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ARTICLE

Route selection in multimodal transportation networks: a hybrid multiple criteria decision-making approach

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ABSTRACT

The objective of this study is to propose a novel hybrid multiple criteria decision-making (MCDM) approach for route selection in multimodal supply chains. The proposed hybrid MCDM approach integrates the analytic hierarchy process (AHP), data envelopment analysis (DEA), and the technique for order of preference by similarity to ideal solution (TOPSIS) to address the problem based on quantitative and qualitative criteria. It utilizes the advantages of each approach, and can reconcile conflicting criteria and divergence of decision makers' judgments to select the most appropriate alternative as well as provide the preferred order of the multimodal routes. Furthermore, an empirical route selection between Thailand and Vietnam is applied to validate the abilities of the proposed hybrid MCDM approach. The new methodological contribution of this study assists decision makers and transport policymakers to design an effective decision support tool for solving transportation and logistical problems in real-world decision-making processes.

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1. Introduction

A multimodal freight transportation system concerning the moving of tangible products between two or more places with at least two modes of transport is a pillar for global supply chains and international distribution systems [1]. Among the numerous components of such a transport system, selection of freight routes is a significant component because it always affects overall cost and distribution efficiencies. The problem has become challenging due to the large variety of maximizations or minimizations in conflicting quantitative and qualitative objectives, and can be considered as a simultaneous multiple criteria decision-making (MCDM) problem [2]. Today's real-world transportation problems, route selection in multimodal transportation networks does not emphasize either the lowest total cost or the shortest time, but attempts to find the most appropriate route, which can simultaneously be defined as one that maximizes benefit criteria and as one that minimizes non-benefit criteria, e.g., decreasing total cost or time, maximizing reliability, increasing security, and minimizing risk; therefore, a decision maker inescapably encounters a trade-off of many criteria with respect to a set of available alternative routes [3]. It is hard to know which one is the better choice, and each conflicting criterion is cumbersome to measure comprehensively due to its specific characteristics. To address the problem of route selection, the best compromise solution between multiple objectives is considered.

Most previous works related to multimodal route selection have considered both quantitative and qualitative criteria from various viewpoints. The quantitative criteria of transportation cost and time have usually been investigated by using the multimodal transport cost-model [4–6]. Qualitative criteria, as non-quantifiable criteria (e.g., risks, reliability, security, capability, reputation), have commonly been examined by MCDM approaches, which can rank alternatives and/or provide the most optimal alternative in accordance with their theories [7]; these approaches are favorable owing to ease-of-use, reasonableness, comprehensibility, intuitive logic, and an ability to evaluate attributes in simple mathematical representation. Nevertheless, the use of a single MCDM approach is less precise than that of a hybrid approach, which integrates several MCDM approaches. This extension is the best method in the real-word decision-making problems because it can eliminate each other's shortcomings and combine each other's advantages [8]. For example, one approach may be used to analyze a prioritization while another approach is employed to rank candidates, thus facilitating a more accurate decision [9]. During the last decades, several studies have implemented various hybrid MCDM approaches to address the problems of route selection from different perspectives. Kengpol et al. [10] developed a computerized program for possible multimodal transportation

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routing, in which analytic hierarchy process (AHP) was adopted to reflect decision maker's preferences and combined with zero-one goal programming (ZOGP). Wang and Yeo [11] performed fuzzy group decision-making (GDM) and elimination et choice translating reality (ELECTRE) for intermodal route selection between Korea and Kazakhstan. Singh and Singh [12] created a hybrid decision support concept, in which AHP was employed to calculate the relative weights of criteria whereas technique for order preference by similarity to ideal solution (TOPSIS) was also adapted to determine a ranking of alternative routes in a multiple criteria environment. Kengpol and Tuammee [13] conceptualized a decision support strategy for selecting ecological routes in multimodal supply chain systems, wherein AHP–data envelopment analysis (DEA) methodology was used to calculate a local weight of each criterion. Meethom and Koohathongsumrit [14] stated fuzzy AHP and TOPSIS as a freight transportation routing algorithm; the most optimal route was obtained by this algorithm. Kaewfak et al. [15] invented a two-stage model of an integrated fuzzy AHP–DEA to rank multimodal freight routes. Meethom and Koohathongsumrit [16] established an interactive software-based system. Multilayer zero goal programming combined fuzzy AHP was introduced to solve the routing problem of road freight transportation. Kengpol et al. [17] conducted a decision-making framework, which consists of AHP, DEA, and ZOGP. This framework can select the most preferable choice.

Although a number of hybrid approaches have been frequently reported from a variety of perspectives, none has presented an approach to identify the most appropriate multimodal route based on the properties of each criterion as well as on decision makers' preferences using a combination of more than two MCDM approaches. There was an attempt to use this idea in the literature for choosing a multimodal freight corridor; nevertheless, it focused on selecting an alternative with regard to individual goals of criteria by minimizing a total deviation. AHP, DEA, and TOPSIS can address these gaps because they each have different merit, as follows: (1) AHP and its expansion have favorably been applied to prioritize criteria, (2) DEA can be used to assess criteria and rank alternatives efficiently, and (3) TOPSIS has been employed to select the best alternative based on the values of the criteria, including the distance between the best and worst alternatives. However, these significant approaches have not been used in combination to solve the route selection problem. Therefore, the key motivation of this study is to construct a new hybrid MCDM approach that utilizes the strengths of the above-mentioned approaches to increase the reliability of decision-making results as well as to decrease the imprecise information and subjective judgments of decision makers.

This study made a three-fold contribution. First, the hybrid MCDM approach, which consists of AHP, DEA, and TOPSIS is proposed; AHP is performed to reflect decision makers' preferences via the relative weights, whereas DEA, with risk assessment, is adopted to compute local risk scores of qualitative criteria with respect to all alternative routes. TOPSIS is also conducted to assign ranks to alternative routes based on the total transportation cost, transportation time, and weighted local risk scores. Second, the most appropriate route, selected from routes ranked in descending order in accordance with their scores between each alternative and the ideal range, represents the best compromise solution among conflicting elements. Third, an empirical study of multimodal route selection between Thailand and Vietnam is carried out to validate the application of the proposed hybrid MCDM approach.

The remainder of this paper is structed as the following: Section 2 reviews the literature on the relevant methods and past hybrid approaches. Section 3 introduces the proposed hybrid MCDM approach for multimodal route selection. Section 4, the case study with real data and discussion validate the proposed methodology. In Section 5, the theorical and practical implications are clarified, Finally, Section 6 is the conclusion of this study.

2. Literature review

This section briefly reviews some features and applications of relevant approaches to route selection in multimodal transportation networks. The related approaches, AHP, DEA, and TOPSIS are combined to establish the new hybrid MCDM approach.

The AHP, which was developed by Saaty in the early 1970s, structures a problem as a hierarchy representing the relationships between a goal, criteria, and objectives, as well as alternatives [18]. The major advantages of this approach lie in the good handling of both qualitative and quantitative data, the ease of comparing each pair of attributes, and its consistency. This approach has some disadvantages, however: it is not suitable for many attributes and cannot measure local scores of criteria. The applications of AHP have taken place in many areas: education, healthcare, chemistry, management, energy, ecology, etc. One early idea used only AHP in the matter of multimodal route selection; more details can be found in various articles [19–22]. Later, this approach and the fuzzy set theory were combined (and named fuzzy AHP) for selecting a multimodal freight route [23,24]. Presently, as described in the previous section, AHP is commonly used in combination with the other MCDM approaches to solve route selection problems. The existing integrations can be found in the literature

[10,12,13,17]. Nonetheless, the use of AHP in combination with DEA and TOPSIS for route selection has not been attempted.

DEA is a nonparametric benchmarking approach to estimate relative efficiency by comparing the production frontier with homogeneous decision-making units containing both multiple outputs and inputs [25]. This approach was first developed by Charnes et al. [26], who extended the measurement of technical efficiency introduced by Farrell [27]. The idea behind DEA is to compare units with a linear combination of others in a sample. It assigns an efficiency score equivalent to one to efficient units, which are placed on the production efficient frontier; in contrast, the inefficient units, with scores that are less than one, are not located on the frontier [28]. The inefficient score reflects the radial distance between the frontier and the inefficient unit. DEA has several benefits: it can be used with many criteria and alternatives, it provides efficiencies of decision-making units, and it has underlying assumption of the shape of the frontier relating to inputs and outputs [29]. In contrast, its limitations are as follows: incapacity for pairwise comparison, lack of rankings for alternatives based on their efficiencies, and an inability to check the final result. DEA has widely been accepted for measuring the performance and efficiency of decision-making units in several sectors: finance, agriculture, education, energy, sport, healthcare, and so on. Despite its popularity, a few studies focus on risk calculation; full details of this scheme can be found in several publications [30–32]. Notwithstanding, few studies have used this approach together with a risk assessment method for route selection. For example, Kengpol and Tuammee [13] combined AHP and DEA to prioritize the risks of a multimodal transportation route. Kaewfak et al. [15] modeled a fuzzy AHP and DEA based on risk analysis. Based on the literature, it observed that DEA combined with AHP and TOPSIS had not been employed to calculate local risk scores of each criterion for route selection.

The TOPSIS, which was originally developed by Hwang and Yoon [33], can identify the best alternative based on the nearest from the positive ideal solution and the farthest from the negative ideal solution [34]. At the core of this approach are a ranking of options based on a compensatory aggregation of the Euclidean distance and an ability to consider a vast number of attributes [35]. Conversely, there are some irrationalities in this approach: ignoring pairwise judgment of attributes and an uncertainty in obtaining relative weights of criteria. Because TOPSIS is simply implementation as well as reliable preference order, it has been applied in numerous areas: manufacturing, business, marketing, tourism, banking, etc. In the past, some earlier studies characterized the route selection problem and related issues by using only TOPSIS; for example, Liang and Meng [2] formulated the improved and developed fuzzy TOPSIS to sort routes. Moon et al. [36] adopted this approach to rank the possible freight corridors from Korea to Europe based on their competitiveness and group solution. Pham et al. [37] dealt with decision making regarding route selection from Hong Kong to New York. Presently, the TOPSIS has been extended for route selection by combining it with other MCDM approaches; the details of this expansion can be found in these studies [12,14]. However, the approach with weighted local risk scores from AHP and DEA as the input has not been investigated for selecting multimodal routes.

The integration of approaches into a hybrid decision analysis is not a new idea; it has been frequently proposed to create a robust approach by taking advantages of their strengths and accompaniments each other's weaknesses [38–40]. There are many articles related to the hybrid MCDM approaches for multimodal route selection. Table 1 summarizes the existing hybrid approaches and single methods in this context.

According to Table 1, the integration of AHP, DEA, and TOPSIS for solving route selection decision-making problems has not been found in the literature. Nevertheless, only a few authors have applied the existing methods integrating these approaches in different fields. For instance, Amiri et al. [30] theorized a robust integrating method to prioritize portfolios in a foreign exchange market, in which the eigenvector-based AHP determined the relative weights; TOPSIS was illustrated to obtain the best portfolio based on the AHP–DEA results. Çelen and Yalçın [41] presented a combined procedure to measure quality performances of the electricity distribution utilities in Turkey; however, the fuzzy AHP was used to determine the relative weights of criteria instead of the AHP, while the TOPSIS was accepted to indicate the qualities. The final results were approved by DEA. Tao et al. [42] showed an integrated model for robot selection, in which the combinations between data and parameters were analyzed by DEA; AHP combined an axiomatic fuzzy set to compute the relative weights of attributes, and TOPSIS was performed to obtain the perfect robot. Yousefi and

Table 1. Existing hybrid and single MCDM approaches on multimodal route selection problem.

Approach applied	Reference
AHP–ZOGP	[10]
ELECTRE–GDM	[11]
AHP–TOPSIS	[12]
AHP–DEA	[13]
Fuzzy AHP–TOPSIS	[14]
Fuzzy AHP–DEA	[15]
Fuzzy AHP–MZOGP	[16]
AHP–DEA–ZOGP	[17]
AHP	[19–22]
Fuzzy AHP	[23,24]
TOPSIS	[36]
Fuzzy TOPSIS	[37]

Hadi-Vencheh [43] employed DEA to evaluate and compare vehicles by using AHP, TOPSIS, and the two combined. Chandra Das et al. [44] aimed to evaluate and prioritize the performances of Indian technical academies, wherein the purpose was applied to solve the problem. The fuzzy set theory was used to improve AHP and TOPSIS. As mentioned above, only a limited number of studies used these three approaches appear in the literature in which a hybrid approach with more than two MCDM approaches for multimodal route selection has not been used. To meet the challenge of integrating a more trustworthy approach, the novel hybrid MCDM approach integrating AHP, DEA, and TOPSIS is proposed in this study.

3. The proposed hybrid mcdm approach for multimodal route selection

In real-world situations, route selection in multimodal transportation networks is more than just determining either the least transportation cost route or the lowest risk route, because this problem involves many conflicting criteria (e.g., cost, time, and risks) and their priorities. A consideration of these criteria in isolation leads decision makers to unsatisfactory results, much to their detriment and that of the organization. Hence, it is necessary to strive for a compromise between quantitative and qualitative criteria including decision makers' preferences. To address the complex problem, the proposed hybrid MCDM approach can be employed effectively to obtain the most appropriate multimodal route. In this section, the details of the proposed hybrid approach are clarified in the following sections and illustrated in Figure 1.

3.1. Calculating relative weights

The goal of this phase is to calculate the relative weights by using AHP because an equal weighting is not suitable for decision-making problems. These weights are analyzed via systematic procedures until an acceptable consistency index is obtained. The details are shown in the following steps:

Step 1: A pairwise comparison matrix is constructed. Decision makers can decide their preference from pairs of homogenous levels by using the scales of importance assessment ranging from "Equal importance" to "Extreme importance," which are given in Table 2 [45]. Let $C = \{C_{ji} \mid j, i = 1, 2, \ldots, m\}$ be the set of criteria, the pairwise comparison matrix is presented in Table 3. However, if the choices are made by more than one decision maker, a geometric mean is computed [46]. The number of comparisons made by the decision makers is equal to $m \times (m - 1)/2$, where m is the number of criteria, where a_{ji} is a crisp scale comparing between the jth and ith criteria; $a_{jj} = 1$; $a_{ij} = 1/a_{ji}$; $a_{ji} \neq 0$; $j, i = 1, 2, \ldots, m$.

Step 2: The normalized pairwise comparison matrix is followed by diving each scale by its column total, as presented in Equation (1).

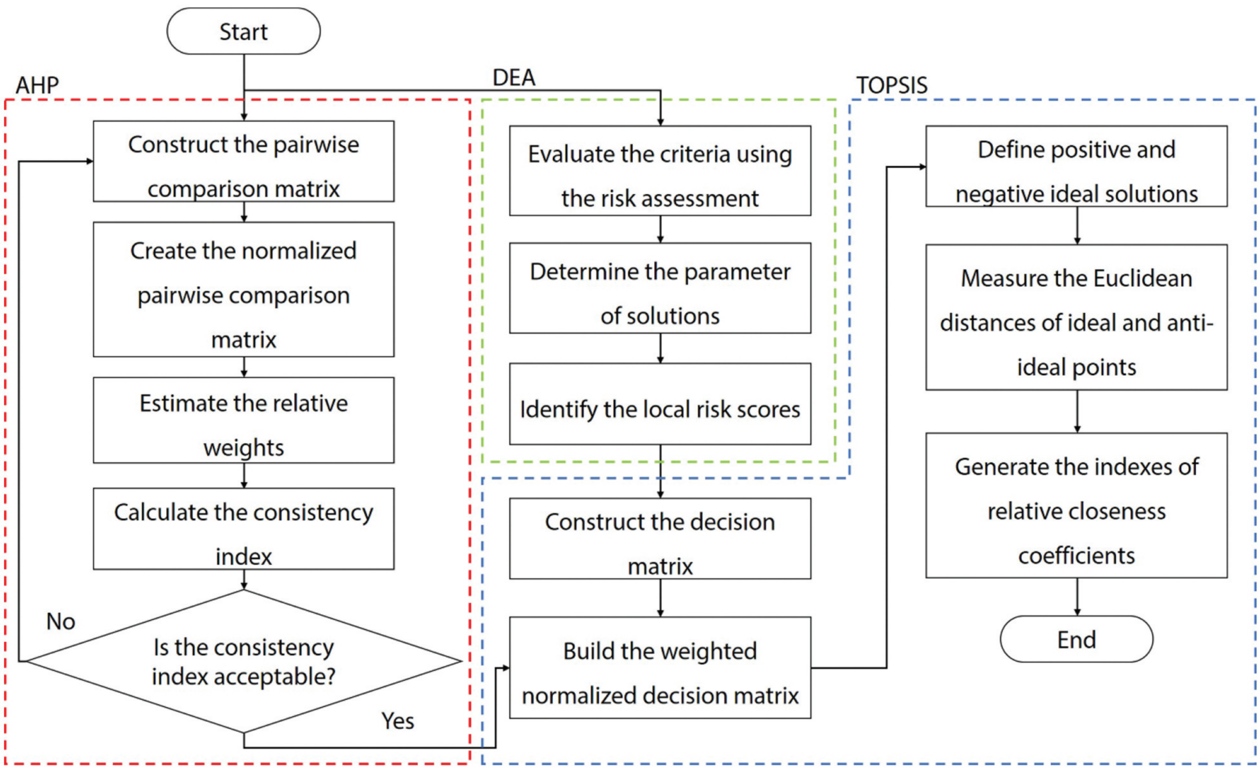

Figure 1. Flowchart of the proposed hybrid MCDM approach.

Table 2. Scale for importance assessment.

Intensity of importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values

Table 3. Pairwise comparison matrix.

Criteria	C_1	C_2	$\cdots$	C_n
C_1	a_{11}	a_{12}	$\cdots$	a_{1m}
C_2	a_{21}	a_{22}	$\cdots$	a_{2m}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
C_m	a_{m1}	a_{m2}	$\cdots$	a_{mm}

$$a^*_{ji} = \frac{a_{ji}}{\sum_{j=1}^{m} a_{ji}} \tag{1}$$

where a^*_{ij} is the normalized rating of the jth and ith criteria.

Step 3: The relative weight of each criterion is estimated by normalizing the summation of the normalized ratings in each row, as shown in Equation (2).

$$w_j = \frac{\sum_{i=1}^{m} a^*_{ji}}{m} \tag{2}$$

where w_j denotes as the relative weight of the jth criterion; $\sum_{j=1}^{m} w_j = 1$; $w_j \geq 0$.

Step 4:A consistency index is calculated. Firstly, the eigenvectors are computed by multiplying the pairwise comparison matrix and the relative weights. Next, the eigenvectors divided by the associated relative weights are averaged to identify the largest eigenvalue [47]. Therefore, the consistency index is identified by Equation (3).

$$\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{m}}{\mathrm{m} - 1} \tag{3}$$

where CI, $\lambda_{\max}$, and m denote as the consistency index, largest eigenvalue, and number of criteria. The consistency ratio is formulated, as given in Equation (4).

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{4}$$

where CR and RI are the consistency ratio and random consistency index; RI can be obtained from Table 4. The CR must not be greater than the acceptable CR, which is dependent on the size of the matrix: 0.05 for the matrix 3×3, 0.08 for the matrix 4×4, and 0.10 for all larger matrices [48–50].

Table 4. Random consistency index.

m	3	4	5	6	7	8	9	10	11	12
RI	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48

If the CR is not acceptable, the pairwise comparison matrix is revised. Generally, the matrix sizes of 1 and 2 are regularly consistent.

3.2. Measuring local risk scores

This phase deals with qualitative criteria, which are difficult to measure because they directly involve human judgment. Risk assessment is the most suited to handling the situation. This technique is a systematic method to measure uncertainty; it is often used to determine risk scores of unexpected events together with MCDM approaches [51]. In the current study, the risk assessment based on DEA is performed to calculate the local risk scores of each qualitative criterion, because decision makers can assign grades to the criteria corresponding to each route as well as find the most optimal solution between decision variables and decision makers' opinions. The procedures for calculating the local risk scores are developed as follows [30–32,44,52]:

Step 1: The criteria are evaluated by the risk assessment. The decision makers, who express their judgments of probabilities and consequences for each risk, identify risk levels by multiplying the scales for likelihood and severity [53]. These levels determine the linguistic assessment grades for each criterion. Assuming $G = \{G_{jg} \mid j = 1, 2, \ldots, m;\ g = 1, 2, \ldots, g_j\}$ be the set of the linguistic assessment grades for the jth criterion, $A = \{A_i \mid i = 1, 2, \ldots, n\}$ be the set of routes, and $ND = \{ND_{ij1}, ND_{ij2}, \ldots, ND_{ijg_j}\}$ be the number of decision makers under the ith route and jth criterion with respect to every grade, the results of assessment can be defined as $R\{C_j(A_i)\} = \{(G_{j1}, ND_{ij1}), (G_{j2}, ND_{ij2}), \ldots, (G_{jg_j}, ND_{ijg_j})\}$. Thus, the distribution decision matrix for the linguistic assessment grades for every route is presented in Table 5, where $\sum_{g=1}^{g_j} ND_{ijg} = N_j$; N_j denotes as the total number of decision makers under the jth criterion; n is the number of routes; m is the number of criteria; g_j is the number of linguistic assessment grades corresponding to the jth criterion; $i = 1, 2, \ldots, n$; $j = 1, 2, \ldots, m$; $g = 1, 2, \ldots, g_j$.

Step 2: A parameter of solutions can parameter of solutions can be obtained by summing the products of the decision variables and the number of decision makers in the associated grade. The following model derived from DEA is mathematically formulated to find the solution.

$$\text{Maximize } \alpha_j \tag{5}$$

$$\text{Subject to}: \alpha_j \leq \sum_{g=1}^{g_j} S(G_{jg})(ND_{ijg}) \leq 1 \tag{6}$$

$$S(G_{j1}) \geq 2S(G_{j2}) \geq \ldots \geq g_j S(G_{jg_j}) \geq 0$$

where α_j represents the parameter of the solution corresponding to the jth criterion; $S(G_{jg_j})$ is the decision variable of the gth grade and jth criterion; $S(G_{j1}) \geq 2S(G_{j2}) \geq \ldots \geq g_j S(G_{jg_j})$ is the strong ordering restriction specified linguistic assessment grades.

Step 3: The local risk scores of each route for all criteria can be identified by the lowest value of the solution's parameters, as shown in Equation (7). The optimal decision variables provide the minimum α.

$$\theta_{ij} = \sum_{g=1}^{g_j} S^*(G_{jg})(ND_{ijg}) \tag{7}$$

where θ_{ij} denotes as the local risk scores of the ith route and jth criterion ranging between 0 to 1; $S^*(G_{jg_j})$ is the most optimal decision variable of the gth grade and jth criterion.

3.3. Selecting the most appropriate multimodal route

This phase aims to rank the preference order of multimodal routes based on the relative weights and the local risk scores by TOPSIS. The procedures for this stage consist of the following steps:

Step 1: Let $x = \{x_{ij} \mid i = 1, 2, \ldots, n; j = 1, 2, \ldots, m\}$ be the set of raw values for all criteria with respect to every alternative [54], the decision matrix is constructed, as shown in Table 6.

Step 2: The normalized decision matrix is determined, as shown in Equation (8).

$$\lambda_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{8}$$

where λ_{ij} is the normalized value of the ith route and jth criterion.

Step 3: The weighted normalized decision matrix is built by multiplying the normalized decision matrix and the relative weights [55], as given in Equ ation (9).

$$v_{ij} = w_j \times \lambda_{ij} \tag{9}$$

where v_{ij} represents the weighted normalized value of the ith route and jth criterion; w_j is the relative weight of the jth criterion and $\sum_{j=1}^{m} w_j = 1$.

Step 4: Both positive and negative ideal solutions are correspondingly elaborated. The positive ideal solution maximizes the beneficial criteria and minimizes the non-beneficial criteria, whereas the negative ideal solution minimizes the beneficial criteria and maximizes the non-beneficial criteria [56], as shown in Equations (10) and (11) accordingly.

$$\begin{aligned} A^+ &= \{v_1^+, v_2^+, \ldots, v_m^+\} \\ &= \{(Max_i\ v_{ij} \mid j \in B), (Min_i v_{ij} \mid j \in NB)\} \end{aligned} \tag{10}$$

$$\begin{aligned} A^- &= \{v_1^-, v_2^-, \ldots, v_m^-\} \\ &= \{(Min_i\ v_{ij} \mid j \in B), (Max_i\ v_{ij} \mid j \in NB)\} \end{aligned} \tag{11}$$

where A^+ is a positive ideal solution and the set of the highest values for each criterion; A^- is a negative ideal solution and the set of the lowest values for each criterion; B and NB relate to beneficial criteria and non-beneficial criteria [57].

Step 5: The Euclidean distance principle is applied to measure the dispersions of the ideal and anti-ideal points [58], as given in Equations (12) and (13), respectively.

$$ED_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^+)^2} \tag{12}$$

$$ED_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^-)^2} \tag{13}$$

where ED_i^+ and ED_i^- denote as the distances from positive and negative ideal solutions for the ith route.

Step 6: The indexes of relative closeness coefficients for each alternative are generated, as shown in Equation (14). These indexes, indicating the distance of both solutions, lie between 0 to 1. A larger value of the index means a better route [59]. Consequently, the route with the largest relative closeness coefficient is the most appropriate alternative. The ranking of the routes is obviously assigned based on the values of the coefficients in descending order.

$$CC_i = \frac{ED_i^-}{ED_i^+ + ED_i^-} \tag{14}$$

where CC_i is the closeness coefficient of the ith route.

Table 5. Distribution decision matrix for linguistic assessment grades.

	C_1			…	C_j			…	C_m		
	G_{11}	…	G_{1g_1}	…	G_{j1}	…	G_{jg_j}	…	G_{m1}	…	G_{mg_m}
A_1	ND_{111}	…	ND_{11g_1}	…	ND_{1j1}	…	ND_{1jg_j}	…	ND_{1m1}	…	ND_{1mg_m}
⋮	⋮	…	⋮	…	⋮	…	⋮	…	⋮	…	⋮
A_i	ND_{i11}	…	ND_{i1g_1}	…	ND_{ij1}	…	ND_{ijg_j}	…	ND_{im1}	…	ND_{img_m}
⋮	⋮	…	⋮	…	⋮	…	⋮	…	⋮	…	⋮
A_n	ND_{n11}	…	ND_{n1g_1}	…	ND_{nj1}	…	ND_{njg_j}	…	ND_{nm1}	…	ND_{nmg_m}

Table 6. Decision matrix.

	C_1	C_2	$\cdots$	C_m
A_1	x_{11}	x_{12}	$\cdots$	x_{1n}
A_2	x_{21}	x_{22}	$\cdots$	x_{2n}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
A_n	x_{n1}	x_{n2}	$\cdots$	x_{nm}

4. Application and discussion

This section outlines a workable step-by-step procedure for applying the proposed hybrid MCDM approach viably. A realistic multimodal route selection problem from a factory located in Ayutthaya province, Thailand to a distribution center in the heart of Haiphong, Vietnam is illustrated through a case study in the automotive manufacturing industry. There are 16 feasible routes for this study. The details of each route, including the transportation cost (USD) and time (hours), are approximated based on a 20-foot container by the multimodal transport cost-model [60], as shown in Table 7.

For a route selection problem, the criteria for its solution are important to decision makers. In this study, the criteria can be broadly classified into two types: quantitative and qualitative criteria. The quantitative criteria are transportation cost and time, while the qualitative criteria are risks known as disruptions or unexpected breakdowns of supply chains obstructing the completion of the transportation in multimodal freight networks [61]. Thus, the criteria for the route selection problem in the current study are the following:

Transportation cost (C_1) means an overall charge involved in the movement of containers between origins and destinations; it includes fixed, variable, and backhaul costs.

Table 7. Details of each route.

	Details	Cost	Time
A_1	Aya– Mdh/Svk – Dsv/Lb – Dht ++ Hpt – Dtc	3,750	102
A_2	Aya – Mdh/Svk – Dsv/Lb – Dnp ## Hpp – Dtc	2,660	115
A_3	Aya – Lcp ## Sgp – Dtc	4,100	133
A_4	Aya – Lcp ## Sgp – Sgt ++ Hpt– Dtc	1,980	158
A_5	Aya – Lcp ## Sgp ## Hpp – Dtc	2,865	167
A_6	Aya – Ayp/Pop – Bav/Mob – Dnp ## Hpp – Dtc	3,200	128
A_7	Aya – Ayp/Pop – Bav/Mob – Dnt ++ Hpt– Dtc	3,950	119
A_8	Aya – Ayp/Pop – Bav/Mob – Sgp ## Dnp – Dnt ++ Hpt – Dtc	4,800	170
A_9	Aya – Ayp/Pop – Bav/Mob – Sgp ## Dnp – Dtc	5,350	144
A_{10}	Aya – Ayp/Pop – Bav/Mob – Sgt ++ Hpt – Dtc	4,440	123
A_{11}	Aya – Ayp/Pop – Bav/Mob – Sgp ## Hpp – Dtc	4,585	154
A_{12}	Aya – Lcp ## Dnp – Dis	3,570	140
A_{13}	Aya – Lcp ## Dnp – Dnt ++ Hpt – Dtc	2,750	173
A_{14}	Aya – Lcp ## Dnp ## Hpp – Dtc	2,900	168
A_{15}	Aya – Lcp ## Hpp – Dtc	2,950	165
A_{16}	Aya – Sva ** Cba – Dtc	6,750	60

Notes: Aya, Ayutthaya; Mdh/Svk, Mukdahan-Savannakhet customs; Dsv/Lb, Dansavanh-Lao Bao customs; Dht, Dong Ha railroad station; Hpt, Hai Phong railroad station; Dtc, distribution center; Dnp, Da Nang port; Hpp, Hai Phong port; Lcp, Laem Chabang port; Sgp, Saigon port; Sgt, Saigon railroad station; Ayp/Pop, Aranyaprathet-Poipet customs; Bav/Mob, Bavet-Moc Bai customs; Dnt, Da Nang railroad station; Sva, Suvarnabhumi international airport; Cba, Cat Bi international airport; –, ##, ++, ** stand for transportation by truck, ship, train, and airplane.

Transportation time (C_2) means the total planned time for taking the container from origins to destinations. This type of criterion typically varies when the destination is reached via diverse cross-docks. The transportation time includes transit time, loading/unloading time, customs clearance time, personal time for traveling, and dwell time.

Security risk (C_3) means inescapable events in the course of meeting contractual demand in terms of products' quantity and quality, physical damage, lost or stolen freight, dented and scratched products, contamination, wet damage, and infestation.

Operational risk (C_4) means losses from inadequate and failed procedures, systems, or policies: employee errors, fraud, unlawful activities, lack of skilled labor, road accidents, derailment, and vessel collision/sinking.

Infrastructure risk (C_5) means unexpected events that occur as a result of fundamental facilities and physical characteristics along the routes: number of lanes, road conditions, flyover, load capacity of rails, gauge of railway tracks, number of terminals, and available handling equipment.

Macro risk (C_6) means disruptions associated with sudden economic changes: fierce competition in the transportation sector, equities and commodities markets, financial crises, and inflation.

Policy and legality risks (C_7) mean threats occurring in the host country's government policies, enactments, laws, and regulations: traffic rules, trade restrictions arbitrarily imposed by governments, customs, protests, smart mob, coup, etc.

Environmental risk (C_8) means impacts of the environment from uncontrollable factors: natural disasters, weather, pollution, and emission.

The proposed hybrid MCDM approach was tested by a realistic case study. A panel of six decision makers, which comprised three senior managers of the case study and three experts in the field of logistics and supply chain management were invited to participate in every process of each phase. The first phase aimed to determine the relative weights of each criterion using AHP. The decision makers separately expressed their judgments on each pair of the criteria using the importance assessment scales. The individual judgments were averaged to construct an aggregated pairwise comparison matrix by using the geometric mean method, as shown in Table 8.

Subsequently, the normalized pairwise comparison matrix was established by using Equation (1), as shown in Table 9 (Columns 2–9). Regarding, Equations (2) to (4), the relative weights of all criteria, including the consistency ratio, were calculated by averaging the row entries in the normalized matrix. The results of AHP are presented in the last column of Table 9. For example, the relative weight of the transportation cost was calculated, as follows:

Table 8. Aggregated pairwise comparison matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	1.0000	0.8909	1.2247	1.0000	2.9417	3.3019	1.2009	2.2894
C_2	1.1225	1.0000	1.0491	0.8327	1.9442	2.2894	0.5302	1.9064
C_3	0.8165	0.9532	1.0000	0.9347	2.8040	3.2377	0.8327	3.5328
C_4	1.0000	1.2009	1.0699	1.0000	1.5131	1.8860	0.6609	1.4422
C_5	0.3399	0.5144	0.3566	0.6609	1.0000	2.0396	1.0000	1.8171
C_6	0.3029	0.4368	0.3089	0.5302	0.4903	1.0000	0.6368	1.3480
C_7	0.8327	1.8860	1.2009	1.5131	1.0000	1.5704	1.0000	1.1776
C_8	0.4368	0.5246	0.2831	0.6934	0.5503	0.7418	0.8492	1.0000

$$w_1 = \frac{(0.1709 + 0.1203 + \ldots + 0.1577)}{8} = 0.1752$$

In this case, C_1 took the most important criteria, followed by C_3, C_7, C_2, C_4, C_5, C_8, and C_6. The results were acceptable because the consistency ratio is less than the threshold value, as 0.0361 < 0.1000. These weights were used together with the local risk scores in the selection by TOPSIS.

In the second phase, the risk assessment method as a risk measure was illustrated: the risk levels were calculated as the products of the likelihood and severity scales, which are given in Table 10 [62]. The

risk levels can be interpreted as the linguistic assessment grades for each qualitative criterion in accordance with a risk matrix adapted from Lu et al. [63] and range from 1 to 25, where 1 and 2 are "Very low (VL)" (in blue), which indicates that the risks do not impact the achievement of transportation; 3 and 4 are "Low (L)" (in green), which indicates that the risks slightly impact the achievement of transportation; 5, 6, 8, and 9 are "Medium (M)" (in yellow), which indicates that the risks impact the achievement of transportation, but not as seriously as the next higher grade; 10, 12, 15, and 16 are "High (H)" (in orange), which indicates that the risks impact the achievement of transportation with serious effects; 20 and 25 are "Very high (VH)" (in red), which indicates that the risks are very serious and impact the achievement of transportation extremely and directly. The risk matrix is depicted in Figure 2. For example, the likelihood and severity scales are equal to 2 (Unlikely) and 3 (Moderate). Therefore, the risk level is "Medium (M)," since 2 × 3 = 6; this result is classified in the yellow zone.

The same group of decision makers evaluated the likelihood and severity scales; accordingly, the

Table 10. Likelihood and severity scales.

	Description	
Scale	Likelihood	Severity
1	Rare	Insignificant
2	Unlikely	Minor
3	Possible	Moderate
4	Likely	Major
5	Almost certain	Catastrophic

linguistic assessment grades were specified. The evaluation results of the security risk are presented in Table 11. However, the transportation cost and time were not investigated in this step because they are quantitative. For example, the risk level of the security risk in the first route from the first decision maker (DM_1) was "Very high (VH)" due to the product of the likelihood and severity scales being 5 × 4 = 20.

The risk levels determine the number of decision makers in each assessment grade in respect of all the routes. For example, the number of decision makers who assess the security risk as very high grade was 2, whereas the number of decision makers for the high grade was 3, and the number of decision makers for the medium grade was 1. The linguistic assessment grades for each qualitative criterion in respect of every route are presented in Table 12.

Using Equations (5) and (6), the mathematical models were developed to obtain the optimal solution from all generated solutions. For example, the formulations for each risk were written, as below:

$$\text{Maximize}\,\alpha_j$$
$$\text{Subjectto}: \alpha_j \leq \sum_{g=1}^{g_l} S(G_{jg})(ND_{ijg}) \leq 1$$
$$S(G_{j1}) \geq 2S(G_{j}2) \geq 3S(G_{j3}) \geq 4S(G_{j4}) \geq 5S(G_{j5}) \geq 0$$

where $i = 1, 2, \ldots, 16$; $j = 3, 4, \ldots, 8$; $g = 1, 2, \ldots, 5$.

The optimal decision variables were then determined based on α^* as the minimal α, for each qualitative criterion as follows:

- For the security risk: $S^*(VH_3) = 0.2609$, $S^*(H_3) = 0.1304$, $S^*(M_3) = 0.0870$, $S^*(L_3) = 0.0652$, $S^*(VL_3) = 0.0522$, and $\alpha_3^* = 0.3652$

Table 9. Results of AHP.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	W_j
C_1	0.1709	0.1203	0.1886	0.1396	0.2403	0.2055	0.1790	0.1577	0.1752
C_2	0.1918	0.1350	0.1616	0.1162	0.1588	0.1425	0.0790	0.1314	0.1395
C_3	0.1395	0.1287	0.1540	0.1304	0.2290	0.2015	0.1241	0.2434	0.1688
C_4	0.1709	0.1621	0.1648	0.1396	0.1236	0.1174	0.0985	0.0994	0.1345
C_5	0.0581	0.0694	0.0549	0.0922	0.0817	0.1269	0.1490	0.1252	0.0947
C_6	0.0518	0.0590	0.0476	0.0740	0.0400	0.0622	0.0949	0.0929	0.0653
C_7	0.1423	0.2546	0.1850	0.2112	0.0817	0.0977	0.1490	0.0811	0.1503
C_8	0.0746	0.0708	0.0436	0.0968	0.0449	0.0462	0.1265	0.0689	0.0715

$\lambda_{max} = 8.3568$ $CI = 0.0509$ $RI = 1.41$ $CR = 0.0361$

	Insignificant (1)	Minor (2)	Moderate (3)	Major (4)	Catastrophic (5)
Rare (1)	Very low (VL) 1 × 1 = 1	Very low (VL) 1 × 2 = 2	Low (L) 1 × 3 = 3	Low (L) 1 × 4 = 4	Medium (M) 1 × 5 = 5
Unlikely (2)	Very low (VL) 2 × 1 = 2	Low (L) 2 × 2 = 4	Medium (M) 2 × 3 = 6	Medium (M) 2 × 4 = 8	High (H) 2 × 5 = 10
Possible (3)	Low (L) 3 × 1 = 3	Medium (M) 3 × 2 = 6	Medium (M) 3 × 3 = 9	High (H) 3 × 4 = 12	High (H) 3 × 5 = 15
Likely (4)	Low (L) 4 × 1 = 4	Medium (M) 4 × 2 = 8	High (H) 4 × 3 = 12	High (H) 4 × 4 = 16	Very high (VH) 4 × 5 = 20
Almost certain (5)	Medium (M) 5 × 1 = 5	High (H) 5 × 2 = 10	High (H) 5 × 3 = 15	Very high (VH) 5 × 4 = 20	Very high (VH) 5 × 5 = 25

Figure 2. Risk matrix for linguistic assessment grades.

Table 11. Evaluations' results of the security risk.

	DM_1			DM_2			DM_3			DM_4			DM_5			DM_6		
	L	*S*	*G*	*L*	*S*	*G*	*L*	*S*	*G*	*L*	*S*	*G*	*L*	*S*	*G*	*L*	*S*	*G*
A_1	5	4	20	4	3	12	5	3	15	3	3	9	5	3	15	4	5	20
A_2	2	2	4	3	2	6	3	4	12	2	2	4	1	4	4	3	4	12
A_3	3	3	9	4	3	12	4	4	16	2	2	4	2	2	4	3	3	9
A_4	3	2	6	3	4	12	5	3	15	4	2	8	4	2	8	5	2	10
A_5	2	2	4	2	3	6	4	1	4	3	3	9	2	5	10	2	2	4
A_6	3	3	9	2	4	8	5	1	5	4	5	20	4	3	12	4	2	8
A_7	4	4	16	2	2	4	3	2	6	3	3	9	2	4	8	4	2	8
A_8	2	1	2	3	4	12	3	3	9	5	2	10	1	2	2	3	4	12
A_9	3	3	9	3	2	6	2	4	8	5	5	25	3	2	6	3	2	6
A_{10}	2	2	4	3	3	9	2	1	2	3	5	15	4	3	12	5	3	15
A_{11}	2	2	4	3	3	9	3	2	6	5	2	10	3	4	12	4	4	16
A_{12}	3	2	6	1	4	4	3	2	6	2	2	4	3	4	12	3	2	6
A_{13}	1	3	3	4	5	20	4	4	16	5	2	10	4	4	16	2	2	4
A_{14}	2	4	8	2	3	6	3	4	12	3	3	9	5	4	20	4	2	8
A_{15}	2	5	10	2	3	6	5	3	15	4	4	16	3	3	9	2	2	4
A_{16}	1	3	3	2	2	4	2	3	6	2	3	6	2	3	6	3	3	9

Note: *L*, *S*, and *G* denote as likelihood, severity, and linguistic assessment grade.

Table 12. Linguistic assessment grades for all criteria and routes.

	C_3					C_4					C_5					C_6					C_7					C_8				
	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL
A_1	2	3	1			2	2	2			1	5					4	2			2	4					2	2	2	
A_2		2	1	3		1	1	1	3			4	2				3	2		1		3	1	2			4	2		
A_3		2	2	2			2	2	2			1	5				2	3	1			3	1	2			1	4		
A_4		3	3				2	1	3		2	4					5		1		1	2	1	1	1			2	4	
A_5		1	2	3			4	2				1	5				2	1	3				4	1	1			3	2	1
A_6	1	1	4				1	2	2	1			3	3			1	5					5		1		3	2	1	
A_7		1	4	1		3	2	1				1	2	3				4	2		1		2	3			3	2		1
A_8		3	1		2	2	1	1	1	1		3	2	1		1	2	3			2	4						3	1	2
A_9	1		5					3	2	1		2		4			1	3	1	1	1	2	3				5	1		
A_{10}		3	1	1	1	1	2	1	2			2	2		2			1	4	1		3	2	1				1	2	3
A_{11}		3	2	1				3	1	2			5		1		2		2	2		3		2	1			3	3	
A_{12}		1	3	2					5	1	3	1			2			2	4		1	2	2	1			4	1		1
A_{13}	1	3		2				2	4			3	1		2		2		4			2	3		1		2		4	
A_{14}	1	1	4					3	1	2			5		1	2	3	1				3	1	2			1	3	2	
A_{15}		3	2	1			2	3	1			3	3				1	2	3			2	2	2			3	3		
A_{16}				4	2		1	1		4	1	2	1	2			3	3				1	2	2	1		5	1		

- For the operational risk: $S^*(VH_4) = 0.2308$, $S^*(H_4) = 0.1154$, $S^*(M_4) = 0.0769$, $S^*(L_4) = 0.0577$, $S^*(VL_4) = 0.0462$, and $\alpha_4^* = 0.3346$
- For the infrastructure risk: $S^*(VH_5) = 0.2500$, $S^*(H_5) = 0.1250$, $S^*(M_5) = 0.0833$, $S^*(L_5) = 0.0625$, $S^*(VL_5) = 0.0194$, and $\alpha_5^* = 0.4375$
- For the macro risk: $S^*(VH_6) = 0.2609$, $S^*(H_6) = 0.1304$, $S^*(M_6) = 0.0870$, $S^*(L_6) = 0.0652$, $S^*(VL_6) = 0.0522$, and $\alpha_6^* = 0.4000$
- For the policy and legality risks: $S^*(VH_7) = 0.2500$, $S^*(H_7) = 0.1250$, $S^*(M_7) = 0.0833$, $S^*(L_7) = 0.0625$, $S^*(VL_7) = 0.0500$, and $\alpha_7^* = 0.4458$

- For the environmental risk: $S^*(VH_8) = 0.3529$, $S^*(H_8) = 0.1765$, $S^*(M_8) = 0.1176$, $S^*(L_8) = 0.0882$, $S^*(VL_8) = 0.0706$, and $\alpha_8^* = 0.5059$

To obtain the local risk scores, Equation (7) was employed by considering the most optimal decision variables of each criterion and the number of decision makers in each grade, as shown in Table 13. For example, the local risk scores of the security risk with respect to every route can be clarified as follows:

$\theta_{13} = (0.2609 \times 2) + (0.1304 \times 3) + (0.0870 \times 1) + (0.0652 \times 0) + (0.0522 \times 0) = 1.0000$

$\theta_{23} = (0.2609 \times 0) + (0.1304 \times 2) + (0.0870 \times 1) + (0.0652 \times 3) + (0.0522 \times 0) = 0.5435$

$$\vdots$$

$\theta_{163} = (0.2609 \times 0) + (0.1304 \times 0) + (0.0870 \times 0) + (0.0652 \times 4) + (0.0522 \times 2) = 0.3652$

The final phase attempted to determine the most appropriate multimodal freight route based on the relative weights and the local risk scores by using TOPSIS. Equation (8) was applied to construct the normalized decision matrix in accordance with the transportation cost, time, and local risk scores. Next, the weighted normalized decision matrix was next formed through Equation (9), as shown in Table 14. For example, the normalized value and weighted normalized value of the first route for the security risk was conducted as follows:

$$\lambda_{13} = \frac{1.000}{\sqrt{1.000^2 + 0.5435^2 + \ldots + 0.3652^2}} = 0.3872$$

$v_{13} = 0.1688 \times 0.3872 = 0.0654$

The ideal solutions were then produced according to the weighted normalized decision matrix via Equations (10) and (11). Because every criterion is non-beneficial, the positive ideal solution can be defined as $A^+ = \{0.0219, 0.0148, 0.0239, 0.0197, 0.0163, 0.0107, 0.0256, 0.0117\}$, while the negative ideal solution was given as $A^- = \{0.0746, 0.0426, 0.0654, 0.0588, 0.0374, 0.0267, 0.0574, 0.0231\}$. Thereafter, the separation measures for each route from both ideal and negative ideal solutions were estimated based on the Euclidean distance prepared by using Equations (12) and (13), as shown in Table 15. For example, the distances from the positive and negative ideal solutions of the second route were expressed:

$$ED_2^+ = \sqrt{(0.0294 - 0.0219)^2 + .. + (0.0218 - 0.0117)^2} = 0.0297$$

Table 13. Local risk scores.

	C_3	C_4	C_5	C_6	C_7	C_8
A_1	1.0000	0.8462	0.8750	0.6957	1.0000	0.7647
A_2	0.5435	0.5962	0.6667	0.6174	0.5833	0.9412
A_3	0.5652	0.5000	0.5417	0.5870	0.5833	0.6471
A_4	0.6522	0.4808	1.0000	0.7174	0.6958	0.5882
A_5	0.5000	0.6154	0.5417	0.5435	0.4458	0.6000
A_6	0.7391	0.4308	0.4375	0.5652	0.4667	0.8529
A_7	0.5435	1.0000	0.4792	0.4783	0.6042	0.8353
A_8	0.5826	0.7577	0.6042	0.7826	1.0000	0.5824
A_9	0.6957	0.3923	0.5000	0.5087	0.7500	1.0000
A_{10}	0.5957	0.6538	0.4556	0.4000	0.6042	0.5059
A_{11}	0.6304	0.3808	0.4361	0.4957	0.5500	0.6176
A_{12}	0.5217	0.3346	0.9139	0.4348	0.7292	0.8941
A_{13}	0.7826	0.3846	0.4972	0.5217	0.5500	0.7059
A_{14}	0.7391	0.3808	0.4361	1.0000	0.5833	0.7059
A_{15}	0.6304	0.5192	0.6250	0.5000	0.5417	0.8824
A_{16}	0.3652	0.3769	0.7083	0.6522	0.4667	1.0000

Table 14. Weighted normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.0415	0.0251	0.0654	0.0498	0.0328	0.0186	0.0574	0.0177
A_2	0.0294	0.0283	0.0355	0.0351	0.0250	0.0165	0.0335	0.0218
A_3	0.0453	0.0327	0.0370	0.0294	0.0203	0.0157	0.0335	0.0150
A_4	0.0219	0.0389	0.0426	0.0283	0.0374	0.0192	0.0399	0.0136
A_5	0.0317	0.0411	0.0327	0.0362	0.0203	0.0145	0.0256	0.0139
A_6	0.0354	0.0315	0.0483	0.0253	0.0164	0.0151	0.0268	0.0197
A_7	0.0437	0.0293	0.0355	0.0588	0.0179	0.0128	0.0347	0.0193
A_8	0.0531	0.0418	0.0381	0.0446	0.0226	0.0209	0.0574	0.0135
A_9	0.0591	0.0354	0.0455	0.0231	0.0187	0.0136	0.0430	0.0231
A_{10}	0.0491	0.0303	0.0389	0.0384	0.0171	0.0107	0.0347	0.0117
A_{11}	0.0507	0.0379	0.0412	0.0224	0.0163	0.0132	0.0316	0.0143
A_{12}	0.0395	0.0344	0.0341	0.0197	0.0342	0.0116	0.0418	0.0207
A_{13}	0.0304	0.0426	0.0512	0.0226	0.0186	0.0139	0.0316	0.0163
A_{14}	0.0321	0.0413	0.0483	0.0224	0.0163	0.0267	0.0335	0.0163
A_{15}	0.0326	0.0406	0.0412	0.0305	0.0234	0.0133	0.0311	0.0204
A_{16}	0.0746	0.0148	0.0239	0.0222	0.0265	0.0174	0.0268	0.0231

Table 15. Distances from positive and negative ideal solutions.

A_1	0.0671	0.0401	A_9	0.0524	0.0519
A_2	0.0297	0.0674	A_{10}	0.0405	0.0569
A_3	0.0354	0.0607	A_{11}	0.0415	0.0623
A_4	0.0416	0.0685	A_{12}	0.0383	0.0655
A_5	0.0343	0.0705	A_{13}	0.0409	0.0685
A_6	0.0343	0.0678	A_{14}	0.0419	0.0670
A_7	0.0500	0.0559	A_{15}	0.0369	0.0650
A_8	0.0607	0.0419	A_{16}	0.0554	0.0706

$$ED_2^- = \sqrt{(0.0294 - 0.0746)^2 + .. + (0.0218 - 0.0231)^2} = 0.0674$$

According to Equation (14), the indexes of relative closeness coefficients for all routes were figured out, as shown in Table 16. The preference order was provided by arranging the routes in descending order of the indexes. Therefore, the most appropriate multimodal freight route is the one with the greatest relative closeness coefficient to the ideal solution, which simultaneously demonstrates the nearest value to the positive ideal solution and the farthest distance value to the negative ideal solution. For example, the relative closeness coefficient of the first route was summarized as follows:

$$CC_1 = \frac{0.0401}{0.0671 + 0.0401} = 0.3739$$

Table 16 shows that A_2 is the most appropriate route, due to the largest relative closeness coefficient, while the least appropriate route was A_1. The final ranking of all the routes is given as: A_2, A_5, A_6, A_{15}, A_3, A_{12}, A_{13}, A_4, A_{14}, A_{11}, A_{10}, A_{16}, A_7, A_9, A_8, and A_1. The best route starts from Ayutthaya to Da Nang port via Mukdahan-Savannakhet and Dansavanh-Lao Bao customs, then by ship to Hai Phong port, and lastly by truck to the distribution center. Although A_2 does not have the best properties for each criterion, this route represents the best reasonable trade-off between all the conflicting attributes.

The result of this study was compared with results obtained from the two existing combinations of the MCDM approaches (i.e., AHP–DEA and AHP–TOPSIS) using the same data. In the first one, the weighted local risk score was used to determine each alternative's priorities. In the other, our DEA model was removed; therefore, the results were obtained based on the relative weights and averaged risk scores, which are computed by the traditional risk assessment method. The rankings of the proposed hybrid MCDM approach compared to the others are tabulated in Table 17 and Figure 3. For this analysis, the most preferable routes from the two existing combinations were A_6 with the lowest weighted local risk score at 0.5210 for AHP–DEA and the highest *CC* value at 0.6819 for AHP–TOPSIS. Hence, the proposed hybrid approach provides a higher index as compared to the others. Additionally, it can be summarized that the most appropriate multimodal route and the ranking obtained by the proposed hybrid approach were completely different to those acquired by both existing integrations, except for some positions that were similar, where A_7 and A_9 were placed in the thirteenth and fourteenth, respectively. Considering the transportation costs, times, and risk levels of all selected routes with respect to every approach, the cost and time of A_2 are significantly lower than A_6. Although A_2 has a higher averaged local risk score than A_6, the risk score slightly impacts the final ranking. Therefore, it is evident that the proposed hybrid MCDM approach, which generates a better result than the previous approaches, can decrease non-beneficial attributes and increase the distribution efficiencies, including the profit margin, in real-world logistical systems.

After applying the proposed hybrid MCDM approach, it was observed that the framework could solve the route selection problem by using the main mechanisms of each approach's advantages: (1) determining the importance of criteria through AHP, (2) calculating the local risk scores of all qualitative criteria via the DEA model, and (3) identifying the ranks of possible routes from TOPSIS. The proposed hybrid approach is not a method that either maximizes or minimizes a single objective because none of the routes with the cheapest transportation cost, the shortest transportation time, and the lowest local risk scores of each risk was selected. The proposed hybrid approach represents the best compromise solution among the local risk scores and their priorities, including transportation cost and time. Moreover, the proposed methodological approach can assist decision-making authorities in easily obtaining reliable results. It should be noted, however, that the final results will likely change with any changes in the relative weights, cost, time, and/or local risk scores.

Table 16. Relative closeness coefficients.

	CC_i		CC_i		CC_i		CC_i
A_1	0.3739	A_5	0.6729	A_9	0.4977	A_{13}	0.6264
A_2	0.6938	A_6	0.6641	A_{10}	0.5840	A_{14}	0.6154
A_3	0.6318	A_7	0.5281	A_{11}	0.6001	A_{15}	0.6377
A_4	0.6220	A_8	0.4087	A_{12}	0.6312	A_{16}	0.5603

5. Implication of the study

The findings of this study provide distinct implications in theory and practice. For theoretical implications, our proposed hybrid MCDM approach puts forward a new direction of integrated approach and novelties of insight for selecting the most appropriate route in multimodal transportation networks. It suggests that AHP, DEA, and TOPSIS can be incorporated to optimize conflicting attributes in transportation and logistics problems. The

Table 17. Rankings of the proposed hybrid MCDM approach compared to the others.

Method	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{16}
Proposed hybrid MCDM approach	16	1	5	8	2	3	13	15	14	11	10	6	7	9	4	12
AHP–DEA	15	3	6	10	2	1	13	16	14	5	8	11	7	12	9	4
AHP–TOPSIS	16	2	9	10	4	1	13	15	14	12	6	5	3	7	8	11

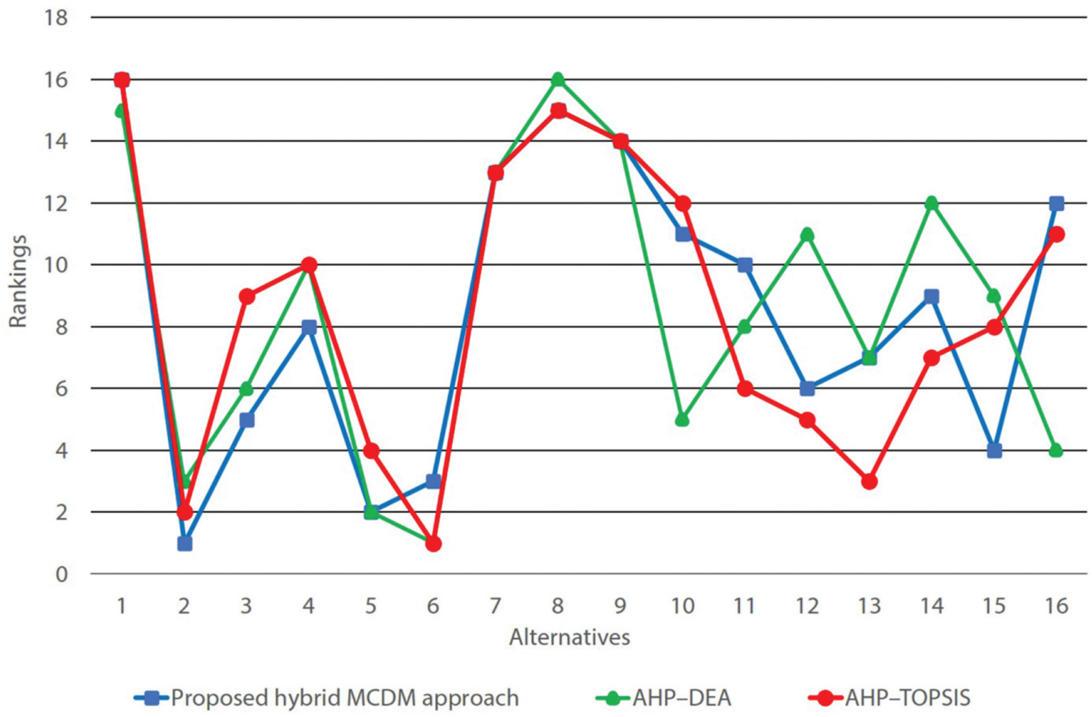

Figure 3. Ranking of routes for each approach.

combination of these approaches points out a particular ability to synthesize objective and subjective judgments as well as quantitative and qualitative criteria for the best compromise solution from all possible routes. Likewise, the proposed hybrid approach is desirable as a decision-making tool because it retains the strengths of the individual approaches and overcomes the weaknesses of each one at the same time. For practical implications, this work achieves a better managerial decision in respect of multimodal route selection for the authorities; it allows for a convenient best trade-off analysis between conflicting criteria and preferences. The proposed hybrid approach also affords the authorities confident judgments in all processes involving route decision-making problems. Practically, the proposed hybrid MCDM methodology can evaluate the resource usage of transportation; the available resources: budget, preferred transportation time, and acceptable local scores of each risk must be considered in the processes. Hence, feasible routes can be eliminated if they have one of the following properties: transportation cost exceeds budget, transportation time is beyond preferred transportation time, and local risk scores are greater than acceptable scores. Another benefit is that the proposed hybrid approach can also be used to handle other MCDM problems of logistics activities: order processing, material handling, warehousing, packaging, etc. According to all the above benefits, the proposed methodology enables the authorities to easily design transportation planning in a cost-effective manner: on time delivery, low risk, and high safety.

6. CONCLUSION

The problem of route selection in multimodal transportation networks can be interpreted as a complex MCDM problems because it concerns many conflicting criteria and alternative routes, as well as contradictory and complex judgments. Many prominent MCDM approaches have successfully been applied to solve problems in many areas and applications. However, using a single MCDM approach is insufficient because it has many drawbacks. To cope with these difficulties, the novel hybrid MCDM approach integrating AHP, DEA, and TOPSIS is first introduced to find an optimal solution for multimodal freight route selection based on the quantitative criteria of transportation cost and time as well as on the qualitative criteria of security, operational, infrastructural, macro, policy, legal, and environmental risks. The proposed hybrid approach can be divided into three main phases: weight calculation, risk measurement, and route selection. For the first phase, AHP was used to reflect the priorities of criteria. For the second phase, DEA was applied for measuring the local risk scores of unexpected events along the corridors while the multimodal transport cost-model was also employed to handle the quantitative criteria. In the final phase, all the input data were synthesized by TOPSIS. To evaluate the proposed hybrid approach, a test was conducted with the empirical case study of route selection between Ayutthaya province and Haiphong to demonstrate its applicability, suitability, and usefulness.

In summary, the proposed hybrid MCDM approach can effectively convert inherent cognitions of decision makers and/or experts into accurate and rational results; it can also eliminate the influence of human subjective judgment on decision results by using the proposed hybrid approach's apparent advantages: (1) the importance judgments with a 9-point intensity scale on pairwise comparison allow for a codification of the priorities of criteria in a transparent manner, (2) the complicated processes of risk calculation are simplified by a DEA-based risk assessment and the mathematical model, which can analyze the number of decision makers in each linguistic assessment grade to approximate risk magnitudes for every route, and (3) all the information with different measurement units is normalized and synthesized to accurately obtain a ranking of multimodal freight routes in accordance with the closeness to the ideal solution by TOPSIS. Additionally, it can be summarized that the proposed approach is more accurate, innovative, flexible, versatile, and unbiased than the previous methods, and can support decision makers in effective decision-making processes.

The merits of this study lie in the new guideline for a decision support framework that integrates more than two MCDM approaches and suggests a choice of proper MCDM approaches for novel integration. Moreover, it offers decision makers an easy solution to complex decision-making problems and yields a consistent result for their judgments. Regarding the application of the case study, it shows that the proposed hybrid approach as a theoretical decision support model is comprehensive, valid, adaptive, and suitable in real-life scenarios. Although the proposed hybrid approach reveals a better ability to distinguish alternatives, it has some limitations compared to the other MCDM and/or hybrid approaches. First, the novel approach is based on a binary logic because the rating scales of each phase are only based on the number in a value that is either completely true or false. Since, in this context, the crisp scales are not obvious, a concept of degree of truth with values ranging between 0 and 1 is necessary for combination with the rating scales. Second, the interrelations of all elements in the proposed hybrid approach are characterized within a hierarchy; however, the dependencies in some situations are rarely interpreted as higher and lower levels for the route selection problem. In this manner, the network relationships of each element should be excogitated. Third, the proposed research methodology overlooks the capacity limits of human perceptual tasks; when the number of criteria is increased to the magical number, these elements should be categorized into groups with a capacity of 7 ± 2 items.

For future research, the fuzzy set theory should be integrated to enhance the capabilities of the proposed hybrid MCDM approach. For example, it can combine with the calculation of weights or route selection. Similarly, the traditional risk assessment should also be upgraded into a fuzzy risk assessment model. Additionally, the related criteria can be grouped by GDM or factor analysis (FA). Lastly, the other MCDM approaches: analytic network process (ANP), preference ranking organization method for enrichment evaluations (PROMETHEE), decision making trial and evaluation laboratory (DEMATEL), complex proportional assessment method (COPRAS), vlse kriterijumska optimizacija kompromisno resenje (VIKOR), etc. should be integrated with the proposed hybrid approach. Another method would be to develop a multiple objective programming model for use with the three-stage methodology for multimodal route selection.

Disclosure statement

No potential conflict of interest was reported by the authors.

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