An intuitionistic fuzzy rough model for maritime transportation chains under disaster effects: the case of COVID-19

Elena Ganshina*

Department of Management, Higher School of Management, Financial University under the Government of the Russian Federation, Moscow, Russian Federation

Abstract. The outbreak of COVID-19 has caused disruptions in port transport infrastructure and shipping, resulting in higher shipping rates in 2022. This article aims to assess the extent of COVID-19 risks on the capacity and concentration of traffic flows, and evaluate the degree of imbalance in the transport system during 2020-2021 compared to the previous period of 2018-2019. The data is analyzed using the Intuitionistic Fuzzy Rough set, which allows the evaluation of multiple heterogeneous measures to produce an aggregate outcome. The model is based on the intensity of non-stationary incoming and outgoing traffic, as well as the intervals between separate ship calls. The data obtained from the study shows the dynamics of changes in traffic flows under the influence of COVID-19. The results indicate a minimal degree of its influence, which did not lead to any failures or modifications in the composition of traffic flows. The method can also allow for the development of complex simulation models to assess the limit of potential deviations, after which, with a high degree of probability, deformation of traffic flows is possible.

1 Introduction

In its full-length Maritime Transport Review 2022, the United Nations Conference on Trade and Development (UNCTAD) emphasized the need for increased investment in maritime supply chains to address the supply chain crisis of the past two years, which experts directly link with the consequences of Covid-19. According to many experts, the primary evidence of this crisis and the resulting supply disturbances may be the spikes in freight rates due to congestion and disruption in global value chains.

For instance, the average value of the China Composite Freight Index (CCFI) for routes from China in the first three months of 2022 exceeded the previous year's level by 78%. At the same time, while spot rates in container shipping reached an all-time high in early 2022, they decreased by mid-2022. The instability of the container transportation market and the growing rates for this type of transport service could naturally be attributed to the strengthening of the imbalance between supply and demand and the uneven recovery of the

* Corresponding author: e.ganshina@gmail.com

© The Authors, published by EDP Sciences. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).
world economy in pandemic conditions. Thus, can we confidently say that Covid-19 caused containers to get stuck in the West while they were needed in Asia?

It is worth noting how rates have risen with the emergence of any new risks. Short-risk markets are fulfilling their role effectively. The risk of investing in the development of transport chains increases significantly if the loading patterns of their sections are not considered. However, it is essential to solve the inquiry into how these risks affect the capacity and concentration of traffic flow more clearly since the rates come into balance with the passage of the first acute phase of the crisis. Accordingly, the degree and dynamics of the exposure of transport flows to the influence of crises require additional analysis and study. On the one hand, ignoring these patterns leads to traffic disruptions due to the overload/underload of separate lines and network nodes. On the other hand, overestimating the impact can lead to unprofitable investments.

The productivity of supply chains and their continuous transshipment and handling activities depend heavily on the flow of goods and transport. Therefore, the efficiency and uniformity of resource utilization in transport chains, as well as the overall congestion, are directly dependent on the characteristics of traffic flow, such as intensity, stability, and trends. Our primary objective is to analyze traffic flow's characteristics, particularly their intensity, stability, and trends, and determine the changes that the Covid-19 pandemic has introduced. We use indicators such as world seaborne trade by types of cargo and by a group of economies and performance statistics such as the annual number of port calls to model the equilibrium state before and during the pandemic.

There are two primary approaches to studying transport equilibrium. The first approach models the problem of transport equilibrium only through flow variables along arcs, and the search for equilibrium is along the arcs of the network (arc algorithms). In the second approach, the primary variable of the problem is the flow along the path, and the iteration is along admissible routes (route algorithms). In both cases, the main difficulty in numerical calculations lies in the large dimension of the problems, especially on natural transport networks.

The Frank-Wolfe method is the most common arc algorithm, but it has a relatively slow convergence rate that slows down significantly when approaching equilibrium [1]. This algorithm is also sensitive to the dimension of the problem. The reason for this is the degenerating nature of the auxiliary linear programming problem and the non-uniform convergence of flows to equilibrium values [2, 3]. In the process of solving, a particular set of arcs is formed along which the flows differ significantly from the equilibrium ones, which does not change during subsequent iterations.

Routing algorithms distribute the traffic directly over a set of alternative routes, and this set is formed in the process of solving [4, 5]. The main idea of these algorithms is sequential flow balancing between alternative routes for each source-sink pair. The absence of the need to a priori specify all admissible routes for each source-sink pair makes path equilibrium search algorithms attractive for use. However, these algorithms minimize the number of paths used, which means that uniform splitting of characteristics over a set of attractive routes is lost. Furthermore, since the redistribution of one flow between routes changes the transport costs in the whole network and thereby affects the distribution of other correspondences, it becomes necessary to repeatedly look through all the flow-forming pairs and repeat the redistribution of flows [6].

Although the apparatus for variational inequalities in evaluating transport chains is well-developed [7, 8], many variables make the problem easier to solve.

The search for transport equilibrium has been studied mainly theoretically, and adequate modeling of traffic flows still requires more fuzzy rough aggregation operators to consider individual characteristics and their interaction.
2 Materials and methods

The concept of rough sets has been expanded by many scientists in various ways. Recent studies have made significant progress in both practical use and theory. Rough set theory has been successfully applied in different fields, such as gaining knowledge [9, 10, 11], process management [12, 13], medical diagnostics [14], expert systems [15, 16] and data mining [17, 18].

Coarse set theory has also been utilized in articles to select the site of small hydropower plants [19], to estimate producers [20] and subcontractors [21], and to evaluate energy-saving green construction design projects [22].

Fuzzy rough sets were introduced by Pawlak in 1982 to study structural relationships in data [23]. The method assumes that information about a fuzzy set is expressed by the degree of membership, and its membership value is limited to the range of 0 to 1.

The first step in applying the method is to generalize attributes using domain knowledge to determine a hierarchy of concepts. After generalization, the next step is reduction, which involves constructing the smallest subset of all generalized attributes. A set of general rules can then be generated from the reduction, including all basic patterns in the data.

IFR sets have high potential and specialization processes in improving and evaluating multiple incompatible measures in research areas to obtain more aggregative results.

We utilized the classical algorithm for the IFR environment, which is described as follows:

1. Collect the generalized attributes:
   1.1. Group of economies and their seaborne trade (tons in millions) by types of cargo:
       1.1.1. Crude oil loaded and discharged
       1.1.2. Other tanker trade loaded and discharged
       1.1.3. Dry cargo loaded and discharged
       1.1.4. Total goods loaded and discharged
   1.2. Additionally, we gathered performance statistics such as the annual number of port calls.

2. Calculate the value of AvS by applying a developed approach for all alternatives under each attribute using the following formula (Eq. (B. 1)):
   \[ AvS = \left[ AvS_j \right]_{1\times n} \]  

3. Based on the determined AvS, we can calculate PDAS and NDAS by utilizing the below formula (Eq. (B. 2)):
   \[ PDAS_{ij} = \left[ PDAS_{ij} \right]_{(m\times n)} \]  
   \[ NDAS_{ij} = \left[ NDAS_{ij} \right]_{(m\times n)} \]  

4. Next, calculate the positive weight distance (SPi) and negative weight distance (SNi) formula (Eq. (B. 3)):
   \[ SP_i = \sum_{n=1}^{n} = PDAS_{ij}, \]  
   \[ SN_i = \sum_{n=1}^{n} = NDAS_{ij} \]  

5. Normalized the SPi and SNi by using the following formula (Eq. (B. 4)):
   \[ NSPi = SP_i / \max_i(SPi), \]  
   \[ NSNi = 1 - SN_i / \max_i(SNi) \]  

6. Based on NSPi and NSNi, calculate the appraisal score (AS) value using the following formula (Eq. (B. 5)):
   \[ AS_i = \frac{1}{2} \times (NSP_i + NSN_i) \]
The analysis was performed on open data that was compiled by the secretariat of UNCTAD, which is the leading UN agency for trade and development. This data provides the most comprehensive information on international maritime trade categorized by type of cargo and by a group of economies [24]. UNCTAD collects data from multiple reporting countries and various official sources, including government and port industry websites. The shipping data is based on information recorded at the ports of loading and unloading. The country of origin or destination for neighboring countries is defined as the country in which the ports are located. In cases where data is not available, estimated volumes are calculated based on secondary sources and reported growth rates. The annual global volumes of goods loaded and discharged may not match due to bilateral asymmetries in international merchandise trade statistics, and the fact that volumes shipped in one year may arrive at the port of destination in the following year.

The port call information is a part of a set of port call statistics and productivity tables that provide insights into the characteristics of ships and the duration of their stay in the country's ports over a specific period [25]. The tables provide statistics for eight commercial markets, showing the number of port calls within a calendar year. UNCTAD obtained the aggregate data by merging Automatic Identification System (AIS) information with Port Mapping information from MarineTraffic. Only arrivals of ships with a gross tonnage of 1000 tons were counted to measure the total number of port calls. To be included in the measurement, there must be ten country-level arrivals by at least five separate vessels. Passenger ships are excluded from the calculation.

The analysis covered seven different commercial markets for each country, including:
1. Liquid bulk carriers: Ships that carry wet bulk cargo such as crude or refined oil products and other liquid cargo except for liquefied gas.
2. Liquefied petroleum gas carriers: Ships that carry Liquefied Petroleum Gas.
3. Liquefied natural gas carriers: Ships that carry Liquefied Natural Gas.
4. Dry bulk carriers: Ships that carry dry bulk cargo such as iron ore, grains, or coal and cargo that cannot be packaged or containerized.
5. Break bulk carriers: General cargo ships that carry dry cargo that is not containerized or in bulk.
6. Roll-on/roll-off ship: RO/RO, such as ferries or vehicle carriers.
7. Container ships: Ships that carry standardized sea containers.

For some cargo, information is presented in aggregated form to match the cargo nomenclature in the data of annual global volumes of goods loaded and discharged, which can be taken into account in the IFR processing.

It's important to note that UNCTAD has only been providing this data since 2018. Additionally, the ASi data obtained from processing by the IFR method for each year were summarized in an all-around table to analyze the result.

3 Results

The Covid-19 pandemic has caused possible imbalances and disruptions in traffic flows, which could have resulted in significant changes in the number of goods entering and leaving, as well as in the number of port calls. If there were significant disruptions in the supply chain, goods would either have to stand idle or be redirected to another destination. Therefore, if we assume that the traffic flows were affected by restrictive measures during Covid-19, we should see significant changes in the transport balance between 2020-2021 compared to 2018-2019. Table 1 demonstrates the transport equilibrium during the most acute phase of Covid-19.
Table 1. The Results of ASi Data (i=1, 2, 3, 4).

<table>
<thead>
<tr>
<th>Group of economies</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northern Africa</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sub-Saharan Africa</td>
<td>0.0864547</td>
<td>0.0868695</td>
<td>0.09670597</td>
<td>0.08840811</td>
</tr>
<tr>
<td>Northern America</td>
<td>0.34253399</td>
<td>0.36775794</td>
<td>0.36358459</td>
<td>0.37285781</td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>0.35091389</td>
<td>0.34097271</td>
<td>0.33854017</td>
<td>0.33137932</td>
</tr>
<tr>
<td>Eastern Asia</td>
<td>0.95180399</td>
<td>0.94988009</td>
<td>0.95205165</td>
<td>0.95142148</td>
</tr>
<tr>
<td>South-eastern Asia</td>
<td>0.45977342</td>
<td>0.48280685</td>
<td>0.49343876</td>
<td>0.49842546</td>
</tr>
<tr>
<td>Southern Asia</td>
<td>0.17532241</td>
<td>0.16552142</td>
<td>0.1741982</td>
<td>0.17502194</td>
</tr>
<tr>
<td>Western Asia</td>
<td>0.41852753</td>
<td>0.4002423</td>
<td>0.40320333</td>
<td>0.40962171</td>
</tr>
<tr>
<td>Europe</td>
<td>0.92826201</td>
<td>0.90891695</td>
<td>0.84978456</td>
<td>0.84752696</td>
</tr>
<tr>
<td>Oceania</td>
<td>0.11681859</td>
<td>0.10179574</td>
<td>0.10659959</td>
<td>0.09311555</td>
</tr>
</tbody>
</table>

According to the IFR optimization problem, the equilibrium flows during Covid-19 have experienced minimal changes. The trends in the cargo turnover growth or reduction in various regions that emerged in 2018-2019 have continued in 2020-2022 as well, as shown in Figure 1.

Fig. 1. The Results of ASi Data (i=1, 2, 3, 4).
It is evident that trends in cargo traffic growth or decline in specific directions were identified prior to the onset of Covid-19. This can be clearly observed by assessing the intensity of cargo traffic by direction (refer to Table 2). The ratings have not significantly changed in most regions, except for Northern America and Latin America and the Caribbean, which have undergone revaluation prior to the pandemic. Therefore, it can be inferred that the changes in these regions are not linked to Covid-19.

Table 2. Ranking Ordered of the Proposed Group of Countries.

<table>
<thead>
<tr>
<th>Country</th>
<th>2018</th>
<th>2019</th>
<th>2020</th>
<th>2021</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northern Africa</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Sub-Saharan Africa</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>Northern America</td>
<td>6</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Latin America and the Caribbean</td>
<td>5</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Eastern Asia</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>South-eastern Asia</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Southern Asia</td>
<td>7</td>
<td>7</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>Western Asia</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Europe</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Oceania</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
</tr>
</tbody>
</table>

It's possible that consumers were willing to pay higher transportation tariffs for the stability of transport flows, thereby supporting the stability of flows. However, it is worth noting that the growth in cargo traffic is observed mainly in the least developed regions, such as Sub-Saharan Africa and Oceania. Let's assume that the decrease in traffic was due to covid restrictions in some regions. Europe experienced the largest drop. However, traffic in these regions did not increase after the removal of most restrictions in 2022.

4 Discussion

The coronavirus pandemic has brought new global challenges, forcing businesses to quickly adapt to unexpected situations. To help companies mitigate pandemic consequences, particular attention is being paid to the operational management of supply chains and disruptions, especially in managing pandemic emergencies [26, 27].

The IFR-based model described in this article was developed to study traffic flows as a self-regulating system with a high potential for rapid recovery through its adaptive capabilities. The methodology was chosen based on this task.

Since the consequences of COVID-19 have not yet completely subsided, the data from a statistical point of view may not be fully representative, or a sufficient layer of information has not been formed for a linear calculation in quantitative analysis. Unlike classical statistical methods, our proposed IFR method does not make assumptions about probability and can provide us with new insights into the data. It is especially suitable for situations where we want to conclude several classes of heterogeneous information.

Quantitative linear analysis methods are based on iteration, which is the repetition of any mathematical operation using the result of a similar operation. In the conditions of data "haze" and being at the epicenter of the crisis, the amount of similar data on transactions is
significantly limited or unavailable. In this case, the IFR method, which works with the data "as it is" - the primary intuitionistic fuzzy rough information - may be significantly helpful.

At the same time, the reliability of the results is achieved by considering various indicators reduced to one. These are not descriptive statistics, but they are not purely quantitative methods either. The model can be described as "quali-quantitative" with the following characteristics [28]:

1. Fuzzy: The model uses fuzzy logic or fuzzy numbers.
2. Empirical: The study is based on the most recent data.
3. Multi-attribute/multi-criteria decision making: The developed model uses IFR methods.
4. Probability: The model is based on the theory of probability or the fact that chance plays a role in predicting future events.
5. Modeling with structural mean equations: Mean values, variances, and covariances of observed data in terms of a smaller number of "structural" parameters defined by the underlying theoretical concept.

Hosseini, Ivanov, and Dolgui (2019), reviewing the methods used in supply chain resilience analysis, proposed the concept of three lines of defense [29]. The first line of defense is absorbency, which is in place before a collapse occurs. The second line of defense is resilience, which refers to the ability of the supply chain to overcome disruptions by implementing unconventional practices without any remedial action. The third line of defense is recoverability, which refers to the system's ability to recover quickly and efficiently when other lines of defense fail. The authors recommend that future research on lines of defense be carried out from a methodological perspective, with particular emphasis on multi-criteria stochastic models.

5 Conclusion

Traffic flow has a significant impact on the transport balance. The article focuses on the main characteristics of traffic flow, including its intensity (i.e., the number of ships entering the port per unit time) and the ratio of incoming and outgoing cargo by directions and types. By analyzing changes in these attributes, we can understand whether the balance is maintained or broken under the influence of any crisis phenomena. This perturbation of the equilibrium state helps assess the long-term consequences of the crisis and provides consistent feedback on the stability of the transport network to external shocks.

In the article, a comparative analysis of traffic flows during the acute phase of Covid-19 and the pre-Covid period was conducted. It was observed that there were no significant deviations from the equilibrium state, indicating that the changes brought about by Covid-19 were not due to a significant drop in freight traffic or traffic intensity by direction or type of cargo. Instead, the changes were primarily speculative.

The article also describes a model based on the IFR method, which can be used to forecast demand for directions in the long term. The IFR method can also be applied to develop complex simulation models to assess the limit of permissible indicators, after which the equilibrium position of traffic flows can be exposed by deformation.

References

4. M. Patriksson *The traffic assignment problem — models and methods* (Utrecht, Netherlands, VSP, 1994)
22. Y. Liang, Symmetry **12**(3) (2020)