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**Citation:**

KAYIKCI, Yasanur and CESUR, Elif (2023). Artificial neural networks-based route selection model for multimodal freight transport network during global pandemic. Academic Platform Journal of Engineering and Smart Systems, 11 (3), 163-173. [Article]

**Research Article**

Academic Platform Journal of Engineering and Smart Systems (APJESS) 11(3), 163-173, 2023

Received: 06-Jun-2023 Accepted: 28-Aug-2023

homepage: https://dergipark.org.tr/tr/pub/apjess

https://doi.org/10.21541/apjess.1294957

# Artificial Neural Networks-Based Route Selection Model for Multimodal Freight Transport Network During Global Pandemic

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## Abstract

The global pandemic caused major disruptions in all supply chains. Road transport has been particularly affected by the challenges posed by the COVID-19 pandemic. The selection of an efficient and effective route in multimodal freight transport networks is a crucial part of transport planning to combat the challenges and sustain supply chain continuity in the face of the global pandemic. This study introduces a novel optimal route selection model based on integrated fuzzy logic approach and artificial neural networks. The proposed model attempts to identify the optimal route from a range of feasible route options by measuring the performance of each route according to transport variables including, time, cost, and reliability. This model provides a systematic method for route selection, enabling transportation planners to make smart decisions. A case study is conducted to exhibit the proposed model's applicability to real pandemic conditions. According to the findings of the study, the proposed model can accurately and effectively identify the best route and provides transportation planners with a viable option to increase the efficiency of multimodal transport networks. In conclusion, by proposing an innovative and efficient strategy for route selection in complex transport systems, our research significantly advances the field of transportation management.

***Keywords:*** Multimodal Transportation; Freight Transportation; Route Selection; Fuzzy Logic; Artificial Neural Network

## 1. INTRODUCTION

The global coronavirus outbreak, also known as COVID-19, has had an unprecedented impact on world trade, causing disruptions to global supply chains and resulting in severe financial losses and operational shutdowns in various industries [1-2]. As businesses face the rapidly evolving challenges arising from the pandemic, companies are becoming proactive in their decision-making processes to ensure business continuity and create flexible business models [3-4].

International transport networks, especially road transport, are seriously affected by this event. The COVID-19 pandemic has posed significant difficulties for transportation companies, particularly in how they manage customer relationships. Mitręga and Choi's multi-method study explores how small and medium transportation companies navigate customer relationships during this pandemic [5]. Additionally, Vrabac et al. have proposed a discrete time SEIR model for analyzing the spread of the virus in transportation networks [6].

Border restrictions and controls imposed by countries, and local traffic restrictions applied by municipalities at city/province entrances and exits lead to long waiting times on roads or at borders, delays in shipment due to labor shortages in warehouses, terminals, and ports, shortages of trucks, truck drivers, vehicles and equipment, and delays in cargo collection and delivery, cargo handling, causing serious impacts on transport networks and operational challenges [7]. This situation forces companies to use advanced logistics infrastructure and technologies that will protect them from vulnerabilities as much as possible, ensure their competitiveness, increase their efficiency, reduce logistics costs, and utilize multimodal transportation solutions that will reduce their dependence on road transport in international freight transportation operations [2, 8].

Multimodal transport refers to carrying transport goods placed in transport units ( e.g., portable containers, trailers, semi-trailers, and similar cases) using various transport means (e.g., RoRo vessels) taken from a place (origin port/departure terminal) in one country to a specified place (destination port/delivery terminal) in another country through at least two different transport modes among land, sea, inland waterways, and air under a single transport contract or bill of lading [9-10]. This enables multimodal transport to provide an international transport network that is focused on productive activities, efficient operations, and sustainability, while including multiple transportation modes, unlike road transport, which is a single mode. In addition, multimodal transport is seen to have greater resilience and elasticity than unimodal transportation types in the event of any epidemic, disaster, or similar situation that may occur in the transport network [8, 10]. Different combinations of transport modes are possible in the organization of multimodal transport, such as rail-road, sea-road, inland waterway-railway, and sea-railway. During the transfer process between transport modes, the transport units cannot be changed, and the loads within them cannot be handled [11].

The COVID-19 pandemic has significantly impacted multimodal transportation systems as well, leading to various challenges. One such challenge is developing appropriate evaluation criteria and assessment methods to measure the resilience of transportation systems [12]. Furthermore, it is crucial to understand the impact of COVID-19 on transport turnover, as COVID-19 has caused people to increase their consumption behaviors through freight transport [13].

The transportation chain includes three levels: pre-haulage, main-haulage, and end-haulage, which are connected to transfer centers that enable changes in transportation modes [14]. These transfer centers can be sea terminals, rail terminals, road terminals, or multimodal transport centers. While road transport is used for the pre-haulage and end-haulage segments, which cover short distances within a country or region, the main-haulage segment, which covers distances greater than 300 km, often crosses different countries and even continents and is carried out by other transportation modes, especially railways and/or sea/inland waterway transportation [14-16]. Road transport is mainly used for operations in the pre-haulage and end-haulage segments, requiring much shorter transport times than the rest of the transport process [8].

Multimodal transport is organized by a multimodal transport provider (MTP) that provides door-to-door or terminal-to-terminal services and consists of a single rail or sea/inland waterway cargo operator or a consortium of multiple rail and sea cargo operators [8, 16]. Based on a cargo transport contract called the multimodal transport document, multimodal transport provides uninterrupted delivery of cargo from the seller's door or origin terminal to the buyer's door or destination terminal [17].

When considering the combination of transportation types in transport networks, there are many alternative routes with different performances. For MTPs, the most important challenge they face is determining which alternative route to choose, especially in the event of supply chain disruptions caused by the global pandemic.

Several methods have been proposed to address the route selection problem in transportation planning. Hybrid multi-criteria decision-making (MCDM) models [18], deep learning methods [19-20], ensembling methods [21], and reinforcement learning methods [20] are some of the recent methods proposed. These approaches provide a promising direction for future research to enhance the efficiency and effectiveness of route selection in transportation systems.

In this study, a route selection model integration of fuzzy logic and an artificial neural network (ANN) approach is proposed to identify the most suitable route among the alternative multimodal freight transportation routes in a transport network. The integrated fuzzy logic approach and ANNs were chosen as a solution methodology to construct a route selection model in a transport network that includes multimodal transportation, allowing practitioners to respond instantaneously to changing business and environmental conditions and make rapid decisions about selecting the best route from the alternatives provided. In particular, MTPs can predict which routes may be more elastic and resilient based on the results of this study and offer these routes as a service to their customers. The integrated fuzzy logic and ANN model considers only sea and rail transportation, which includes operations in the main transportation segment from terminal/port to terminal/port, while road transport is excluded from the model.

The remainder of the paper is structured as follows. Firstly, a comprehensive literature review is presented, and its relevance to the research topic is provided. Then, the methodology including fuzzy logic and ANNs, used for the proposed model in the article is demonstrated. In the following section, the proposed model is applied with a case study, and its analysis is performed. Then, the results are obtained, and discussions are presented. Finally, the article ends with a conclusion section.

## 2. LITERATURE REVIEW

Transport networks should be designed flexibly to easily adapt to changing business and environmental conditions, as well as unexpected events such as natural disasters (earthquakes, tsunamis, floods, droughts, etc.) and various pandemics (COVID-19, SARS, MERS and H1N1) to enhance resilience [22]. Providing different multimodal freight transportation routes for the main transportation segment in the transportation chain to customers engaged in international trade is a critical decision for MTPs [9-10]. Planning a multimodal freight route allows carriers to maximize profitability, minimize shipping costs across all service lines and also negotiate a more favorable price with MTPs using appropriate pricing strategies [9, 23]. Factors such as transport cost, on-time service quality, transportation risk, scheduled transportation types and delivery times, and transportation economies of scale all exert their influence on the decision-making process. Balancing these diverse objectives adds complexity to an already intricate task. [24]. In addition, capacity constraints of transfer centers can create problems when switching from one mode of transportation to another [25-26].

Route selection is a crucial problem in transportation planning, and various methods have been proposed in the literature to tackle this issue. Qu and Chen proposed a hybrid MCDM model that combines the Fuzzy Analytic Hierarchy Process (AHP) and ANN theory [18]. They obtained a more effective route selection process by considering multiple criteria simultaneously. On the other hand, Campigotto et al. proposed a personalized favorite route recommendation algorithm that utilized Bayesian learning techniques. This approach considered users' preferences and past behavior to provide a customized route recommendation [27]. Abduljabbar et al. proposed the use of artificial intelligence (AI) methods as a smart solution to handle complex transportation systems that cannot be managed by traditional methods. They proposed the use of deep learning methods to learn and optimize the routing decisions in real-time [28]. Additionally, Abedalla et al. proposed a weighted average ensembling method of Convolutional Neural Network and Gradient-Boosted Decision Trees for route selection. The results showed promising accuracy rates for the proposed method [21]. Chen and Chang addressed the route selection problem using a semi-supervised learning method [29]. This approach utilized prior training data to identify the best route while considering the trade-off between accuracy and computation efficiency. Finally, Koohathongsumrit and Chankham proposed a route selection model in multimodal supply chains by integrating fuzzy risk assessment model (FRAM), best-worst method (BWM), and measurement of alternatives and ranking according to the compromise solution (MARCOS) [30].

Although many existing studies have already modeled the multimodal transportation route selection problems [24, 31], there is currently no study that includes an approach to route selection problems for multimodal transportation services within the framework of the literature review. Moreover, there has been a dearth of studies that propose a solution methodology by combining the fuzzy logic approach and Artificial Neural Networks (ANNs). This innovative fusion remains unexplored in the existing literature. Therefore, this study will represent a first in this sense. ANNs are practically employed in solving learning, generalization, specification, identification, classification, association, and optimization problems. With this method, information obtained from the samples is recorded in networks, essentially networks are trained with the data, over time the networks become better at making decisions, recognizing patterns, and producing reliable results in similar situations [32] and also during the COVID-19 pandemic [33]. The reason for using this integrated methodology is its applicability to redirecting alternative multimodal transportation routes in response to changes or fluctuations in fare rates, contracts and weather conditions in freight cases. The utilization of fuzzy logic theory facilitates a comprehensive comparison of alternative routes based on multiple targets. This approach ensures the maintenance of transport service quality at the desired level, while simultaneously minimizing transport time and cost. By employing fuzzy logic, the model selects the most suitable route that optimally meets the specified criteria. Route selection also takes into account the scheduling of different transport modes and capacities. For each identified route, the proposed model employs data on time, cost, and dependability of transport as input parameters. The route performance is calculated as the output parameter following the use of the fuzzy logic technique. Then, the data set is used as training data for ANNs together with the obtained route performance values. Subsequently, the performance predictions are made based on this training data by applying ANNs to a data set that includes much larger multimodal transportation routes. Practitioners can make informed decisions regarding the selection of a route by evaluating the calculated performance. A greater level of route efficiency suggests that MTPs are more likely to provide this particular multimodal transport path to their clients, and the senders.

## 3. RESEARCH METHODOLOGY

In this study, a model is proposed that integrates the fuzzy logic method and ANN approach. In the model, firstly, the performance of the routes is calculated using fuzzy logic algorithms based on the dataset of existing routes on the transport network. Then, together with the obtained performance values, this dataset is used as the training data for the ANN approach to train the transport network and calculate the performance values of the dataset containing alternative routes. The flowchart showing the proposed model is given in Figure 1.

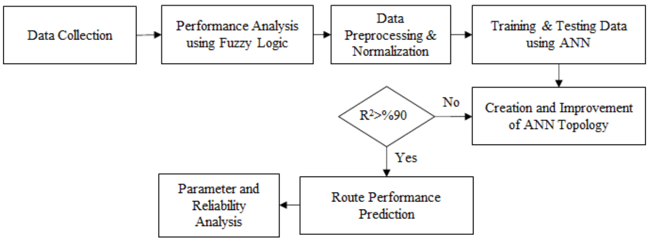


**Figure 1.** Model flowchart integrated with fuzzy logic approach and ANNs.

### 3.1. Fuzzy Logic Approach

Recently, an increasing number of research studies have used the fuzzy logic approach to apply the definition of human behavior in social environments, customer requirements in dynamic markets, logistics, and various other fields. As a well-known approach, the fuzzy logic method is attracting growing attention among both academicians and practitioners alike, as it can work with both numerical and non-numerical characters and generate classes to make better decisions [34].

The challenges presented by the COVID-19 pandemic have necessitated the development of new models to evaluate transportation-related risks. One such model, proposed by Tang et al., integrates an extended type-2 fuzzy model with a Bayesian network to evaluate COVID-19 medical waste transportation risk [35]. To effectively manage public transportation during the pandemic, Deveci et al. proposed a fuzzy Einstein model to evaluate and rank prioritization [36]. Özden & Celik sought to identify critical service quality priorities in cargo transportation before and during the COVID-19 outbreak using the Fuzzy Importance-Performance-Impact Analysis method [37].

The fuzzy logic approach is used in this work to create a rule-driven model to predict route performance by considering some basic characteristics of routes on the transport network, including transport cost, transport time, and transport reliability.

Within the literature, numerous fuzzy models are categorized into three primary classifications: 1) the Mamdani model, also referred to as the Max-Min method [38], 2) the Takagi-Sugeno model [39], and 3) Kosko's model [34]. For the purposes of this study, the widely recognized Mamdani model was adopted, wherein the following rules were repeatedly applied:

- Firstly, fuzzification is performed, where all input variables are transformed into fuzzy variables.
- Then, the output detection step applies the pre-defined fuzzy rules to the input values.
- The output accumulation stage, which totals up all fuzzy rules to finish the output, is crucial.
- Finally, defuzzification ties the fuzzy output with its original form.

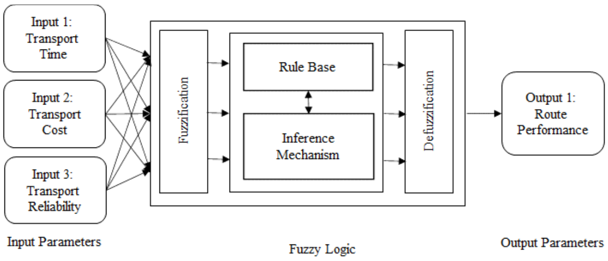


**Figure 2.** Fundamentals of Fuzzy Logic.

The fundamental principles of fuzzy logic are illustrated in Figure 2. The fuzzy set theory employs membership functions $\mu_a(a)$, $\in [0,1]$ which assigns a degree of membership to each object on a given scale [40]. Various fuzzy membership functions have been used, including triangular, Gaussian, and trapezoidal membership functions [11]. Figure 3 shows the triangular fuzzy numbers $\mu_a(a)$ and trapezoidal fuzzy numbers $\mu_b(b)$. For this study, triangular membership functions are adopted as they are the most widely used membership functions [41]. A triangular fuzzy number a can be defined by a triplet $(a1, a2, a3;$ $a1 \leq a2 \leq a3)$, and the membership function $\mu_a(a)$ is presented in Equation (1):

$$\mu_a(a) = \begin{cases} (a-a1)/(a2-a1) & a1 \leq a \leq a2 \\ (a-a3)/(a3-a2) & a2 \leq a \leq a3 \\ 0 & a < a1 \text{ or } a > a3 \\ 1 & a = a2 \end{cases} \qquad (1)$$

The fuzzy approach is a method that employs pre-established rules composed of a series of fuzzy "if-then" statements, gathered in the form of linguistic expressions through expert opinions obtained through questionnaires or Delphi sessions. Each rule is understood as an "implication" and comprises an "antecedent" (the "if" part) and a "consequent" (the "then" part). The fuzzy rule's general format is presented in Equation (2):

$$If\ it\ is\ A, Then\ is\ B \qquad (2)$$

where A and B are, respectively, linguistic concepts in the language universe that are specified by sets of fuzzy concepts.

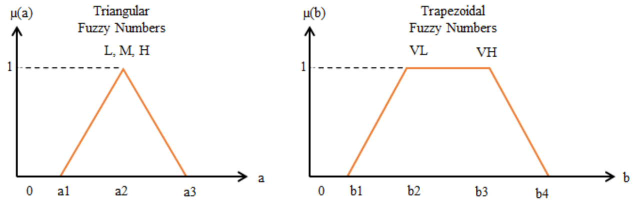


**Figure 3.** Triangular and trapezoidal fuzzy numbers.

### 3.2. Artificial Neural Network

The ANNs have been developed as generalizations of mathematical models of biological nervous systems. An ANN is a network consisting of collections of very simple processors (neurons) each of which has (a small amount of) local memory, and which operates only on their local data and receives inputs via connections, or links, that are typically unidirectional [42]. Each unit in the network has a rule for computing its output signal by collecting incoming signals and calculating an output signal that is then sent to other units in the network. The rule for computing the output is known as an activation function [43]. The structure of a neural network consists of three layers. The first layer is the input layer that directly interacts with the external world. The second layer is the hidden layer where the computation is performed according to the provided function. The last layer is the output layer where we obtain the output. Information in neural networks is stored as synaptic weights between neurons. The network propagates the input data layer by layer until the output data is generated. If the networks, such as multi-layer perceptrons, with a backpropagation algorithm, have outputs different from the desired output, an error is calculated. Then the error propagates back through the network, and the synaptic weights are adjusted as the error propagates [44]. Generalization is the unique ability that makes ANNs such a powerful tool. In general, neural networks (represented as mathematical models) are a collection of simple computing units connected by a connectivity system. Figure 4 illustrates the fundamental principles of ANN.

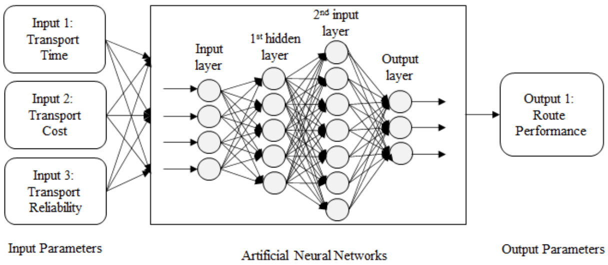


**Figure 4.** Basic Principles of ANN.

## 4. CASE STUDY

### 4.1. Case Presentation and Data Collection

An international multimodal freight transport company in Istanbul specializes in offering comprehensive services for sea and rail transportation using a variety of transport means (e.g., RoRo ships, RoLa trains, ISUs) to provide frequent services from Turkey to Europe, particularly using semi-trailers as transport units for daily shipments. During a global pandemic, road transport between Turkey and Germany was seriously affected. In particular, long queues built up at border crossings and continued throughout the border closure. On the other hand, there was an increase in demand for multimodal services between Istanbul and Hamburg. This chaotic situation led to taking some measures. The company decided to offer a new service route that is suitable for potential customers (freight forwarders) between the origin-destination (O-D) points. The proposed new service route entails operating from a loading terminal in Istanbul to a unloading terminal in Hamburg. These terminals, which can be either port terminals or inland rail terminals, serve as O-D nodes respectively. Additionally, there may exist multiple transfer terminals, known as multimodal centers, where modal shifts occur. These centers enable the transition between transportation modes, whether it involves changing within the same modes (e.g., sea-sea, road-road) or between diverse modes (e.g., road-rail, rail-sea), along the route between the O-D points. The new service route should be innovative enough to reduce transport time and cost, increase transport reliability, and provide high transport route performance. In making the decision, the company assigned three expert interns who searched for all possible routes between the O-D points and identified 17 various routes where any given transportation unit (cargo) is transferred once or twice (modal shift).

**Table 1.** The list of alternative routes

| # | OD | Node (n1) | Leg (l1) | Node (n2) | Leg (l2) | Node (n3) | Leg (l3) | Node (n4) | Time (day) | Cost (€) | Reliability (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Pendik-Kiel | Pendik | Sea | Trieste | Rail | Kiel | n/n | n/n | 4 | 3298 | 90 |
| 2 | Pendik-Hamburg | Pendik | Sea | Trieste | Rail | Vienna | Rail | Hamburg | 6 | 2958 | 86,7 |
| 3 | Pendik-Hamburg | Pendik | Sea | Trieste | Rail | Linz | Rail | Hamburg | 6 | 3078 | 86,7 |
| 4 | Istanbul-Hamburg | Istanbul | Rail | Köln | Rail | Hamburg | n/n | n/n | 6 | 2750 | 75 |
| 5 | Pendik-Hamburg | Pendik | Sea | Trieste | Rail | Kiel | Rail | Hamburg | 6 | 3448 | 85,0 |
| 6 | Pendik-Hamburg | Pendik | Sea | Trieste | Rail | Köln | Rail | Hamburg | 6 | 3298 | 83,3 |
| 7 | Pendik-Hamburg | Pendik | Sea | Trieste | Rail | Salzburg | Rail | Hamburg | 7 | 2898 | 86,7 |
| 8 | Pendik-Hamburg | Pendik | Sea | Trieste | Rail | Duisburg | Rail | Hamburg | 7 | 3398 | 80,0 |
| 9 | Pendik-Hamburg | Pendik | Sea | Trieste | Rail | Milano | Rail | Hamburg | 7 | 2561 | 86,7 |
| 10 | Istanbul-Kiel | Istanbul | Sea | Trieste | Rail | Kiel | n/n | n/n | 5 | 3213 | 87,5 |
| 11 | Istanbul-Hamburg | Istanbul | Sea | Trieste | Rail | Linz | Rail | Hamburg | 6 | 2993 | 85,0 |
| 12 | Istanbul-Hamburg | Istanbul | Sea | Trieste | Rail | Salzburg | Rail | Hamburg | 6 | 2813 | 85,0 |
| 13 | Istanbul-Hamburg | Istanbul | Sea | Trieste | Rail | Vienna | Rail | Hamburg | 6 | 3113 | 85,0 |
| 14 | Istanbul-Hamburg | Istanbul | Sea | Trieste | Rail | Duisburg | Rail | Hamburg | 6 | 3313 | 78,3 |
| 15 | Istanbul-Hamburg | Istanbul | Sea | Trieste | Rail | Ludwigs-hafen | Rail | Hamburg | 6 | 2913 | 85,0 |
| 16 | Istanbul-Hamburg | Istanbul | Sea | Trieste | Rail | Milano | Rail | Hamburg | 6 | 2476 | 85,0 |
| 17 | Istanbul-Hamburg | Istanbul | Sea | Trieste | Rail | Budapest | Rail | Hamburg | 7 | 2613 | 78,3 |

In this paper, the dataset encompasses sea and rail cargo alternative paths operated by an MTP between different terminals or ports. These routes may involve multiple steps and nodes, including transfer stations, within the network. The design of the overall multimodal freight route can incorporate both sea and rail transport modes or utilize either of them individually. Table 1 presents a compilation of 17 existing multimodal routes from Istanbul to Hamburg, specifying the presence of one or two transfers. Among these routes, #1 from Pendik to Kiel, #10 from Istanbul to Kiel, and #4 from Istanbul to Hamburg involve one transfer each. The transfer terminals, such as Trieste and Cologne, facilitate the shift between transport modes, be it from sea to rail or vice versa, or from rail to rail. The remaining routes involve two transfers.

Since performance continuity cannot be easily evaluated by only considering some parameters, the achievement of performance usability for all multimodal transportation systems is a significant concern. However, accurate performance usability values for all systems cannot be guaranteed by using simple equations. In addition, it is quite difficult to express the correlation between control parameters and performance usability with a mathematical function. Therefore, performance usability can be formulated using fuzzy logic rules [45].

### 4.2. Application of Fuzzy Logic

In this study, the fuzzy logic model receives input parameters, it calculates the corresponding output parameters to facilitate the route selection decision-making process. The input parameters are described in such a way:

Transport time: This parameter signifies the total number of travel days required for transportation between O-D points.

Transport cost: This parameter encompasses the overall costs associated with rail and/or sea transportation, including expenses for port/terminal operations, loading/unloading and customs procedures.

Transport reliability: This parameter reflects the percentage of transportation services that reach their destinations within the specified time (on-time arrival). Notably, railway services often face challenges in completing their journeys without delays due to congestion in the railway network and limited operational flexibility. Leading railways employ digital technologies to optimize tariffs and control the network, thereby increasing reliability even with increased train frequency, aiming to overcome operational challenges.

The output parameter, route performance, holds significant importance in ensuring the timely provision and evaluation of multimodal services.

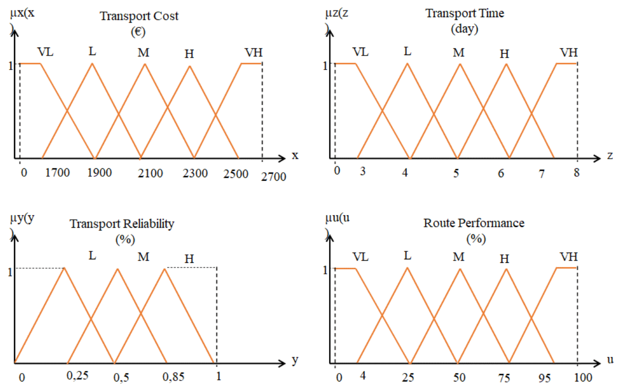


**Figure 5.** The fuzzy sets for output and input variables

The fuzzy set of input and output parameters is given in Figure 5, where membership functions ($\mu_x(x), \mu_z(z), \mu_y(y), \mu_u(u)$) are created by determining five linguistic variables for transport cost, transport time, and route performance, namely; Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). However, the transport reliability parameter is characterized by three linguistic variables: Low (L), Medium (M), and High (H). The determination of membership functions and the maximum/minimum inference range is based on expert opinions. For instance, the transport cost ranges from €2300 to €3800, while the transport time spans from 3 to 8 days with an increment of 1. On the other hand, both transport reliability and route performance range from 0 to 100, divided into 25 intervals. As a result of the maximum/minimum inference, the membership functions exhibit overlapping pairs.

For this research, 75 fuzzy "if-then" rules are generated based on expert opinions. An example of such a rule #34 can be given as follows:

| | |
|---|---|
| IF | Transport Cost = Medium (M), and |
| | Transport Time = High (H), and |
| | Transport Reliability = Low (L) |
| THEN | Route Performance = Very Low (VL) |

The Appendix contains a comprehensive inventory of fuzzy "if-then" rules, in which cost, reliability, and time form the "if part," while performance constitutes the "then part" of the fuzzy rules.

### 4.3. Artificial Neural Network Topology

The most important factor in predicting route performance with ANNs is to construct the neural network architecture correctly. First, we divide our data into training and test data to make predictions. The current data set is divided into 75% training data and 25% test data. ANNs try to extract models by observing existing patterns in the training data. However, encountering two problems during this process is very common: 1) Overfitting or 2) Underfitting. In this case, the model will not work correctly and the error rate between actual and predicted values will be high.

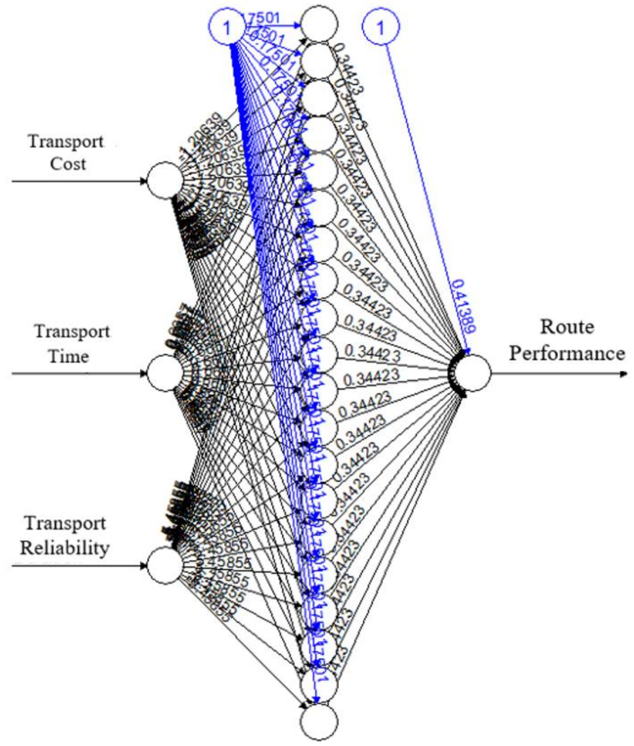


**Figure 6.** Structure of ANN.

In the scope of the case study, performance predictions were made for a data set containing 273 different route alternatives based on the performance values obtained from the Fuzzy model, which is the first step of the study. Figure 6 shows the ANN design. It can be seen that there are three evaluation criteria (input) and one outcome parameter (output). When the neural network topology is examined in detail, 20 hidden layers are used, and “logistic sigmoid” is chosen as the activation function. The logistic sigmoid with an S-shaped structure is a good classifier with the best-known neural network activation function and prevents some generated values from being lost as it produces values between [0,1]. A very small error rate of “0.00005” was determined as the threshold value. A fixed number of “0.5” was assigned as the initial input weight. The “feed-forward” method was used as the ANN algorithm. The sum of squared errors (SSE) was selected as the error function parameter. Since the activation function for the linear output parameter was determined as the logistic sigmoid, the value “false” was assigned.

## 5. RESULT AND DISCUSSION

In the first step of the study, the performance results calculated using the fuzzy logic approach are given in Figure 7. Three out of the 17 multimodal cargo routes accomplished higher performance according to the results: Pendik-Kiel with 89%, Istanbul-Hamburg with 83%, and Istanbul-Kiel with 82% route performance, respectively. Semi-trailers between Istanbul and Kiel made one transfer while cargos between Istanbul and Hamburg made two transfers. Therefore, it is possible to say that the number of transfers also has an impact on route performance. Delays and cancellations may occur for various reasons (such as infrastructure deficiencies, capacity problems, etc.) However, container transportation, which standardizes dimensions and properties, can decrease multimodal transfer times, and raise cost and fuel efficiency. In addition, automatic transfer management systems such as ISU, Megawing, Flexiwaggon, ModaLohr and so on can facilitate transfer operations and optimize efficiency on platforms, which can also increase route performance. MTP could determine one of the top three routes with the highest performance and if there is any interruption in the chosen route, the others can be considered as alternative routes. As a result of this case study, a novel multimodal cargo transportation route between Istanbul and Kiel has been selected as a cargo route, and the additional two routes between Istanbul and Hamburg will be considered as alternative route opportunities.

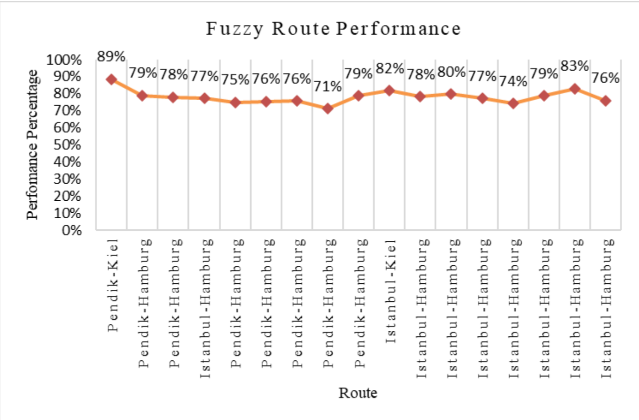


**Figure 7.** Evaluation of the performance of different route options

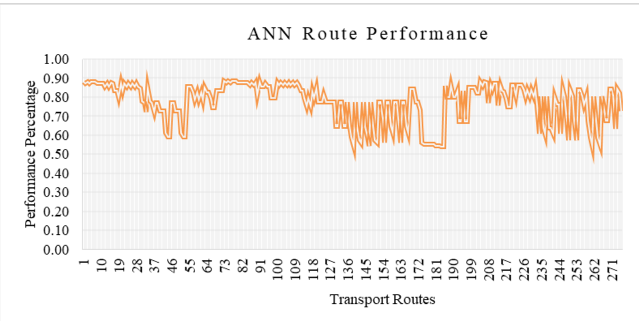


**Figure 8.** Route performance using ANN.

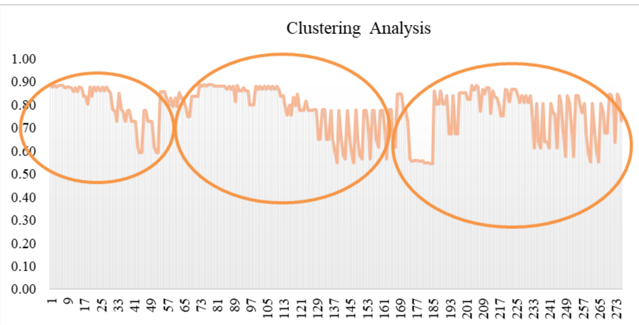


**Figure 9.** Clustering analysis using ANNs.

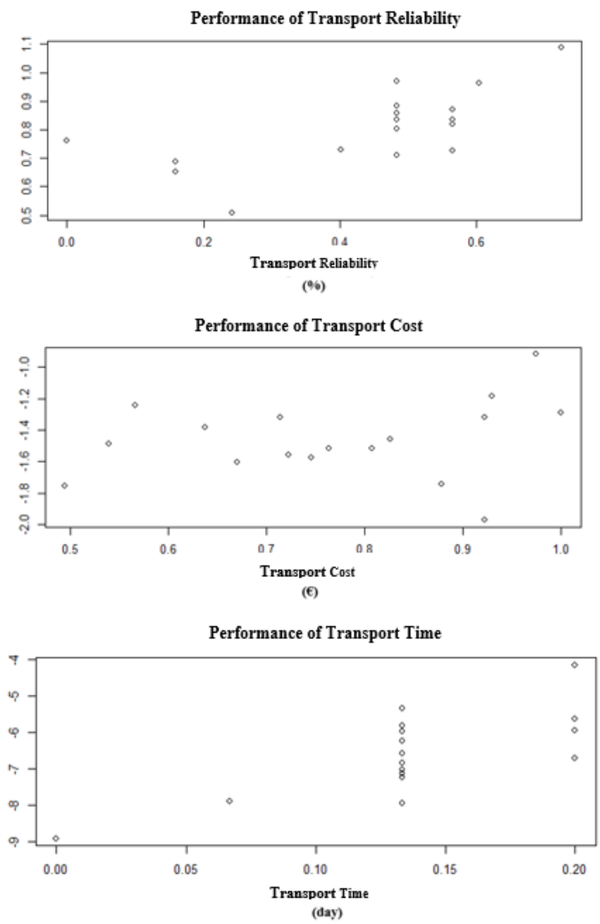


**Figure 10**. Parameter analysis as a result of ANN.

As a second stage of the case study, the results obtained from fuzzy logic were used to train ANNs to solve the pattern between route safety, transport time, and cost parameters. In this stage, the ANN method is one of the best methods that can be used when there is not enough information about the relationship between input values, and when the positive and negative effects of these values are considered to predict the output value. The method can make predictions about route performance on the test data set using the patterns it obtained in its training data. In this study, the success of the ANN model is shown to have a correlation coefficient of 96%, indicating that the model performs well. Figure 8 illustrates that the route performances in the new data set for which predictions are being requested exhibit a significant amount of fluctuation.

In Figure 9, a clustering was performed to provide more detailed information about the predictions made, and it was observed that the common feature exhibited by these alternatives was that the travel time was very long. This directly affected the performance of the route and caused it to be at very low levels.

The relationship between the evaluation criteria: transport cost, route safety, transport time, and route performance, are summarized in the following graphs in the parameter analysis conducted through the ANN method. When we look at the relationship between transport cost and performance, we can see that the effect of cost fluctuates around the 0-axis. It is known that cost is an important parameter in determining route performance, but it is not a very significant input in distinguishing. It has only shown an effect between 1.0-2.0. The main determinant is seen to be the effect of transport time. Transport time has become the most distinctive parameter (4.0-9.0) and decreases in route performance are observed when each day increases. The effect of route reliability has only been effective in the range of 0.5 - 1.1. In Figure 10, it can be seen how much each input value affects the route performance result.

## 6. CONCLUSION

The COVID-19 epidemic has had a significant impact on transportation infrastructure across the world. It is obvious that the pandemic has accelerated current trends and generated new problems for the sector, even though the full amount of the impact is still unknown. Transportation networks will need to be redesigned as the globe adjusts to the pandemic to make sure they can meet modifying needs in society. Especially due to the lockdowns, travel restrictions, and social distancing measures implemented by the government, finding, and evaluating alternative routes has become critically important. At this point, this study proposes a novel approach for selecting the most suitable route among alternative multimodal freight transport routes using an ANN integrated with a fuzzy logic model. By considering transport time, cost, and reliability data, the proposed model predicts which routes are more elastic and resistant to vulnerabilities. As a result of the proposed ANN integrated with a fuzzy logic model, it was determined that the Pendik and Kiel route is the most suitable route. When looking at the characteristics of this route, even though transportation cost is high, it is seen that it is selected as the best route since transportation reliability and transportation time values are low. Considering the transportation under COVID-19, the alternative route of Pendik-Kiel is more reliable in terms of COVID-19 transmission due to the short distance, and it is a fast route against lockdown problems, which is very significant.

This allows MTPs to offer more reliable and efficient services to their customers. The model was trained using a dataset that includes route performance estimates as output parameters and performance predictions were made for a larger dataset of multimodal transportation routes. Overall, this approach can improve the decision-making process in the selection of optimal routes for multimodal freight transportation services.

Future research can expand on the proposed route selection model by incorporating additional parameters like road, construction, accident situations transportation volume, and distance, transportation risk. Furthermore, including road transport in the model can aid in determining the location of inland terminals for sea and rail transportation based on O-D flows analyzed through data analytics. The performance of the model can also be compared to other machine learning algorithms such as random forest and support vector machine methods. These potential advancements can further improve the accuracy and efficiency of the route selection process in multimodal freight transportation services.

## ACKNOWLEDGEMENT

The first author, Dr. Yasanur Kayikci, gratefully acknowledges the support provided by the Scientific and Technological Research Council of Turkey under grant number 116C048 for this research.

**Author contributions:** Concept – Y.K., E.C.; Data Collection & Processing – Y.K, E.C.; Literature Search – Y.K., E.C.; Writing – Y.K., E.C.
**Conflict of Interest:** No conflict of interest was declared by the authors.
**Financial Disclosure:** Scientific and Technological Research Council of Turkey, Grant/Award Number: 116C048.

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## APPENDIX

**Table 2.** Fuzzy rule based on the experts' opinions

| Rule Number # | *If part* Cost (€) | Reliability (%) | Time (day) | *Then part* Performance (%) | Rule Number # | *If part* Cost (€) | Reliability (%) | Time (day) | *Then part* Performance (%) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | VL | L | VL | M | 39 | M | M | H | L |
| 2 | VL | L | L | M | 40 | M | M | VH | L |
| 3 | VL | L | M | L | 41 | M | H | VL | VH |
| 4 | VL | L | H | L | 42 | M | H | L | VH |
| 5 | VL | L | VH | VL | 43 | M | H | M | H |
| 6 | VL | M | VL | VH | 44 | M | H | H | M |
| 7 | VL | M | L | H | 45 | M | H | VH | L |
| 8 | VL | M | M | M | 46 | H | L | VL | L |
| 9 | VL | M | H | L | 47 | H | L | L | L |
| 10 | VL | M | VH | L | 48 | H | L | M | VL |
| 11 | VL | H | VL | VH | 49 | H | L | H | VL |
| 12 | VL | H | L | H | 50 | H | L | VH | VL |
| 13 | VL | H | M | H | 51 | H | M | VL | M |
| 14 | VL | H | H | H | 52 | H | M | L | M |
| 15 | VL | H | VH | M | 53 | H | M | M | L |
| 16 | L | L | VL | M | 54 | H | M | H | VL |
| 17 | L | L | L | M | 55 | H | M | VH | VL |
| 18 | L | L | M | L | 56 | H | H | VL | H |
| 19 | L | L | H | L | 57 | H | H | L | M |
| 20 | L | L | VH | L | 58 | H | H | M | M |
| 21 | L | M | VL | H | 59 | H | H | H | L |
| 22 | L | M | L | H | 60 | H | H | VH | VL |
| 23 | L | M | M | M | 61 | VH | L | VL | L |
| 24 | L | M | H | M | 62 | VH | L | L | L |
| 25 | L | M | VH | L | 63 | VH | L | M | VL |
| 26 | L | H | VL | VH | 64 | VH | L | H | VL |
| 27 | L | H | L | H | 65 | VH | L | VH | VL |
| 28 | L | H | M | H | 66 | VH | M | VL | L |
| 29 | L | H | H | H | 67 | VH | M | L | L |
| 30 | L | H | VH | M | 68 | VH | M | M | L |
| 31 | M | L | VL | M | 69 | VH | M | H | VL |
| 32 | M | L | L | L | 70 | VH | M | VH | VL |
| 33 | M | L | M | L | 71 | VH | H | VL | M |
| 34 | M | L | H | VL | 72 | VH | H | L | L |
| 35 | M | L | VH | VL | 73 | VH | H | M | L |
| 36 | M | M | VL | M | 74 | VH | H | H | VL |
| 37 | M | M | L | M | 75 | VH | H | VH | VL |
| 38 | M | M | M | M | | | | | |

Legend: Very Low (VL), Low (L), Medium (M), High (H), Very High (VH)