1 knapsack problem, is the following: "*Given a set of items, each with a weight and a value, determine the items to include in a collection so that the total weight is less than or equal to a given limit and the total value is as large as possible*" [13].

The proposed decision-aid tool was developed to solve an actual problem faced by many small islands such as the dependencies of SIDS during the pandemic. Small island states are highly dependent on imports, and any lockdown can negatively impact their supply line. These disruptions could cascade into a severe humanitarian crisis. In general, in a situation of cargo backlog, the frequency of the distribution is increased and larger, or a greater number of, vessels are deployed. These solutions are thought to be impractical for small island states due to logistical constraints. For instance, small islands have peculiar port characteristics (restricted access, single berth, lengthy loading/unloading process, limited storage/transport capacity) and are served by small vessels, often not that frequently.

This is actually the case for Rodrigues Island, which will be used as a case study to demonstrate the practical applicability of our model. Rodrigues Island is one of the dependencies of Mauritius, an African SIDS member state situated in the Indian Ocean; see Section 2.1 for more. This case study fits well into our problem, and we also had access to the actual decision-makers. It is clear that, given the specific needs during a pandemic or a similar large-scale event, a decision support system is needed to minimise disruptions and to avoid a potential humanitarian crisis [14]. Furthermore, such a system entails a more systematic approach—as opposed to arbitrary selection—and is, therefore, a fairer system.

The rest of the paper is structured as follows. Section 2 presents some information on Small Island Developing States and Island Territories, many of which could benefit from our proposed decision-support model. In addition, the need for cargo prioritisation is presented. Section 3 describes the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the knapsack problem and our integrated methodology. Section 4 presents the characteristics of our case study, Rodrigues

Island, and the results of an application of our methodology. Finally, Section 5 concludes the paper with some discussion that summarises the findings and proposes some further research.

2. Background and Literature Review

2.1. Small Island Developing States (SIDS) and Other Island Territories

The United Nations Office of the High Representative for the Least developed countries, Landlocked developing countries and Small island developing states (UN-OHRLLS) defined Small Island Developing States as a heterogeneous group of 58 members sharing strong commonalities and facing unique social, economic and environmental challenges [15].

Petzold and Magnan [16] categorised other island territories as dependent islands or Sub-National Island Jurisdictions (SNIJ). Dependent islands follow the same governance pattern as the sovereign country, whereas SNIJs manifest "*diverse expressions of governance within typically asymmetrical relationships with a much larger state*" [17]. For example, Gran Canaria is a dependent island of Spain while BOT, such as the Pitcairn Islands and St Helena, are SNIJs [16,18].

The authors also stressed that, although the SIDS main island, SNIJ and other dependent islands had contrasting political governance, demographic and infrastructural disparities, on a global scale, these islands still showed comparable similitudes. In comparison to other states, most islands have a restricted economic base and high vulnerabilities to exogenous shocks.

The remoteness and dispersed populations of some small island states hamper the development of a diversified economic market. Thus, small islands tend to focus on a restricted number of sectors such as tourism, agriculture, fishing, light manufacturing, natural resource extraction and other services. A gradual decrease has been observed in agricultural production for most small island states over the last few decades. According to the Food Agricultural Organisation (FAO) of the United Nations, the decline was attributed to limited investment in commercial agriculture and technology, followed by climate change impacts [19]. As a result, the FAO [19] estimated that food imports for SIDS members are extremely important, with numerous members importing over 80% of their food consumption. In addition, the majority of small islands spent a substantial part of their national budget on fossil fuel imports [20].

The vulnerabilities of island states, coupled with their limited adaptive capability to large scale economic and environmental forces, make them highly exposed to exogenous stressors [21]. Exogenous stressors are classified as environmental or natural disasters, trade-related shocks, infectious disease disasters and other man-made related disasters [22–24].

The outbreak of coronavirus and the resulting restriction on international mass mobility has driven the tourism sector into an unprecedented era, with a sharp fall in revenues for most island states [25]. It was also stressed that it is essential to ensure a continuous supply of food, medical supplies and fuel to these islands to mitigate the risk of a humanitarian crisis [26].

The remoteness of small islands from continental plates means that they need to rely on air and maritime transport for cargo transportations. Generally, sea cargo is considered as being the cheapest cost option and the least polluting in terms of CO_2 emissions per ton-km of cargo. Raghoo et al. [27] also highlighted that most SIDS are outside the major shipping lanes, which results in higher freight costs. Moreover, trade imbalances—the need to carry empty containers on the return leg—and inefficient domestic port characteristics also increase the freight costs of small islands [28]. High discrepancies exist between the main islands and their dependencies in terms of their Port Liner Shipping (PLS) connectivity index [29]. For a detailed analysis of the severe structural, operational and development obstacles faced by the world's SIDS, including a number of statistical data, the interested reader is referred to the 2014 United Nations Conference on Trade and Development (UNCTAD) Review of Maritime Transport [30].

With the limited connectivity, unconventional port infrastructural characteristics and high freight costs, the need for prioritising and delivering the right supplies to these islands remains crucial. This is obviously considerably more important in the case of a disruption such as a pandemic, but it can also be the case for other extreme events.

2.2. The Need for Cargo Prioritisation

In a world of depleting resources and increasing demands, the importance of prioritisation and optimisation is attracting considerable attention in various fields [31,32]. There is an extensive list of prioritisation and optimisation techniques [33]. A large number of these techniques have been applied in the maritime logistics fields, especially for maximising profit and minimising the cost of cargo transportation [34].

However, the literature related to cargo prioritisation is rather limited. For instance, Tong and Nachtmann [35] identified nine major categories for cargo prioritisation related to inland waterway disruptions. These include prioritisation factors related to economics (revenues and profitability), time (arrival date, loading availability), risks (economic, health and safety, security), weight (cargo draft and the actual weight of the cargo), urgency, importance (commodity needs, national security, important for food security) and others (such as seasonal advantages, availability of substitute materials, capacity of port infrastructure, vessels' transport ability, presence of fuel oil and/or perishable cargo).

UNCTAD's Review of Maritime Transport confirmed that SIDS face many challenges that are affecting, among other things, shipping services, transport costs, port infrastructure and equipment, as well as markets and operations. These challenges include small volumes and trade imbalances, limited access to global shipping networks, lack of adequate shipping services, limited port infrastructure and equipment, a high degree of dependency on energy imports and high freight rates and shipping costs [30].

At the same time, the islands face increasing exposure to natural hazards of tectonic and meteorological origin, including earthquakes, volcanic eruptions, tsunamis, hurricanes and others. Most importantly, according to the UN Intergovernmental Panel on Climate Change (IPCC), small islands face a plethora of climate change-related risks, including sea-level rise, tropical and extratropical cyclones, increasing air and sea surface temperatures and changing rainfall patterns [36]. Birchenough [37] added that small island states are naturally blessed with a pristine biodiversity and environment, which has to be sustainably preserved. For instance, a risk assessment should be carried out before allowing a highly polluting vessel entering a lagoon for the unloading of supplies. The same is true for assessing the risk of oil pollution. There is, therefore, a need for a more sustainable approach to cargo prioritisation.

2.3. Cargo Prioritisation: The Objectives

During normal commercial operations, the economic factors, such as the maximisation of revenue, is the single most important objective. This is not the case, however, in the circumstance of an extreme event, such as a pandemic or a disaster, where prioritisation factors such as urgency, risk reduction and others are much more important than the economic ones. We should note that there is a parallel body of literature in the field of disaster relief logistics and emergency logistics; see [38–42] for more. Many papers in the area of disaster or humanitarian logistics use optimisation models related to, for example, optimal resource allocation, location-routing and scheduling problems [41,43]. The objectives include the minimum transportation cost, the shortest emergency time, the least unmet quantity, the least number of deaths and the shortest transportation time, among others. Research on epidemic control and logistic operations have also gaining much attention recently, although the area is not new; see, for example, [44]. Note that the disasters caused by epidemic outbreaks are essentially different from other disasters due to two specific features: their long-term disruption and their increasing propagation; see [14] for more. MCDA methods have also been used; see, for example [45], where TOPSIS is used to prioritise the disaster areas to determine the relief distribution.

The maximisation of profit, the clear goal of commercial endeavours, is not very relevant for the non-profit entities that typically provide humanitarian aid. For these entities, maximising some measure of service is much more important. Note that, in our case study, and this is also the case for other islands, the shipping company is state-owned; therefore, economic criteria are not the only ones that are considered during the cargo prioritisation.

During normal circumstances, there is a range of items that are usually shipped, say to the domestic islands from the main island. Although it might be of lesser importance in times of crisis, there is a need to ensure that legal due date delivery is not overly violated. The above factors can be taken into account in our model; they could also be modified dynamically to fit the specific applications and needs. For instance, during or after a pandemic, the needs might change. Cargos such as face masks and hand sanitisers were, both during and after the pandemic, much more important than they were before. Even during the pandemic, needs can change; in the early stages of the coronavirus pandemic, there were shortages of toilet paper and pasta—both of which were probably driven by news attention and not rationality [46]. In any case, our model can handle all these considerations. In our case study, these are mainly set by a group of experts in a similar way to what will happen in reality. In practice, there will be a small group of government officials, port and shipping line representatives and other stakeholders who will be setting out the factors to be considered and setting the priorities.

3. Methodology

The rationale of our decision-aid tool is simple: Our problem is, given a set of available containers, which, in multi-attribute decision analysis, is called the 'alternatives', how to select the ones that will be loaded into the vessel. We use expert judgement to select the attributes—which, in TOPSIS, is referred to as 'attributes' or 'criteria'—of the containers that are important in the decision-making process. Note that, based on our literature review, a number of attributes have been identified and these were discussed with the experts for inclusion in the final set of criteria. These were the waiting time in port (the time a container has been waiting to be loaded), the actual weight of the cargo and, finally, its importance. The latter is a rather interesting but not well-defined attribute. Private companies that are actually focusing on income maximisation might be tempted to serve mainly small containers, in order to increase the number of items carried and thus the profit, or load items which are associated with higher profit. The value of the cargo (of the container) might also be a decisive parameter. However, in many island states, the operator is a state-owned or state-controlled company, which does not operate based on pure commercial criteria. Given the nature of the situation, i.e., a pandemic, the import priorities are different as, for instance, medical equipment and medical supplies should be prioritised.

Experts are therefore used to determine (a) the 'criteria' (the important attributes of each container) to be taken into account when prioritising cargo and (b) the importance of the above criteria in the overall selection; this is referred to as the 'weights'.

The set of experts can be a group of stakeholders, e.g., the ship operator, port authority or local government officials. Note that the attributes are all numerical and are well defined. An attribute that might not be easy to estimate is the importance of each container. In our analysis, a container's importance is based on a numerical scale, from 1–10, based on the content as defined by the experts. The weight of each attribute is calculated based on group decision making; see Step 1 (Section 3.3) for more. The overall methodology is illustrated in Figure 1; see Section 3.3 for more details.

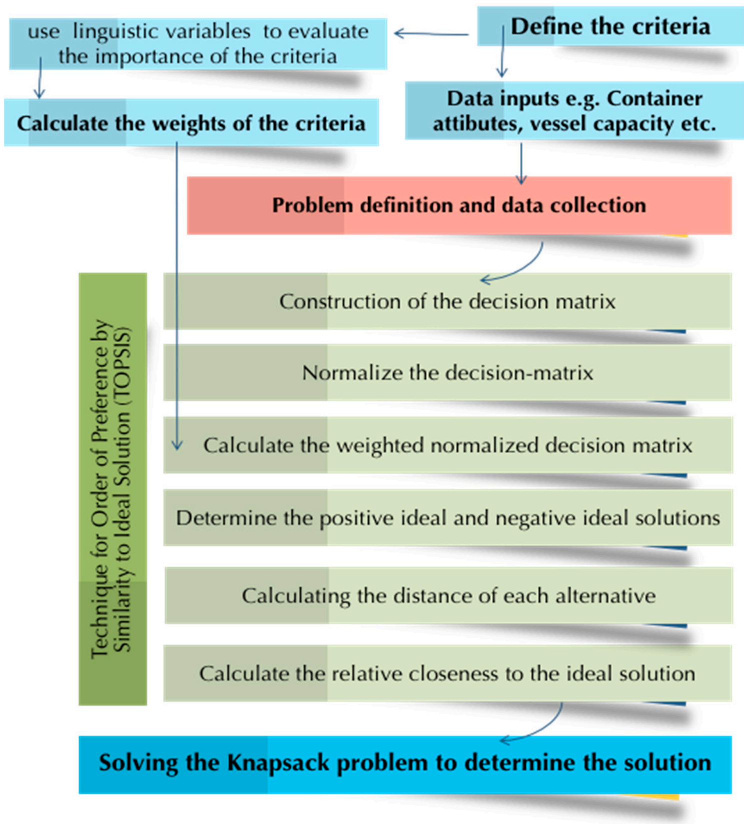

Figure 1. The integrated TOPSIS-Knapsack methodology—Source: Authors.

Step 1 of the Algorithm actually deals with the selection of the attributes and how the relevant attributes can be obtained (data collection). In addition, the weights are calculated. We then utilise the TOPSIS methodology to rank the containers that are available to be loaded (Steps 2–7 in the Methodology). The result of this process is a list of containers ranked based on their closeness to the ideal solution. Finally, we solve the knapsack problem (Step 9): Given the set of containers (each with a weight and value, i.e., the relative closeness to the ideal solution), we determine the solution (items to be loaded on the vessel) so that the total weight of the selected containers is less than or equal to the payload of the vessel, and the sum of the closeness to the ideal solution is maximised.

Note that there are very few papers in the literature that combine TOPSIS and the knapsack problem. İç et al. [47] present a model based on Fuzzy TOPSIS-Knapsack for the order selection problem for a bakery firm, whereas a Knapsack-TOPSIS approach was also in some telecommunication applications, such as in handovers techniques that facilitate service continuity for mobile users [48]. To that extent, the integration of the two methods is also methodologically interesting.

The following sub-Sections present, in brief, the TOPSIS method and the knapsack problem.

3.1. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a classical multi-criteria decision analysis method, which was originally developed by Hwang and Yoon [11] and modified by Hwang et al. [12]. It ranks alternatives based on the concept that the best alternative should have the shortest distance from the 'positive ideal solution' (PIS) and the longest distance from the negative one—the 'negative ideal solution' (NIS). TOPSIS is one of the most well-established methods and has been applied in many fields due to its advantage of being intuitive and easy to implement [49]. In this study, we have selected TOPSIS as it fits well into our problem and because of its rationality, computational efficiency and ability to measure the relative performance for each alternative in a simple but mathematically sound way. For a literature review of

TOPSIS application, the interested reader is referred to Behzadian et al. [50]. Note that using other similar MCDA tools is straightforward.

Generally, the main steps of applying the TOPSIS method include identifying alternatives and criteria to establish a decision-making matrix, constructing the weighted normalised decision matrix, determining the positive and negative ideal solutions and calculating the separation measures for each alternative. At the end of the process, the relative closeness coefficient is calculated and the alternatives are ranked according to the descending order of the closeness coefficient. In our analysis, the last step (ranking) is not necessary as the main input of the knapsack problem is the relative closeness of each alternative—what we refer to as the TOPSIS score.

3.2. The Knapsack Problem

The knapsack problem is very well-studied in combinatorial optimisation; its name dates back to the early works of Dantzig and refers to the common problem of packing the most valuable or useful items without overloading the luggage [51]. Our problem, which is referred to as the 0–1 knapsack problem, is the following: "*Given a set of items, each with a weight and a value, determine the number of each item to include in a collection so that the total weight is less than or equal to a given limit and the total value is as large as possible*". The mathematical formulation of the problem is presented in Section 3.3; see Step 8.

The knapsack problem is extremely interesting as it falls into a class of problems that are difficult to solve; the problem is what we call NP-complete; i.e. a problem that cannot be solved in polynomial time. Depending on whether p_i and/or w_i are integers or not, several solution techniques can be used. In the 1950s, Bellman's dynamic programming theory was used in the first algorithms to exactly solve the 0–1 knapsack problem, and Dantzig [51] presented an efficient method to determine the solution to the continuous relaxation of the problem [52]. Lagrangian relaxation, heuristics and other methods have been used to solve the knapsack problem [13,53]. Presenting the solution techniques of the problem is out of the scope of this paper. In this work, we use an open-source solver, namely the GNU Linear Programming Kit (GLPK) [54], to obtain the optimal solution for the knapsack problem.

3.3. The Integrated TOPSIS-Knapsack Problem

Step 1. Problem definition and data collection

In this step, we gather all the data that are necessary to solve the problem. In most multi-criteria decision analysis methodologies, the inputs are a set of alternatives (in our case, the available containers), a set of criteria/parameters, the weights of each criterion (w_j) and the rating (x_{ij}) of alternative $\mathrm{A_i}$ with respect to criterion C_j. Through literature review and expert judgement, we can identify several criteria (or attributes) that are important in the selection of the containers to be loaded on the vessel, and therefore to be transferred to the final destination. Note that these criteria can have different scales; e.g., waiting time can be expressed in days and the weight in tonnes. Group decision making could be easily incorporated into this step if needed; see [55] for the extension of TOPSIS for group decision making.

Aggregation of the importance of the criteria—weighting.

A reasonable approach to obtain importance weights involves the utilisation of the expert opinion (i.e., through group decision-making) on the relative importance of the attributes/criteria concerned. This can either be done within the TOPSIS methodology (this is called internal integration) or externally, either before or after the TOPSIS methodology; see [55] for more. In fact, several papers present the extension of TOPSIS to a group decision environment, some of them in a fuzzy environment. The importance weight of each criterion can be either assigned directly or obtained indirectly using various methods, such as pairwise comparisons; the latter is widely used in the Analytic Hierarchy Process (AHP) method. For example, in [56] weights are based on the weighted sum of the expert's subjective importance of the criterion (these are on a scale of 1–9).

In here, it is suggested that the decision-makers use the linguistic variables to evaluate the importance of the criteria. In line with [57], a group of experts (in our case, stakeholders) provide their opinions on the importance of each criterion using linguistic variables (see Table 1). The weights for each expert are therefore represented as triangular fuzzy numbers.

Table 1. Linguistic variables for the importance weight of each criterion—Source: [57].

Linguistic Variable	Fuzzy Number
Very low (VL)	(0, 0, 0.1)
Low (L)	(0, 0.1, 0.3)
Medium low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium high (MH)	(0.5, 0.7, 0.9)
High (H)	(0.7, 0.9, 1.0)
Very high (VH)	(0.9, 1.0, 1.0)

Assuming that there are K decision-makers, then the importance of the criteria can be calculated as the simple average:

$$\widetilde{w}_j = \frac{1}{K}\left(\widetilde{w}_j^1 \oplus \widetilde{w}_j^2 \oplus \ldots \oplus \widetilde{w}_j^K\right) \tag{1}$$

where $\widetilde{w}_j^K$ is the importance weight (represented as a fuzzy triangular number) of the K-th decision-maker. The crisp number for each weight is then calculated using the graded mean integration. Note that the crisp number (P) of a fuzzy triangular number $\widetilde{w} = (a, b, c)$ can be calculated as follows:

$$P(\widetilde{w}) = \frac{1}{6}(a + 4b + c) \tag{2}$$

The weights are then normalised by dividing each of them by the total sum.

Step 2. Construction of the decision matrix

Based on the selected attributes of each container, a decision matrix, D = (x_{mn}), can be established.

Step 3. Normalisation of the decision matrix

The decision matrix can be normalised as follows:

$$r_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^2}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \tag{3}$$

where m is the number of available containers and n is the number of criteria.

Note that, in the classical TOPSIS, the decision matrix is normalised using Equation (3) [11]. Normalisation is an operation to make these scores conform to, or be reduced to, a norm, i.e., the normalised values will be positive values between 0 and 1. Based on [11,55,58], we present the most common normalisation methods; see Figure 2.

1 Vector normalization
$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, i = 1, \ldots, m;\ j = 1, \ldots, n.$

2 Linear normalization (1)
$r_{ij} = \frac{x_{ij}}{x_j^*}, i = 1, \ldots, m;\ j = 1, \ldots, n;\ x_j^* = \max_i \{x_{ij}\}$ for benefit attributes
$r_{ij} = \frac{x_j^{\sim}}{x_{ij}}, i = 1, \ldots, m;\ j = 1, \ldots, n;\ x_j^{\sim} = \min_i \{x_{ij}\}$
or $r_{ij} = 1 - \frac{x_{ij}}{x_j^*}, i = 1, \ldots, m;\ j = 1, \ldots, n;\ x_j^* = \max_i \{x_{ij}\}$ for cost attributes

3 Linear normalization (2)
$r_{ij} = \frac{x_{ij} - x_j^{\sim}}{x_j^* - x_j^{\sim}}$ for benefit attributes
$r_{ij} = \frac{x_j^* - x_{ij}}{x_j^* - x_j^{\sim}}$ for cost attributes

4 Linear normalization (3)
$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, i = 1, \ldots, m;\ j = 1, \ldots, n.$

Figure 2. Normalisation methods for TOPSIS—Source: [55].

Several issues have actually been identified in the literature using standard TOPSIS; issues, for example, related to the different scales used and the effect of the normalisation on the results. These issues are addressed with different methods of normalisation. Celen [59] suggests that vector normalisation and linear scale transformation (max method) outperforms other normalisation procedures. This is in line with [60], which compares the normalisation procedures for the TOPSIS method and supports the use of vector normalisation. Therefore, in our study, we use the classical vector normalisation; using other methods is straightforward.

Step 4. Construction of the weighted normalised decision matrix

In this step, the columns of the normalised matrix are multiplied by the associated weights to obtain the weighted decision matrix $A = (v_{mn})$:

$$v_{ij} = w_j . r_{ij}, i = 1, 2, \ldots, m, j = 1, 2, \ldots, n \tag{4}$$

Step 5. Calculating the positive and negative ideal solution

The positive ideal solutions (PIS), denoted by A^+, and the negative ideal solutions (NIS), denoted by A^-, are defined as follows:

$$\begin{aligned} A^+ &= (v_1^+, v_2^+, \ldots, v_n^+) = \left\{ (\max_i \{v_{ij}\} \middle| j \in J_1), (\min_i \{v_{ij}\}) \middle| j \in J_2 \right\}; \\ A^- &= (v_1^-, v_2^-, \ldots, v_n^-) = \left\{ (\min_i \{v_{ij}\} \middle| j \in J_1), (\max_i \{v_{ij}\}) \middle| j \in J_2 \right\} \end{aligned} \tag{5}$$

where J_1 and J_2 represent the set of benefit and cost criteria, respectively.

Step 6. Calculating the distance of each alternative

The Euclidean distances of each alternative from the PIS (d_j^+) and the NIS (d_j^-) can be calculated as:

$$\begin{aligned} d_i^+ &= \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j{}^+)^2}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n; \\ d_i^- &= \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j{}^-)^2}, i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \end{aligned} \tag{6}$$

Note that, in this work, we use the Euclidean distance, which is used in the classical TOPSIS. Several other distance measure functions have been used in the literature, such as the Manhattan or Tchebycheff distance [61].

Step 7. Calculating the relative closeness to the ideal solution and score the alternatives

Finally, the relative closeness (S_i) to the ideal solution is calculated as:

$$S_i = \frac{d_i^-}{d_i^+ + d_i^-}, i = 1, 2, \ldots, m \quad (7)$$

where $0 \le S_i \le 1$. For each alternative (i.e., in our case, each container under consideration to be loaded), the relative closeness can be calculated. We can rank the containers according to the relative closeness. Containers with higher S_i are supposed to be more important and are given a high priority.

Step 8. Determine the alternatives to be included in the solution

This is actually the most important step in the proposed decision-making tool. Which containers should be loaded on the vessel? One might utilise a simplistic approach: Given the rank (produced using the TOPSIS algorithm), start loading the container that ranked first, then the one that ranked second, and so on, until the capacity of the vessel (payload) has been reached. We shall call this approach 'Highest-Ranked-First-Served' (HRFS) in line with the 'First come, first served' principle, which describes a situation whereby customers are served in the order in which they arrive; those who arrive first are served first.

This is indeed an acceptable algorithm. However, there is one main issue with this approach. Remember that each container is given a score based on its closeness to the ideal solution. The above algorithm does not maximise the sum of the scores of the loaded container—something that we can achieve by solving the related 0–1 knapsack problem. Note also that loading a container into the vessel on a HRFS basis does not make much practical sense. Containers are actually stowed—A problem that is referred to as the 'container stowage planning'—based on several considerations, including the stability of the vessel and other port-related factors such as quay crane schedules and yard truck availability; see Wilson and Roach [62,63] for more.

Therefore, realistically speaking, we just need to determine the set of containers to be loaded into the vessel and not their loading sequence. This is thus more preferable for solving the 0–1 knapsack problem, which is formulated as follows.

Given a set of m containers with:

S_i = the relative closeness of container i to the ideal solution (obtained in Step 7);
$Weight_i$ = the actual weight of the container (not to be confused with the weight of each criterion);
C = the payload of the vessel (the maximum cargo weight that the vessel can carry).

Select a subset of the containers so as to:

$$maximize\ z = \sum_{i=1}^{m} S_i \cdot x_i$$

$$subject\ to \sum_{i=1}^{m} Weight_i \cdot x_i \le C$$

$$x_i = 0\ or\ 1,\ i\ \in M = \{1, , m\}\ where\ x_i = \begin{cases} 1\ if\ item\ i\ is\ selected\ ; \\ 0\ otherwise \end{cases}$$

A solution can be obtained by various methods, as described in Section 3.2. As this mathematical problem is not easy to solve, we use an open-source solver, namely the GNU Linear Programming

Kit (GLPK), which is used for solving linear programming (LP), mixed integer programming (MIP) and other related problems. Note that a dynamic programming solution can also be used in cases where the container weights are integers. By using the solver, the input parameters can be real and/or integer numbers.

4. An Application—A Case Study of the Rodrigues Island

4.1. Background Information—The Rodrigues Island

Rodrigues is the smallest (110 km^2), least populated (43,040 inhabitants) and most isolated of the Mascarenes islands, lying almost 3000 km off the southeast coast of the African continent [64]. The island has an autonomous status and is governed by the Rodrigues Regional Assembly (RRA). An increasing trend has been observed for the arrival of tourists, public expenses, registered vehicles and electricity consumption of the island in the past five years. This has resulted in an increase of the number of containers transported to the island, which are primarily shipped from Mauritius. The sole port of Rodrigues is situated in Port Mathurin and is under the aegis of the Mauritius Ports Authority (MPA). In the 1990s, major port infrastructural works, such as quay construction and dredging works, were undertaken by the government to allow safe berthing of cargo vessels inside Mathurin Bay.

The interisland cargo vessels are under the supervision of Mauritius Shipping Corporation Ltd. (MSCL), a state-controlled company [65]. The MSCL was incorporated in 1986 as a private limited company and presently owns 'M/s Mauritius Trochetia'. As the national shipping line, MSCL ensures shipping connections among the major islands (Rodrigues and Agalega) of the Republic of Mauritius. The MSCL also hired the services of the cargo ship 'MV Black Rhino' to ensure continuous inter-island trade between Rodrigues and Mauritius. These cargo vessels are specially designed to carry containerised cargo, breakbulk cargo, heavy fuel oils, vehicles, transportation fuels and cooking gas, among other things. MV Black Rhino (IMO No: 9148790) is a Cyprus-flagged cargo vessel with a deadweight of 5.113 tonnes. On average, the island receives around 40 berth calls per year. The vessel spends three to four days for the loading and unloading process.

As per the cargo manifests, cargo transported to the island mainly falls into the following categories: food and beverages, cement and construction materials, heavy fuel oil for electricity, cooking gas, fuel for transport, livestock feed/plantation seeds, information technology equipment/related items and pharmaceuticals products. Each container is assigned an 'importance value' based on its content; the priorities that determine these values are decided by a committee that is mainly formed by government officials; see also the discussion in Section 2.1. Note that the content of containers is known because it is stated in various documents; for example, the cargo manifest. In many countries, a harmonised system is used—the so-called Harmonized Commodity Description and Coding System, generally referred to as "Harmonized System" or simply "HS". This is developed by the World Customs Organization (WCO).

In April 2020, the WCO, with input from the World Health Organization (WHO), produced a list of medical supplies and medicines that were critical to deal with COVID-19 or where interrupted supply could result in serious health consequences. Such lists can be used in setting the 'importance value' during a pandemic or other emergencies [66].

Based on the latest data from the Mauritius Ports Authority, 4061 full containers were transported from Mauritius to Rodrigues in 2014, up from 3444 containers in 2010 [67]. Note that the number of empty containers transported per year was less than 10. Therefore, empty containers are not taken into account in our model, as it deals with cargo destined for Rodrigues Island. This is not the case for the return leg; in 2014, 3212 empty containers were transported from Rodrigues to Mauritius, while only 611 full containers were transported.

Cargo Prioritisation during the Coronavirus Pandemic

As of 1 August 2020, Rodrigues was one of the rare territories still being recognised as COVID-19 free [68]. The early decision of the local government to cancel all flights and maritime schedules prevented the virus from reaching the island. However, due to the island's high reliance on cargo imports and the resulting commodities shortage during the beginning of the lockdown, the governing body ultimately allowed the cargo feeder vessel to berth in the island to unload the much-needed supplies. The cargo prioritisation was decided by public officials and port authorities, along with the ship operator; following, however, no formal process. Our methodology can thus provide a rational way to prioritise cargo that can be used in extreme situations, such as a pandemic, but it can also be used in other emergency situations as well; see discussion in Section 2.1.

4.2. Input Parameters

We illustrate the application of our decision-support system using some realistic inputs, as follows. Input has been provided by five experts working for the relevant stakeholders, namely, the port authority, the shipping company and the local government.

Based on our literature review and expert opinion, the attributes of the containers that were considered important in the decision process were as follows:

- The actual weight of the container;
- The economic value—that is the declared value of the goods as inserted in the Bill of Lading;
- The waiting time in port—the time that the container spends in port waiting to be loaded;
- Their 'importance value'—this is related to the commodity.

All of the above are considered known and well-defined, except for the 'importance value' parameter attributed to each container. A value will be assigned to each container based on its content. This will be, in practice, determined by a group of experts. For instance, during a pandemic, containers carrying goods that fall into the category of 'pharmaceuticals products' will be assigned a high value. The priorities, and thus the importance value, of each container might change over time—see the discussion earlier on face masks, sanitisers and pasta that have, in general, a low per unit price; assigning such a number based on the commodity is therefore a dynamic process.

The experts also provided minimum and maximum values for the above attributes. An instance with the following parameters and characteristics was created: Waiting time was set as a random number between 3 and 25 days, the value of the container was between 3 and 10 thousand USD, the importance value was set between 1 and 10 and the weight of the containers varied between 10 and 20 tonnes. The number of containers simulated was 500; see Figure 3 for the histograms of the relevant parameters. The capacity of the vessel was set to 4000 tonnes, which is close to the actual capacity of the vessel. Note that it is very difficult to obtain real data, but the instance created is very realistic and can illustrate the application of our model. Other distributions (e.g., normal) could have been used to create the sample attributes, but it is no loss of generality to assume a uniform distribution.

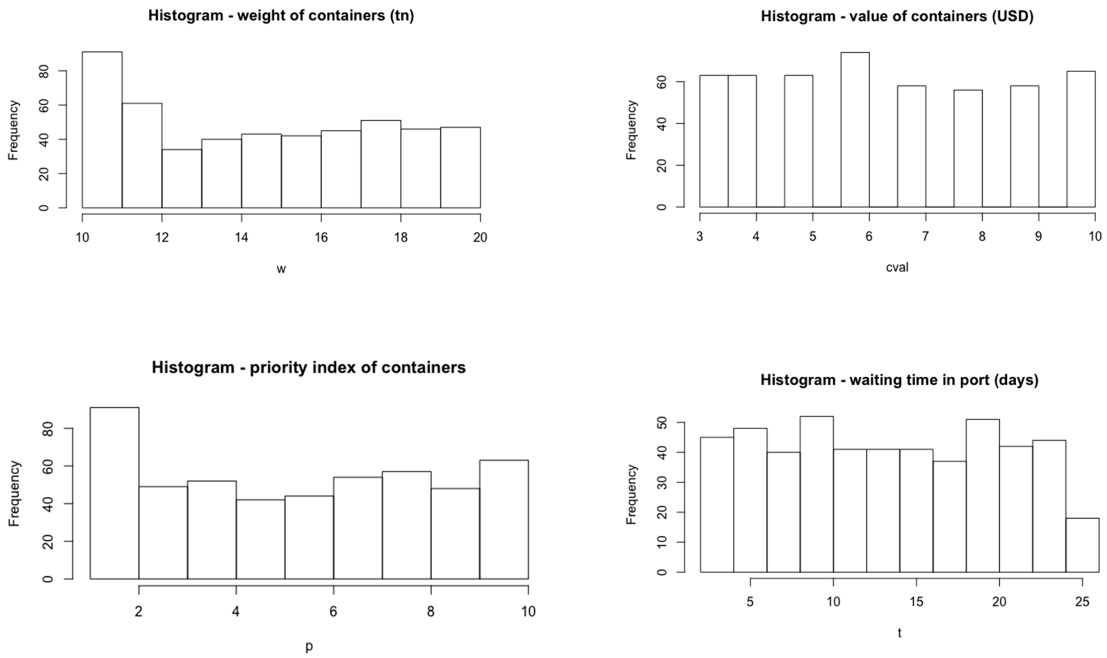

Figure 3. Histograms of the input values—sample of 500 random containers.

Weights of Attributes

In our case study, we used a questionnaire to elicit the significance of each criterion; see Table 2 for the values that each of the five experts attributed to the criteria. Following Step 1, as described in Section 3.3, the linguistic weights from the individual experts—as obtained through the questionnaires—are converted into triangular fuzzy numbers, the averages are calculated and, then, their crisp numbers are obtained. The weights are normalised so that they all sum to 1. The final weights are presented in Table 2 (in the second column). Based on the experts' opinion, the most important parameter in prioritising the cargo containers is the priority number, following by their economic value.

Table 2. The importance weight of the criteria.

Attribute	Weight	DM1	DM2	DM3	DM4	DM5
Economic value	0.240	ML	H	H	M	H
Importance value	0.328	VH	H	VH	VH	H
Waiting time of the container in Port	0.220	ML	VH	H	M	M
Weight of the container	0.212	ML	H	H	ML	MH

The weighting of the parameters is actually the single most crucial factor in any multi-criteria decision analysis method; there are other methods, such as a pairwise comparison, similar to the one used in the AHP, that could be utilised in future research.

4.3. Results

Following the algorithm presented in Section 3.3, the relative closeness to the ideal solution—what we refer to as the TOPSIS score—was calculated for each container, and containers were ranked based on their score. Using the first solution technique, based on 'Highest-Ranked-First-Served' approach, a total number of 273 containers are included in the solution, having a total weight of 3,995 tonnes and a total TOPSIS score (the sum of the relative closeness to the ideal solution of the selected containers) of 170.9. The combined TOPSIS-Knapsack approach leads to a solution that includes 290 containers, has a total score of 175.09 and a total weight of 4000 tonnes; see Table 3 for more.

Table 3. Comparison of the possible cargo loading methods.

Method	Number of Containers	Total Score	Total Weight
'Highest-Ranked-First-Served'	273	170.924	3995
Our approach: TOPSIS-Knapsack	**290**	**175.097**	**4000**
Random selection (min)	260	126.896	3983
Random selection (mean)	269	134.891	3992.58
Random selection (max)	277	143.419	4000

The two approaches lead to different solutions; there are 234 containers (or 83.2%) that appear in both solutions. The TOPSIS-Knapsack approach leads, in general, to solutions that have a higher score—the sum of the relative closeness to the ideal solution of the containers included in the solution—as the total weight is higher. This is because solutions of the knapsack problem have a total weight that is close, if not equal, to the given maximum capacity (vessel payload); this is not the case in the 'Highest-Ranked-First-Served' approach.

We believe that similar results will be obtained using different data instances. In addition, as we mentioned earlier, the weights of each attribute are very important parameters; this is the case for all MCDA methods. In many papers that use an MCDA method, a sensitivity analysis is presented. The sensitivity analysis is performed by varying the weights and looking at the final rank. However, in our case, the number of alternatives, which is actually the number of containers, is very high; 500 random containers are included in our instance. A graphical representation is therefore impossible. We believe that a sensitivity analysis is also not very meaningful. It is evident that our proposed methodology depends on the importance of weights as given by experts. Nevertheless, we present the results of a simple sensitivity analysis in Section 4.4.

We feel that there is nothing wrong with the small number of experts used; in reality, the size of the group of people who will be responsible for making the relevant decisions will be relatively small, i.e., between three and five experts. This will include representatives of the local government and the port and the ship operator. Therefore, although the number of experts used in our experiment is realistic, we feel that more research is needed on the way the weights could be obtained. Other methods could also be used; see Step 1, Section 3.1 for more.

Finally, a note on the implementation and the execution of the algorithm. The integrated problem was solved using R, a programming language and free software environment for statistical computing. The TOPSIS method was coded in R, although several packages could be used; the TOPSIS and the MCDM package contain functions to implement the TOPSIS technique. To solve the knapsack problem, the RGLPK package was used, which is the R interface to the GNU Linear Programming Kit (GLPK) [54]. The instance containing 500 containers was solved on a laptop computer (1.4 GHz Intel Core i5 with 4 GB RAM) in less than a second. Large instances of 5000 containers (with integer attributes) were solved in around 6.5 s; whereas more computationally challenging instances of 1500 containers with real numbers as attributes were solved in less than 5 s. Therefore, it is safe to say that the proposed decision-support system can be easily applied as it does not make use of any computationally intensive algorithm.

4.4. Sensitivity Analysis

For illustrative purposes, we have performed a simple sensitivity analysis by slightly varying the original weights and observed how the original solution is affected. We use only the TOPSIS-knapsack solution; that is, we do not compare the two solution techniques as before. We modify the weight of the most important factor, which is the priority index, from 0.328 to 0.428 and we then uniformly change the other weights so that the sum is 1. We observe that, by increasing the weight of the priority index, the number of common containers in the two solutions drops to 91.7%; the total number of containers in the solution decreases, whereas the total score increases. When the weight decreases from 0.328 to 0.228 (and the other weights increase uniformly), the number of containers in the solution increases but the total score decreases. The number of common containers drops to 89%. More details on the sensitivity analysis can be found in the 'Supplementary Material'; see Table S1.

We feel that, although the sensitivity analysis shows that small changes in the weights do not much affect the results (the resulting solutions are at least 90% similar to the original one), we cannot draw any concrete results from any sensitivity analysis as results greatly depend on the instance and the constrains. It is also important to stress that the main reason for including a case study is to illustrate the way our decision-support tool can be used and not do provide any specific recommendations.

4.5. Comparison of Different Approaches

An interesting question is the following: How much better is this system compared to a random allocation? Firstly, our system is fairer and more transparent. All shipping companies have their own terms and conditions, for example, as per the Mauritius Shipping Corporation's 'Conditions of Carriage of Cargo' the company has the "*liberty to ship all cargo in such order, and at such time as they see fit without reference to the order of booking*" [65]. Using a systematic approach similar to the one we propose, the carrier (which, in this case, is also a public company) can justify the selection of cargo to be transported. Furthermore, in an arbitrary selection—which could be totally random or less random by selecting containers taking into account the waiting time in port or their value—there is only a capacity constraint, i.e., the total weight of the container cannot be more than the available cargo space. This selection has no objective and will not—unless by coincidence—maximize any of the following: total weight, total score or total importance value (that is the sum of the weight of the selected containers, their TOPSIS score and their importance value, respectively). The random allocation will also, in general, be inferior to a solution based on the 'Highest-Ranked-First-Served' approach. Note that, by definition, the solution to the knapsack problem is the mathematically optimal one—this means that there exists no solution with a larger objective value i.e., the sum of the weighted priority score (TOPSIS score) of the selected containers.

To put this into perspective, we performed 100 random allocations using the instance mentioned earlier (see Figure 2) and we compared them with the solutions obtained using our two approaches. Table 3 presents a comparison between these approaches. Although the random allocation can produce solutions that can have a total payload equal to the maximum, they were, as expected, inferior even to the 'Highest-Ranked-First-Served' approach. Our proposed approach, when compared to the average of the 100 random allocations, was able to produce a solution where 7% more containers were loaded and the TOPSIS score was almost 30% higher. Although the exact results depend on the instance, we feel that we have been able to show that our system is better and fairer compared to an arbitrary one.

5. Discussion and Conclusions

The proposed decision-aid tool was developed to solve an actual problem faced by many remote areas, especially islands such as Small Island Developing States and small island dependencies, during a pandemic. Many island states are highly dependent on imports, and any disruption, such as the 2020 pandemic lockdowns, can have a negative impact on their supply chains, which could even lead to a severe humanitarian crisis. These islands are mainly served by small vessels, and the sailings are not frequent. Thus, solutions that could work in other cases, for example, increasing the throughput by increasing the service frequency or by deploying more vessels or using larger ones, are not possible. It is therefore imperative to develop a cargo prioritisation process to ensure that essential commodities are transported based on a fair decision-support system, as opposed to the less systematic or even arbitrary approach that is used in most cases. The proposed decision-aid tool integrates two methods, namely, (a) the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and (b) the knapsack problem.

Although our proposed system can realistically support the decision-making process associated with the prioritisation of cargo, several steps in our methodology could be further investigated to arrive at a more robust model. There are two significant parameters in our model. These are related to (a) selecting the important attributes of each container and (b) placing a weight on each of them. In our model, based on both literature review and expert judgement, four distinct attributes, namely, the importance of the cargo, the waiting time in port, the economic value and the container weight, have been used. While it is straightforward to add more parameters into the prioritisation process, we feel that more research is needed in this area. In any case, or in such emergency cases, it will be a local board who will decide on these parameters, and they are therefore responsible for including or excluding various aspects. In addition, most of these attributes are known exactly and there is no uncertainty associated with them, as in, for instance, the value of the container as declared by the shipper and the container weight as stated in the loading documents, and this is actually the reason why fuzzy TOPSIS has not been used in our methodology. However, attributes such as the importance value need to be better defined by the decision-makers. Regarding the methodology, different methods to obtain the weight of these attributes (as discussed in Step 1), normalisation methods (see Step 3) and distance measure functions to calculate the distance of each alternative (see Step 6) could be used and are briefly described in the relevant steps of our methodology. These modifications of our algorithm are straightforward.

In addition, there are many possible extensions to our proposed model. First, its scope could be extended. The decision-support system can be used not only during a pandemic similar to the one that happened in 2020 [14,44] but also during any disruption, such as natural disasters; see the earlier discussion on the areas of 'disaster relief logistics' and 'emergency logistics' [38,39]. This is in line with previous research, which has shown that small islands face increased exposure to natural hazards of tectonic and meteorological origin, including earthquakes, volcanic eruptions and tsunamis.

Furthermore, this approach could be used for various ship types. Many islands are served by vessels that are not pure containerships. Multipurpose cargo vessels are, for instance, used to serve many islands—this is also the case for the M/V Black Rhino that serves Rodrigues Island [65]. These vessels can carry standard containers, refrigerated containers—or reefers, which are containers used in freight transport that are refrigerated for the transportation of temperature-sensitive cargo—but can also carry liquid cargo, and they also have cargo holds for bags, bales, pallets, grain, etc. Taking this into account, it is actually straightforward: For example, if fuel needs to be transported in the vessel's tanks or reefer containers, then we assume that these will be prioritised over the rest of the cargo, thus reducing the available capacity. The knapsack problem will then be solved using the reduced available capacity.

Regarding possible mathematical model extensions, many other multiple criteria decision-making techniques could be used; it is straightforward to use Simple Additive Weighting (SAW) [69,70] or Multi-Objective Optimisation by Ratio Analysis (MOORA) [71] or Vise Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [72,73] to score (and rank) the containers instead of TOPSIS. The knapsack problem could then be solved to obtain the solution, as described in Step 8 of our methodology. Other extensions include integration with optimisation problems, such as the 'container stowage planning problem' (CSPP) or the 'container loading sequence' problem (CLSP) [62,63,74,75]. The first is related to the placement of containers within the cargo-space of a container ship, i.e., stowing them in stacks respecting several constraints such as the maximum number of containers that each stack can hold or constrains associated with the ship's stability [63].

The second problem is related to the sequence that the containers are loaded in; taking into account their position in the yard and under various constraints such as placing fully and heavily loaded containers at the bottom of the stack. Given an initial layout of a bay in the yard (known as the yard plan) and a final layout of a bay on the containership (known as the stowage plan), the CLSP yields the container retrieval sequence that retrieves all containers that need to be loaded, such that the number of container relocations is minimised [76].

Last but not least, further research on the prioritisation of cargo under sustainability constraints is needed. Environmental considerations are as important as economic and social ones. Small islands face a plethora of climate change related risks including sea-level rise, tropical and extratropical cyclones, increasing air and sea surface temperatures and changing rainfall patterns [36]. At the same time, they are naturally blessed with a pristine biodiversity and environment, which has to be sustainably preserved. Minimising ship emissions during transportation at sea and in port, and also reducing the risk of accidental pollution such as oil spills, is of paramount importance.

Supplementary Materials: The following are available online at https://doi.org/10.5281/zenodo.4002965; Table S1: Details of the model instance, Table S2: Results—Outputs, Table S3: Results of the sensitivity analysis.

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