

Article

Sustainable Freight Modal Allocation Using an Integrated Modelling and CRITIC–SREM Framework

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Abstract

Freight modal allocation requires balancing economic efficiency, operational performance, environmental impacts, reliability, and infrastructure capacity. This study develops an integrated ANN–CRITIC–SREM framework for evaluating alternative freight allocations among road, rail, and inland waterway transport. The framework is demonstrated through a case study of the Prahovo–Šabac corridor in Serbia. Latin hypercube sampling was used to generate representative system states for training and validating a multi-output feed-forward artificial neural network employed as a surrogate model for simultaneously estimating six decision criteria. The CRITIC method was used to determine objective criterion weights, while SREM was applied to rank the alternatives. The ANN showed close agreement with engineering-generated reference values on an independent testing subset within the defined parameter ranges. Under the adopted baseline assumptions, the alternative comprising 60% road and 40% rail transport achieved the highest overall score. Sensitivity analysis showed that this alternative remained preferred for most analysed values of the SREM balancing coefficient, whereas urgent-delivery, environmental-priority, and capacity-priority scenarios favoured different modal structures. The results indicate that the integrated framework provides a transparent and flexible decision-support basis for evaluating freight modal allocation under changing economic, operational, environmental, and capacity-related priorities.

Keywords: freight modal allocation; sustainable freight transport; multi-criteria decision-making; CRITIC; SREM; artificial neural network; modal shift

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1. Introduction

Freight transport plays an essential role in economic development, industrial supply chains, and regional connectivity. At the same time, freight flows are increasingly influenced by environmental targets, infrastructure constraints, service reliability, and transport-related external effects. Consequently, freight transport planning can no longer be based exclusively on the minimisation of direct transport costs or delivery time [1–3].

This is particularly relevant on corridors where road, rail, and inland waterway transport can be used individually or combined within different modal allocation structures.

Road freight transport provides flexibility, direct accessibility, and relatively short delivery times, but is generally associated with higher energy consumption, greenhouse gas emissions, congestion, noise, and external costs. Rail and inland waterway transport may offer environmental and economic advantages for larger freight volumes and longer distances, although their applicability depends on terminal accessibility, service frequency, transshipment requirements, infrastructure conditions, and available capacity [4–7]. Therefore, the most sustainable modal allocation is not necessarily the cheapest or fastest solution, but the one that provides an appropriate compromise among economic, operational, and environmental performance.

Freight modal allocation is inherently a multi-criteria decision problem. Alternative modal structures must be evaluated according to conflicting criteria such as direct transport cost, delivery time, greenhouse gas emissions, external costs, reliability, and capacity feasibility. Multi-criteria decision-making methods provide a structured and transparent basis for integrating these criteria and comparing the relative performance of alternatives [8]. However, their application requires reliable estimates of criterion values under different combinations of freight demand, operating conditions, infrastructure capacity, and modal shares.

Artificial intelligence and machine-learning methods are increasingly used in transport and logistics because of their ability to represent nonlinear relationships among system variables. Freight mode-choice studies have demonstrated their capacity to capture complex relationships between shipment characteristics, transport-service variables, geographical conditions, and modal decisions [9,10]. Their application to performance and energy-related variables also supports their wider use as data-driven surrogate models. Computational modelling and simulation have been employed to analyse complex dynamic behaviour in transport-related engineering systems [11], while machine-learning-based surrogate models have been incorporated into integrated prediction and optimisation frameworks [12]. Artificial neural networks are particularly suitable for approximating complex input–output relationships and have been applied to freight transport mode combinations and their environmental effects [13], as well as to problems involving heavy-duty vehicle emissions and operational costs [14].

Nevertheless, most machine-learning studies in freight transport focus on predicting individual mode choices rather than estimating multiple performance criteria for predefined modal structures. Economic, operational, environmental, reliability, and capacity-related indicators are also less frequently integrated within a unified modelling and multi-criteria evaluation framework. This creates a need for decision-support approaches that combine surrogate estimation with transparent evaluation of alternative freight modal allocations.

To address this research gap, the present study develops an integrated modelling and CRITIC–SREM framework for sustainable freight modal allocation. A multi-output feed-forward ANN is employed as a surrogate model to estimate criterion values under different operating conditions and modal shares. These estimates form the decision matrix, while the CRITIC method determines objective criterion weights by considering criterion variability and inter-criterion conflict [15]. The Square-Root based Evaluation Method (SREM) is subsequently used to rank the alternatives [16]. The framework thus connects surrogate modelling, objective weighting, and multi-criteria evaluation within a unified decision-support procedure.

The framework is demonstrated through a case study of freight transport on the Prahovo–Šabac corridor in Serbia. Seven alternatives with different shares of road, rail, and inland waterway transport are evaluated according to six criteria covering economic,

operational, environmental, reliability, and capacity-related performance. The analysis combines publicly available information, engineering calculations, and explicitly stated market-based assumptions to provide a transparent basis for evaluating alternative modal structures.

The study makes three main contributions. First, it develops an integrated modelling structure in which a multi-output ANN surrogate estimates six performance criteria for predefined freight modal allocations. Second, the resulting estimates are combined with CRITIC objective weighting and SREM ranking within a unified decision-support framework. Third, the stability of the preferred modal allocation is examined through sensitivity analyses involving the SREM balancing coefficient and different decision-making priorities.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature and identifies the research gap. Section 3 presents the methodological framework, while Section 4 describes the case study, alternatives, criteria, and modelling assumptions. Sections 5 and 6 present the surrogate model and CRITIC–SREM results, respectively. Section 7 provides the sensitivity analyses, and Section 8 presents the conclusions, limitations, and directions for future research.

2. Literature Review and Research Gap

2.1. Sustainable Freight Modal Allocation

The freight transport mode selection has traditionally been based on cost, delivery time, shipment characteristics, service availability, and distance. Contemporary planning must also consider emissions, external costs, infrastructure capacity, and reliability, which may require allocating the same freight flow among road, rail, and inland waterway transport [6,7].

Road transport provides flexibility and short delivery times but generally generates higher energy consumption, emissions, congestion, noise, and external costs. Rail and inland waterways may offer economic and environmental advantages for larger volumes and longer distances, although their competitiveness depends on infrastructure, terminals, service frequency, transshipment requirements, prices, and reliability [6,17]. Complementary research has examined low-carbon transport infrastructure [18], railway vehicle–track dynamics [19,20], transport-related greenhouse gas trends [21], external costs of road and rail freight in Serbia [22], and alternative fuel pathways [23].

Intermodal service quality, infrastructure development, operating efficiency, and pricing are among the main factors supporting modal shift [7,17]. Modelling and simulation studies have analysed the effects of policy measures, investments, operating costs, vehicle utilisation, and environmental impacts [24,25]. Their effectiveness depends on corridor and shipment characteristics, infrastructure availability, and transferable freight volumes [26]. Broader studies additionally emphasise logistics costs, investment, freight rates, time-related costs, and service efficiency [27–29]. Global and regional analyses confirm the decarbonisation potential of modal shift while showing that its effects differ across countries, corridors, and transport configurations [30–33].

These findings indicate that sustainable freight planning should evaluate feasible modal combinations rather than prescribe an unconditional shift from one transport mode to another.

2.2. Artificial Intelligence and Surrogate Modelling in Freight Transport

Artificial intelligence and machine learning are applied in freight transport for mode-choice classification, forecasting, travel-time and emissions estimation, routing, and logistics optimisation. Comparative studies have evaluated neural networks, support vector machines, decision trees, random forests, boosting, and bagging [9], while ensemble models have incorporated commodity-specific and geographical characteristics [10]. Other applications include interpretable mode-choice modelling [34], analysis of preference heterogeneity [35], and identification of freight suitable for transfer from road to rail [36].

ANN-based models have been used to approximate nonlinear relationships in engineering systems [37–39] and combined with discrete-event simulation for optimisation [40]. In freight transport, neural networks have supported the evaluation of modal combinations, environmental effects, operational costs, and railway demand [13,14,41]. Surrogate neural-network models have also approximated computationally intensive relationships for subsequent operational evaluation [42].

Most existing studies predict the mode selected for an individual shipment rather than the performance of predefined modal allocations. In this study, the ANN therefore acts as a surrogate model that estimates six economic, operational, environmental, reliability, and capacity-related criteria. These estimates form the decision matrix, while the preferred alternative is determined by the MCDM procedure.

2.3. MCDM Methods in Transport and Logistics

MCDM methods provide a structured basis for weighting conflicting criteria and ranking transport alternatives. Reviews of intermodal freight applications identify cost, emissions, delivery time, reliability, flexibility, and frequency as the most common criteria [43]. Numerous methods, including AHP, TOPSIS, VIKOR, PROMETHEE, BWM, EDAS, CODAS, CRITIC, SWARA, and MARCOS, have been applied in transport and logistics [44].

Because the selected method may influence the final ranking [45], contemporary frameworks frequently combine weighting, ranking, sensitivity analysis, and uncertainty modelling [46,47]. Integrated MCDM approaches have addressed technological, operational, economic, and infrastructure-related logistics problems [48,49]. They have also been combined with simulation for intermodal freight evaluation [50], applied to sustainable freight mode selection [51,52], and integrated with routing, last-mile delivery, resilient supply-chain design, sustainable delivery concepts, and alternative propulsion assessment [53–57].

Objective weighting methods derive criterion importance from the decision matrix. LOGSTA represents one such procedure [58], while CRITIC considers both criterion variability and inter-criterion conflict [15] and has been applied in railway decision problems [59]. SREM combines square- and root-transformed normalised values through a balancing coefficient to rank alternatives [16]. Recent studies also integrate artificial intelligence with MCDM in sustainable transport [60] and apply model-driven operations-research approaches to intermodal freight systems [61]. Nevertheless, direct integration of multi-output ANN estimation, objective weighting, and multi-criteria evaluation of predefined modal allocations remains limited.

2.4. Research Gap and Contributions

The literature demonstrates progress in modal-shift analysis, machine-learning-based mode-choice modelling, and multi-criteria transport evaluation. However, machine-learning studies generally predict individual mode choices rather than several performance criteria for predefined modal structures. Economic, operational, environmental, reliability, and capacity indicators are also rarely integrated within a single framework. In

addition, intermodal freight research highlights the importance of variability and uncertainty in costs, emissions, demand, capacity, and reliability [62].

The study addresses these gaps by: (1) using a multi-output ANN surrogate to estimate six criteria for predefined road, rail, and inland waterway allocations; (2) integrating these estimates with CRITIC objective weighting and SREM ranking; and (3) examining ranking stability under different balancing-coefficient values and decision-making priorities. The resulting framework identifies context-dependent modal allocations rather than prescribing a universally optimal modal split.

3. Methodological Framework

The proposed ANN–CRITIC–SREM framework integrates surrogate estimation, objective criterion weighting, multi-criteria ranking, and sensitivity analysis for evaluating sustainable freight modal allocation alternatives. As illustrated in Figure 1, case-study data, scenario variables, and modal alternatives constitute the model inputs. The ANN estimates the criterion values, CRITIC determines their objective weights, and SREM ranks the alternatives. Sensitivity analyses subsequently examine the influence of the SREM balancing coefficient and different decision-making priorities.

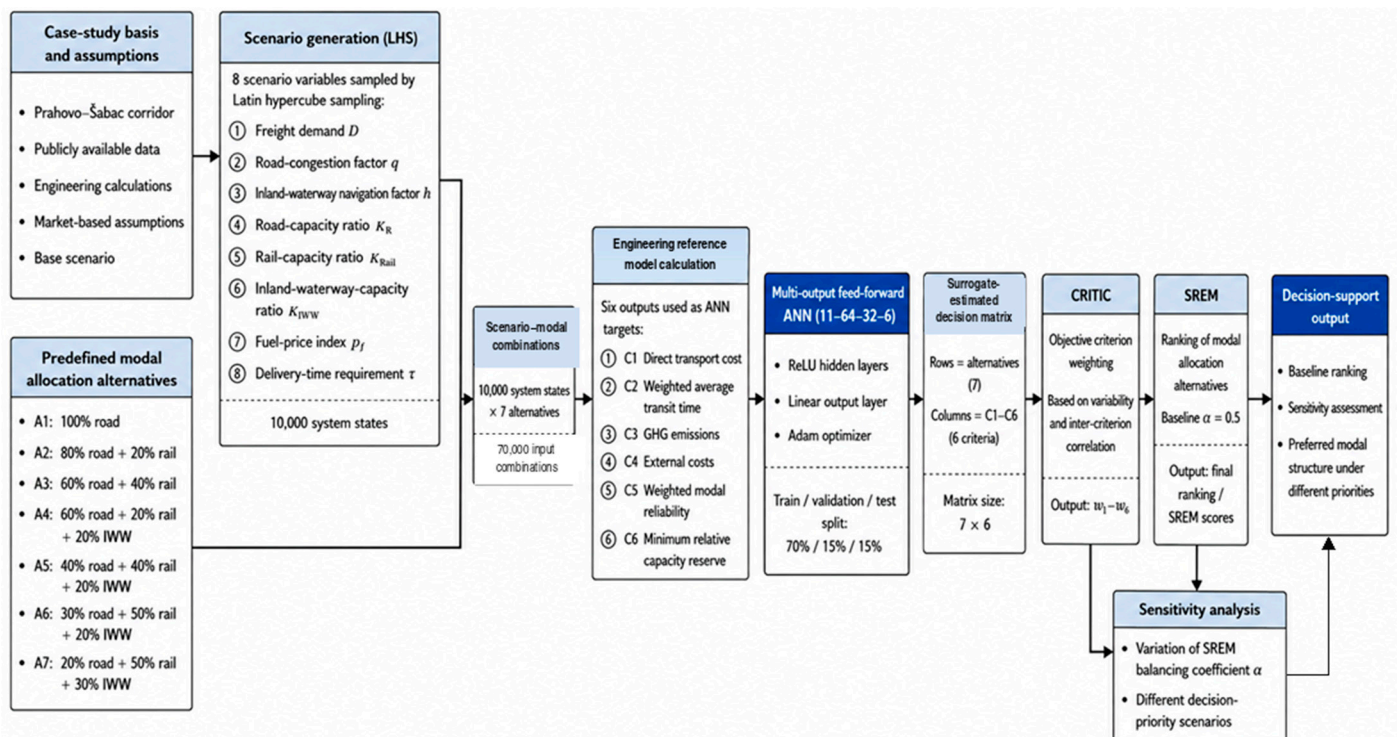


Figure 1. Structure of the proposed ANN–CRITIC–SREM framework.

Within the framework, the ANN serves as a surrogate model for constructing the decision matrix, while the preferred modal allocation is determined through CRITIC weighting and SREM evaluation.

3.1. Problem Formulation and Modal Allocation Model

Let A_i , $i = 1, 2, \dots, m$, denote the i -th freight modal allocation alternative. Each alternative is defined by the shares of road, rail, and inland waterway transport:

$$A_i = (s_{R,i}, s_{Rail,i}, s_{IWW,i}) \quad (1)$$

where $s_{R,i}$, $s_{Rail,i}$, and $s_{IWW,i}$ denote the respective modal shares.

The modal shares must be non-negative and their sum must be equal to one:

$$\begin{aligned} s_{R,i} + s_{\text{Rail},i} + s_{\text{IWW},i} &= 1 \\ s_{k,i} &\geq 0, \quad k \in \{R, \text{Rail}, \text{IWW}\} \end{aligned} \quad (2)$$

For a total freight demand D , the freight quantity assigned to transport mode k under alternative A_i is:

$$D_{k,i} = D s_{k,i} \quad (3)$$

Let K_k denote the available weekly capacity of transport mode k . A modal allocation alternative is operationally feasible when:

$$D s_{k,i} \leq K_k, \quad \forall k \in \{R, \text{Rail}, \text{IWW}\} \quad (4)$$

For each transport mode included in alternative A_i , the relative capacity reserve is calculated as:

$$r_{k,i} = 1 - \frac{D s_{k,i}}{K_k} \quad (5)$$

The capacity feasibility criterion is defined as the minimum relative capacity reserve among the transport modes used in alternative A_i :

$$C_{i6} = \min_{k:s_{k,i}>0} \left(1 - \frac{D s_{k,i}}{K_k} \right) \quad (6)$$

This formulation identifies the most capacity-constrained transport mode within each modal allocation alternative. A value close to zero indicates that at least one transport mode is operating near its available capacity, whereas a higher value indicates a larger capacity reserve.

The modal allocation alternatives are evaluated according to six criteria:

$$\mathcal{C} = \{C_1, C_2, C_3, C_4, C_5, C_6\}$$

where C_1 is direct transport cost, C_2 is weighted average transit time, C_3 is greenhouse gas emissions, C_4 is external cost, C_5 is weighted modal reliability, and C_6 is the minimum relative capacity reserve.

Thus, Equations (1)–(6) define the modal allocation structure, freight distribution, and capacity-feasibility conditions used throughout the analysis.

3.2. ANN-Based Surrogate Model

A feed-forward artificial neural network is employed as a surrogate model to estimate the criterion values for different combinations of operating conditions and modal shares. Feed-forward neural networks are suitable for approximating nonlinear relationships between input and output variables [63]. The ANN input vector associated with alternative A_i is defined as:

$$\mathbf{x}_i = [D, q, h, \kappa_R, \kappa_{\text{Rail}}, \kappa_{\text{IWW}}, p_f, \tau, s_{R,i}, s_{\text{Rail},i}, s_{\text{IWW},i}]$$

where D is freight demand, q is the road-congestion factor, h is the inland-waterway navigation factor, κ_R , κ_{Rail} , and κ_{IWW} are the modal-capacity ratios, p_f is the fuel-price index, τ is the delivery-time requirement, and $s_{R,i}$, $s_{\text{Rail},i}$, $s_{\text{IWW},i}$ denote the respective modal shares.

The corresponding available capacity of transport mode k is obtained as $K_k = \kappa_k D$ and is used in the calculation of the capacity-feasibility criterion.

The ANN output vector is:

$$\hat{\mathbf{y}}_i = [\hat{C}_{i1}, \hat{C}_{i2}, \hat{C}_{i3}, \hat{C}_{i4}, \hat{C}_{i5}, \hat{C}_{i6}]$$

where $\hat{C}_{ij}$ represents the surrogate-estimated value of criterion j for alternative i .

The ANN input–output mapping is defined by Equation (7):

$$\hat{y}_i = f_{\text{ANN}}(\mathbf{x}_i; \boldsymbol{\theta}) \quad (7)$$

where f_{ANN} denotes the trained neural-network function and $\boldsymbol{\theta}$ represents the network parameters, including weights and biases.

For a scenario-generated training dataset containing N input–output samples and six output variables, the network parameters are estimated by minimising the mean squared error. The target values are obtained from the engineering reference calculations described in Section 4. Accordingly, the ANN approximates the engineering reference model rather than learning directly from observed operator data. The optimisation problem defined by Equation (8) is solved during ANN training:

$$\mathcal{L}(\boldsymbol{\theta}) = \frac{1}{6N} \sum_{\ell=1}^N \sum_{j=1}^6 (y_{\ell j} - \hat{y}_{\ell j})^2 \quad (8)$$

The detailed ANN architecture, activation functions, input and output normalisation, dataset division, optimisation algorithm, and surrogate-performance indicators are presented in Section 5.

After training, the ANN surrogate is applied to the predefined modal allocation alternatives. The resulting estimates form the initial decision matrix:

$$\hat{\mathbf{X}} = [\hat{c}_{ij}]_{m \times 6} = \begin{bmatrix} \hat{c}_{11} & \hat{c}_{12} & \hat{c}_{13} & \hat{c}_{14} & \hat{c}_{15} & \hat{c}_{16} \\ \hat{c}_{21} & \hat{c}_{22} & \hat{c}_{23} & \hat{c}_{24} & \hat{c}_{25} & \hat{c}_{26} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \hat{c}_{m1} & \hat{c}_{m2} & \hat{c}_{m3} & \hat{c}_{m4} & \hat{c}_{m5} & \hat{c}_{m6} \end{bmatrix}$$

The rows of matrix $\hat{\mathbf{X}}$ represent the modal allocation alternatives, while the columns represent the surrogate-estimated decision criteria.

3.3. CRITIC Objective Weighting Method

The CRITIC method is applied to determine objective criterion weights from the surrogate-estimated decision matrix. The method evaluates the information contained in each criterion by combining its contrast intensity, represented by standard deviation, and its conflict with the remaining criteria, represented by inter-criterion correlation [15].

For a benefit-type criterion, the normalised value is calculated as:

$$z_{ij} = \frac{\hat{c}_{ij} - \hat{c}_j^{\min}}{\hat{c}_j^{\max} - \hat{c}_j^{\min}}, \quad j = 5, 6 \quad (9)$$

For a cost-type criterion, normalisation is performed as:

$$z_{ij} = \frac{\hat{c}_j^{\max} - \hat{c}_{ij}}{\hat{c}_j^{\max} - \hat{c}_j^{\min}}, \quad j = 1, 2, 3, 4 \quad (10)$$

The mean normalised value of criterion j is:

$$\bar{z}_j = \frac{1}{m} \sum_{i=1}^m z_{ij} \quad (11)$$

The contrast intensity of criterion j is represented by its standard deviation:

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^m (z_{ij} - \bar{z}_j)^2}{m - 1}} \quad (12)$$

The Pearson correlation coefficient between criteria j and k is calculated as:

$$\rho_{jk} = \frac{\sum_{i=1}^m (z_{ij} - \bar{z}_j)(z_{ik} - \bar{z}_k)}{\sqrt{\sum_{i=1}^m (z_{ij} - \bar{z}_j)^2} \sqrt{\sum_{i=1}^m (z_{ik} - \bar{z}_k)^2}} \quad (13)$$

The information content of criterion j is:

$$I_j = \sigma_j \sum_{k=1}^6 (1 - \rho_{jk}) \quad (14)$$

Finally, the objective CRITIC weight of criterion j is calculated as:

$$w_j = \frac{I_j}{\sum_{k=1}^6 I_k} \quad (15)$$

subject to:

$$\sum_{j=1}^6 w_j = 1, \quad w_j \geq 0 \quad (16)$$

A criterion receives a higher weight when it exhibits greater variation among alternatives and contains information that is less strongly correlated with the remaining criteria.

It should be emphasised that the CRITIC weights are derived from a scenario-based decision matrix rather than observed operational data. Consequently, the resulting weights reflect the variability and interrelationships of the modelled criteria under the adopted assumptions and should not be interpreted as empirically established criterion importance.

3.4. SREM Ranking Method

The Square-Root based Evaluation Method (SREM) is used to rank the freight modal allocation alternatives [16]. SREM integrates squared and square-root transformations of percentage-normalised criterion values. The relative contribution of these transformations is controlled by the balancing coefficient α .

For benefit-type criteria, percentage normalisation is performed as:

$$m_{ij} = \frac{\hat{c}_{ij}}{\sum_{i=1}^m \hat{c}_{ij}} \cdot 100, \quad j = 5, 6 \quad (17)$$

For cost-type criteria, reciprocal values are used before percentage normalisation:

$$m_{ij} = \frac{1/\hat{c}_{ij}}{\sum_{i=1}^m (1/\hat{c}_{ij})} \cdot 100, \quad j = 1, 2, 3, 4 \quad (18)$$

The elements of the squared-transformed matrix are calculated as:

$$S_{ij} = \frac{m_{ij}^2}{\sum_{i=1}^m m_{ij}^2} \quad (19)$$

The elements of the square-root-transformed matrix are calculated as:

$$R_{ij} = \frac{\sqrt{m_{ij}}}{\sum_{i=1}^m \sqrt{m_{ij}}} \quad (20)$$

The squared- and square-root-transformed components are integrated as:

$$a_{ij} = \alpha S_{ij} + (1 - \alpha) R_{ij}, \quad 0 \leq \alpha \leq 1 \quad (21)$$

when $\alpha = 1$, only the squared-transformed component is considered. When $\alpha = 0$, only the square-root-transformed component is considered. In the baseline calculation, $\alpha = 0.5$ is used, providing equal contributions from the two transformed components.

The weighted fused values are calculated as:

$$n_{ij} = a_{ij}w_j \quad (22)$$

The final SREM score of alternative A_i is:

$$F_i = \sum_{j=1}^6 n_{ij} \quad (23)$$

The alternatives are ranked in descending order of F_i . Therefore:

$$A_{\text{best}} = \arg \max_{A_i} F_i \quad (24)$$

where A_{best} denotes the most favourable freight modal allocation alternative.

SREM was selected because its squared and square-root transformations allow different aggregation behaviours to be examined within a unified ranking framework. The balancing coefficient α controls the relative contribution of these transformations and is treated as a methodological parameter rather than an empirically established representation of decision-maker preferences. Its influence on ranking stability is examined in Section 7.1.

3.5. Sensitivity Analysis Procedure

The stability of the baseline CRITIC–SREM ranking is examined through two complementary sensitivity analyses.

First, the sensitivity of the SREM ranking to the balancing coefficient α is analysed. The coefficient is varied over the range from 0 to 1 using the values:

$$\alpha \in \{0, 0.25, 0.50, 0.75, 1.00\}$$

This analysis examines whether the identification of the preferred modal allocation depends strongly on the relative contribution of the squared- and square-root-transformed components of the SREM method.

Second, the influence of different decision-making priorities is examined by applying alternative criterion-weight scenarios. For each scenario s , the criterion weights satisfy:

$$w_j^{(s)} \geq 0, \quad \sum_{j=1}^6 w_j^{(s)} = 1 \quad (25)$$

The analysed scenarios include the baseline CRITIC weights, economic priority, urgent-delivery priority, environmental priority, capacity priority, and equal criterion weights. These scenarios are used to examine how changes in the relative importance of economic, operational, environmental, reliability, and capacity-related criteria affect the preferred modal allocation.

Together, these analyses provide an assessment of the robustness of the baseline ranking with respect to both the internal SREM balancing parameter and changes in decision-making priorities.

4. Case Study, Alternatives and Data Assumptions

The proposed framework is demonstrated through a scenario-based case study of freight modal allocation on the Prahovo–Šabac corridor in Serbia. The analysed transport task considers the allocation of the same weekly freight demand among road, rail, and inland waterway transport under predefined operating and capacity conditions.

Prahovo and Šabac were selected as the endpoints of the modelled corridor because both locations are associated with officially declared port areas [64]. The inland waterway component of the corridor is represented by the Danube and Sava waterways, using official navigational charts and waterway information provided by the Directorate for Inland Waterways [65]. The selection of Prahovo is supported by the ongoing development and capacity-expansion activities related to the Port of Prahovo [66]. The corresponding road and rail components are defined using the official road-network reference system and published railway distance and tariff documents [67,68].

The case study does not reproduce an existing commercial transport contract or a currently operated scheduled trimodal service. Instead, it evaluates modelled modal allocation structures under a common freight demand and explicitly defined operating assumptions. Its purpose is to demonstrate the application of the proposed decision-support framework and to examine the compromise between economic, operational, environmental, reliability, and capacity-related criteria. Accordingly, the results should be interpreted as scenario-based estimates rather than as measured performance of an existing transport service.

4.1. Study Area, Data Sources, and Modelling Assumptions

The scenario-based case study combines publicly available infrastructure and transport data [64–68], engineering calculations based on established emission and external-cost methodologies [2,69,70], explicitly stated market-based assumptions, and scenario variables used to generate the surrogate-model dataset. The corresponding data structure and source status are summarised in Table 1.

Table 1. Data basis and source status used in the scenario-based case study.

Data Group	Examples of Variables	Data Status	Source/Reference
Publicly available data	port areas and terminal availability	public/official	[64,66]
Publicly available data	inland waterway route and navigation conditions	public/official	[65]
Publicly available data	railway distances and tariff elements	public/pub- lished	[67]
Publicly available data	road-network routes and distances	public/official	[68]
Engineering calculations	GHG emissions	calculated	[69,70]
Engineering calculations	external costs	calculated	[2]
Market-based assumptions	commercial prices, capacities, and reliability coefficients	assumed	Authors' assumptions
Scenario parameters	demand, congestion, navigation, and fuel-price factors	scenario-based	Defined by the authors

The adopted data structure enables transparent evaluation of modal allocation alternatives under explicitly defined assumptions and is intended for decision support rather than detailed operational or commercial planning.

The assumed transport costs, reliability coefficients, and capacity values were adopted as illustrative inputs due to the limited availability of detailed operator-level data. These assumptions are explicitly distinguished from official data and engineering calculations in Tables 1 and 2. Consequently, the numerical results should be interpreted as scenario-dependent estimates rather than empirically validated operational outcomes.

Table 2. Baseline numerical assumptions used in the scenario-based case study.

Parameter	Road	Rail	Inland Waterway	Source/Status
Transport distance—km	390	520	415	road [68]; rail [67]; IWW [65]
Unit transport cost—EUR/t	19.94	8.78	31.13	rail tariff [67]; road and IWW values assumed
Modal transit time—h	8.0	24.0	60.0	engineering estimate
GHG coefficient—t CO ₂ e/t	0.02418	0.00720	0.01087	calculated using [69,70]
External cost coefficient—EUR/t	13.65	5.20	6.23	calculated/adapted using [2]
Reliability coefficient—dimensionless	0.950	0.900	0.850	assumed
Available weekly capacity—t/week	5000	3000	2500	scenario assumption

The proposed framework represents a simplified strategic-level assessment rather than a detailed operational transport model. Infrastructure bottlenecks, terminal handling, service frequencies, and seasonal navigation restrictions are not explicitly modelled. Furthermore, criterion C₆ represents a simplified relative capacity-reserve indicator and should not be interpreted as a comprehensive measure of infrastructure capacity or operational feasibility.

4.2. Definition of Freight Modal Allocation Alternatives

Seven alternatives are considered, representing different allocations of the same freight demand among road, rail, and inland waterway transport, including a fully road-based option, road–rail combinations, and trimodal structures.

The modal composition of the considered alternatives is illustrated in Figure 2.

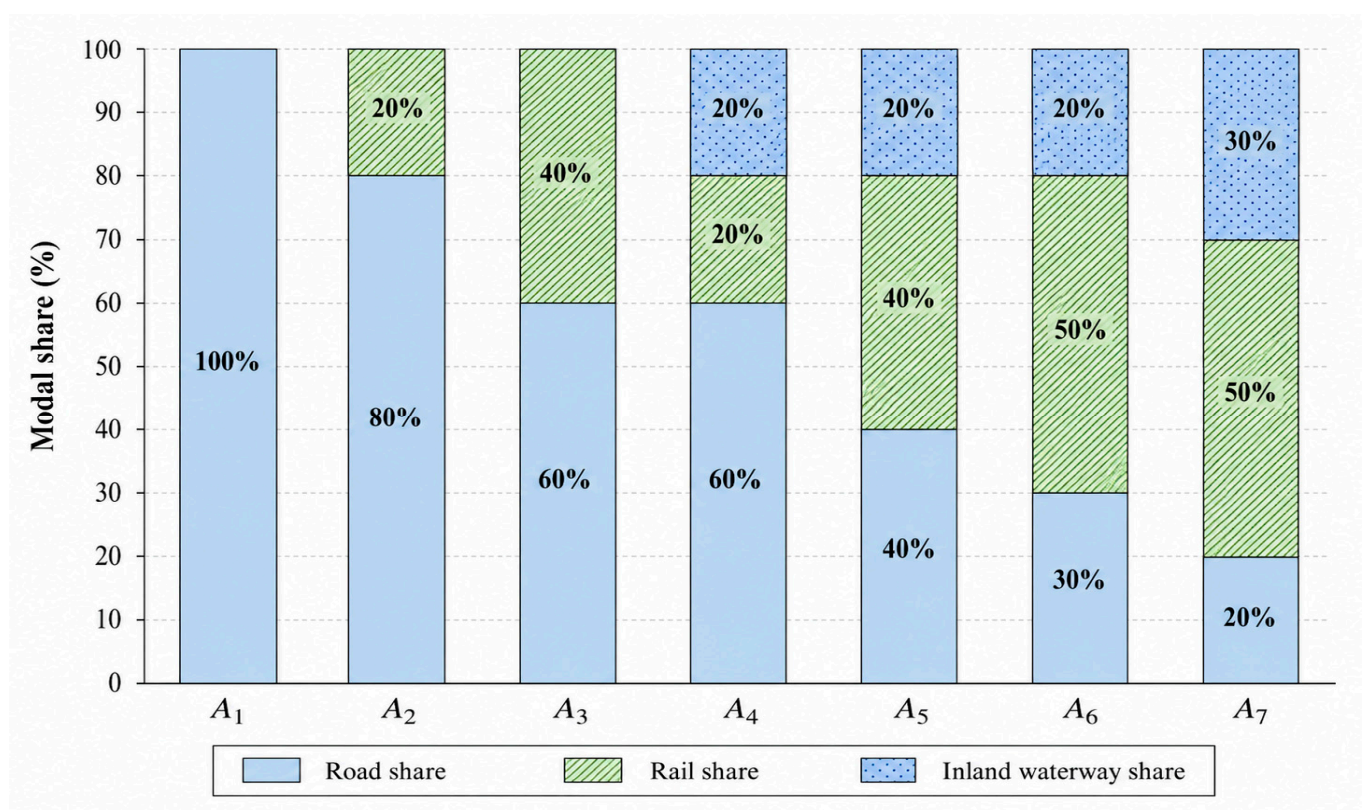
**Figure 2.** Modal composition of the considered freight allocation alternatives.

Figure 2 illustrates the gradual transition from the fully road-based alternative A₁ towards structures with increasing rail and inland-waterway shares. All alternatives represent modelled modal allocations under the same weekly freight demand rather than existing commercial transport arrangements.

The considered alternatives constitute illustrative scenarios rather than an exhaustive set of feasible modal allocations. Other modal combinations could produce different rankings and should therefore be considered in future applications.

4.3. Decision Criteria

The selected decision criteria are presented in Table 3.

Table 3. Decision criteria used in the case study.

Criterion	Description	Unit	Type
C ₁	Direct transport cost	EUR/week	min
C ₂	Weighted average transit time	h	min
C ₃	Greenhouse gas emissions	t CO ₂ e/week	min
C ₄	External costs	EUR/week	min
C ₅	Weighted modal reliability	index	max
C ₆	Minimum relative capacity reserve	index	max

The alternatives are evaluated using six criteria covering economic, operational, environmental, reliability, and capacity-related performance (Table 3). GHG emissions are calculated according to ISO 14083:2023 [69] and relevant modal emission guidance [70], while external costs follow the European Handbook on the External Costs of Transport [2]. Weighted modal reliability represents the assumed service reliability of the modal structure, whereas the minimum relative capacity reserve reflects the most capacity-constrained mode within that structure. Criteria C₁–C₄ are minimisation criteria, while C₅ and C₆ are maximisation criteria.

4.4. Base Scenario and Numerical Assumptions

The base scenario considers a weekly freight flow of:

$$D = 5000 \text{ t/week}$$

The adopted transport distances, unit costs, modal times, emission coefficients, external cost coefficients, reliability coefficients and available weekly capacities are shown in Table 2.

The adopted values serve as reference values for generating the scenario-based input–output samples and define the base operating scenario. In addition to the modal shares, the scenario variables include the road-congestion factor, inland-waterway navigation factor, fuel-price index, and delivery-time requirement. For the base scenario, the following values are adopted:

$$Q = 1.00, h = 1.00, p_f = 1.00, \tau = 72 \text{ h}$$

where q is the road congestion factor, h is the inland waterway navigation factor, p_f is the fuel price index, and τ is the delivery-time requirement.

These data and assumptions provide the basis for scenario generation and surrogate estimation of the six decision criteria described in Section 5.

5. ANN Surrogate Model Development and Decision Matrix Construction

The development, training, and validation of the artificial neural network used as a surrogate model are described below. The ANN is trained using scenario-based input–output samples derived from the corridor data and numerical assumptions presented in Section 4. After validation, the trained surrogate is applied to the seven predefined alternatives under the base operating scenario. The resulting estimates form the decision matrix used in the CRITIC–SREM evaluation.

5.1. Generation of the Scenario-Based Dataset

The surrogate-model dataset was generated using Latin hypercube sampling (LHS), which provides stratified coverage of a multidimensional input space [71]. A total of 10,000 system states was generated by varying eight scenario variables within the ranges presented in Table 4. Continuous uniform distributions were assumed because reliable probability distributions were unavailable, while the modal shares were fixed according to the seven alternatives defined in Table 5. Each system state was combined with all seven modal structures, producing 70,000 scenario-based input–output samples. Together with the three modal shares, the eight scenario variables form the 11 ANN inputs.

Table 4. Input-variable ranges used for scenario generation.

Input Variable	Symbol	Base Value	Minimum	Maximum	Sampling Rule
Freight demand	(D)	5000 t/week	4000 t/week	6000 t/week	LHS, continuous uniform range
Road-congestion factor	(q)	1.00	0.90	1.20	LHS, continuous uniform range
Inland-waterway navigation factor	(h)	1.00	0.90	1.20	LHS, continuous uniform range
Road-capacity ratio	(κ_R)	1.00	1.00	1.30	LHS, continuous uniform range
Rail-capacity ratio	(κ_{Rail})	0.60	0.50	0.80	LHS, continuous uniform range
Inland-waterway-capacity ratio	(κ_{IWW})	0.50	0.30	0.60	LHS, continuous uniform range
Fuel-price index	(p _i)	1.00	0.85	1.25	LHS, continuous uniform range
Delivery-time requirement	(τ)	72 h	24 h	72 h	LHS, continuous uniform range
Modal shares	($s_R, s_{\text{Rail}}, s_{\text{IWW}}$)	Table 5	Fixed	Fixed	Seven predefined alternatives

Table 5. Freight modal allocation alternatives.

Alternative	Road Share	Rail Share	Inland Waterway Share	Description
A ₁	100%	0%	0%	fully road-based transport
A ₂	80%	20%	0%	road-dominant road–rail option
A ₃	60%	40%	0%	mixed road–rail option
A ₄	60%	20%	20%	road-dominant trimodal option
A ₅	40%	40%	20%	balanced trimodal option
A ₆	30%	50%	20%	rail-dominant trimodal option
A ₇	20%	50%	30%	rail–waterway-oriented trimodal option

The adopted range of the inland-waterway navigation factor represents moderate variations around normal navigational conditions and does not explicitly account for extreme hydrological events, such as prolonged low-water periods or floods that may severely restrict inland-waterway operations.

The input variables were sampled independently; therefore, possible empirical correlations among freight demand, congestion, navigation conditions, and fuel prices were not represented. This assumption should be addressed in future applications using observed data.

The following equations define the six target variables used to generate the ANN training dataset. For each modal allocation alternative i , the criteria are calculated as follows:

$$\begin{aligned}
 C_{i1} &= Dp_f(s_{R,i}c_Rq + s_{\text{Rail},i}c_{\text{Rail}} + s_{\text{IWW},i}c_{\text{IWW}}h) \\
 C_{i2} &= s_{R,i}t_Rq + s_{\text{Rail},i}t_{\text{Rail}} + s_{\text{IWW},i}t_{\text{IWW}}h \\
 C_{i3} &= D(s_{R,i}e_Rq + s_{\text{Rail},i}e_{\text{Rail}} + s_{\text{IWW},i}e_{\text{IWW}}h) \\
 C_{i4} &= D(s_{R,i}x_Rq + s_{\text{Rail},i}x_{\text{Rail}} + s_{\text{IWW},i}x_{\text{IWW}}h) \\
 C_{i5} &= (s_{R,i}r_R + s_{\text{Rail},i}r_{\text{Rail}} + s_{\text{IWW},i}r_{\text{IWW}})\min\left(1, \frac{\tau}{C_{i2}}\right) \\
 C_{i6} &= \min_{k:s_{k,i}>0}\left(1 - \frac{Ds_{k,i}}{K_k}\right)
 \end{aligned} \tag{26}$$

where:

- c_k denotes the modal unit transport cost;
- t_k denotes the modal transit time;
- e_k denotes the modal GHG emission coefficient;
- x_k denotes the modal external-cost coefficient;
- r_k denotes the modal reliability coefficient reported in Table 2;
- D is the weekly freight demand;
- p_f is the fuel-price index;
- q is the road-congestion factor;
- h is the inland-waterway navigation factor;
- τ is the delivery-time requirement;
- $s_{k,i}$ is the share of transport mode k in alternative i ;
- K_k is the available weekly capacity of transport mode k .

For the base scenario, $q = h = p_f = 1$, and $\tau = 72$ h, which yields the criterion values used for the baseline modal allocation analysis.

For each scenario-based input–output sample, the six reference target values were calculated using the engineering relationships defined in Equation (26), linking freight demand, modal shares, operating-condition factors, modal coefficients, and capacity ratios to the corresponding criteria.

The engineering reference model is explicitly defined by Equation (26), using the parameters and assumptions presented in Tables 2 and 4. The resulting deterministic estimates serve as reference targets for ANN training and validation. Consequently, the ANN outputs remain conditional on the adopted mathematical relationships and scenario assumptions rather than observed transport operations.

Although the engineering reference equations can be evaluated directly, the ANN provides a unified multi-output surrogate for estimating all six decision criteria under varying scenario conditions. Its principal contribution is methodological integration rather than demonstrated computational superiority over the simplified reference model.

The framework can also accommodate more complex simulation-based or empirical reference models in future applications.

5.2. Data Preprocessing and Dataset Division

The 10,000 system states were divided into training, validation, and testing subsets in proportions of 70%, 15%, and 15%, respectively. Division was performed at the system-state level, ensuring that all seven modal alternatives derived from the same state belonged to the same subset and preventing information leakage. This resulted in 49,000 training, 10,500 validation, and 10,500 testing input–output samples. A fixed random seed of 42 was used. Normalisation parameters were estimated exclusively from the training subset and subsequently applied to the validation and testing data [72,73].

5.3. ANN Architecture and Training Procedure

A fully connected multi-output feed-forward ANN with an 11–64–32–6 architecture was developed. ReLU activation was used in the hidden layers and linear activation in the output layer. Network weights were initialised using the Glorot/Xavier scheme [74]. Training was performed using the Adam optimiser [75] to minimise the mean squared error, while early stopping based on validation loss was applied to reduce overfitting [76]. The adopted parameters are summarised in Table 6.

Table 6. ANN architecture and training parameters.

Parameter	Adopted Value
ANN architecture	11–64–32–6
Hidden-layer activation	ReLU
Output activation	Linear
Weight initialisation	Glorot/Xavier
Optimiser	Adam
Initial learning rate	0.001
Batch size	256
Maximum epochs	180
Loss function	Mean squared error
Early-stopping patience	20 epochs
Random seed	42
Training/validation/testing split	70%/15%/15%

The adopted ANN architecture was selected as a compact multi-output surrogate configuration suitable for the considered input–output mapping. A separate hyperparameter optimisation procedure or k-fold cross-validation was not performed. Instead, a fixed training, validation, and testing split was used, together with early stopping to reduce overfitting. Generalisation performance was assessed on an independent testing subset using RMSE, MAE, R^2 , and NRMSE, as reported in Table 7.

Table 7. ANN surrogate performance on the testing subset.

Output	RMSE	MAE	R ²	NRMSE
Direct transport cost	679.12 EUR/week	519.06 EUR/week	0.9987	0.0055
Weighted average transit time	0.0718 h	0.0558 h	0.9999	0.0025
GHG emissions	0.3557 t CO ₂ e/week	0.2723 t CO ₂ e/week	0.9998	0.0028
External costs	189.96 EUR/week	145.49 EUR/week	0.9998	0.0027
Weighted modal reliability	0.00103	0.00048	0.9990	0.0032
Minimum relative capacity reserve	0.00450	0.00330	0.9989	0.0084

The architecture of the developed multi-output feed-forward ANN is illustrated in Figure 3. The network contains eleven input neurons, two fully connected hidden layers with 64 and 32 neurons, respectively, and six output neurons corresponding to the decision criteria.

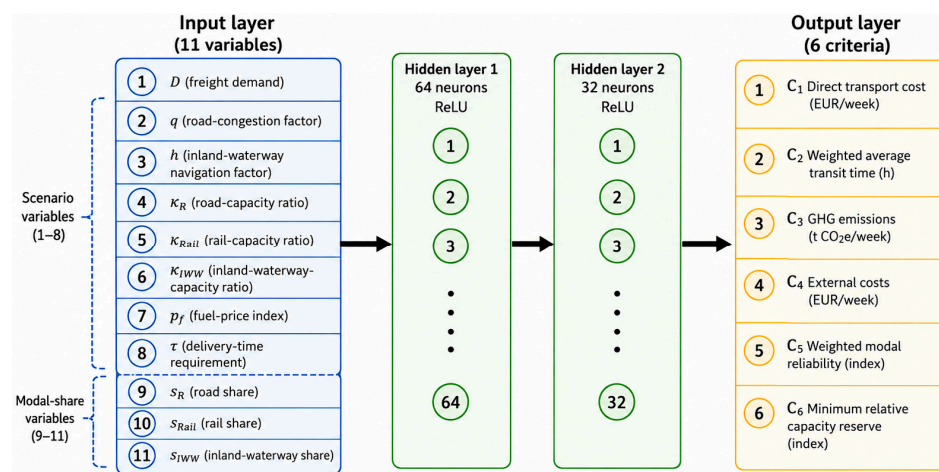
**Figure 3.** Architecture of the multi-output feed-forward ANN.

Figure 3 illustrates the eleven inputs, two hidden layers, and six simultaneously estimated decision-criterion values.

All numerical calculations, including Latin hypercube sampling, ANN training and validation, CRITIC weighting, SREM ranking, and sensitivity analyses, were performed using MATLAB R2018b (MathWorks, Natick, MA, USA). The comparative TOPSIS analysis presented in Section 6.3 was performed using Python 3.11 with NumPy 1.26.4.

5.4. ANN Surrogate Performance

The approximation performance of the trained ANN surrogate was evaluated using the independent testing subset. The results presented in Table 7 show close agreement between the engineering-calculated reference values and the surrogate estimates. The coefficient of determination exceeded 0.998 for all six outputs, while the normalised RMSE remained below 1%. The use of RMSE and MAE as complementary error metrics follows established guidance on their interpretation [77].

The lowest relative estimation errors were obtained for weighted average transit time, GHG emissions, and external costs. The minimum relative capacity reserve exhibited the highest normalised error, although its NRMSE remained below 0.01.

The obtained results show that the ANN accurately reproduces the input–output relationships of the engineering reference model within the analysed parameter ranges. This evaluation represents internal surrogate-model validation against engineering-generated reference values rather than external validation against observed operational data.

NRMSE was calculated by dividing RMSE by the range of the corresponding reference values in the testing subset.

The ANN surrogate estimates closely reproduce the engineering-calculated reference values, with small approximation differences arising from the surrogate-modelling process. The values are reported in Table 8 in rounded form for presentation, whereas the unrounded ANN outputs were used in all subsequent CRITIC and SREM calculations.

Table 8. Surrogate-estimated decision matrix for the Prahovo–Šabac corridor.

Alternative	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
A ₁	99,699.27	8.053	120.876	68,278.90	0.950701	0.003422
A ₂	88,912.86	11.213	103.968	59,840.96	0.940586	0.195346
A ₃	77,464.61	14.392	86.679	51,198.11	0.930346	0.331882
A ₄	99,893.75	21.644	90.346	52,252.35	0.919960	0.397885
A ₅	88,908.82	24.777	73.406	43,747.57	0.910132	0.333846
A ₆	83,242.52	26.423	64.898	39,572.13	0.904618	0.166151
A ₇	88,094.67	31.570	58.345	35,896.30	0.894569	0.165906

The surrogate-estimated decision matrix reveals clear trade-offs among the alternatives. A₁ provides the shortest transit time and highest reliability but also the highest GHG emissions and external costs, whereas A₇ shows the opposite pattern. A₃ achieves the lowest direct transport cost under baseline conditions. Since no alternative dominates across all criteria, the complete decision matrix is subsequently evaluated using the CRITIC–SREM procedure.

6. CRITIC–SREM Calculation and Ranking Results

The surrogate-estimated decision matrix is evaluated using the integrated CRITIC–SREM procedure. The CRITIC method first determines objective criterion weights based on criterion variability and inter-criterion correlations. The resulting weights are then incorporated into the SREM method to calculate the final performance scores and rank the considered freight modal allocation alternatives.

6.1. Objective Criterion Weights Obtained Using the CRITIC Method

The CRITIC method was applied to the surrogate-estimated decision matrix according to the procedure defined by Equations (9)–(16) in Section 3.3. The resulting objective criterion weights are presented in Table 9.

Table 9. CRITIC weights of the decision criteria.

Criterion	Description	Type	CRITIC Weight
C ₁	Direct transport cost	min	0.1361
C ₂	Weighted average transit time	min	0.2054
C ₃	GHG emissions	min	0.1555
C ₄	External costs	min	0.1565
C ₅	Weighted modal reliability	max	0.2053
C ₆	Minimum relative capacity reserve	max	0.1411

Weighted average transit time and weighted modal reliability receive the highest CRITIC weights, 0.2054 and 0.2053, respectively, indicating the greatest discriminatory information within the analysed decision matrix. GHG emissions, external costs, capacity

reserve, and direct transport cost receive relatively similar weights, showing that no single criterion strongly dominates the objective weighting structure.

6.2. SREM Ranking Results

The CRITIC weights were subsequently applied in the SREM ranking procedure defined by Equations (17)–(24). The baseline calculation was performed using a balancing coefficient of $\alpha = 0.5$. This value assigns equal contributions to the squared- and square-root-transformed components of the method. The resulting SREM scores and final ranking are presented in Table 10.

Table 10. Comparative ranking results obtained using SREM and TOPSIS.

Rank	Alternative	SREM Score	TOPSIS Score	TOPSIS Rank
1	A ₃	0.15284	0.72371	1
2	A ₁	0.14450	0.46377	5
3	A ₅	0.14409	0.56666	4
4	A ₄	0.14214	0.61281	2
5	A ₇	0.14037	0.40011	7
6	A ₂	0.14010	0.58811	3
7	A ₆	0.13597	0.43569	6

The baseline SREM ranking is:

$$A_3 > A_1 > A_5 > A_4 > A_7 > A_2 > A_6.$$

To provide a clearer comparison of the final performance values, the baseline SREM scores are graphically presented in Figure 4. The alternatives are arranged according to their descending SREM scores.

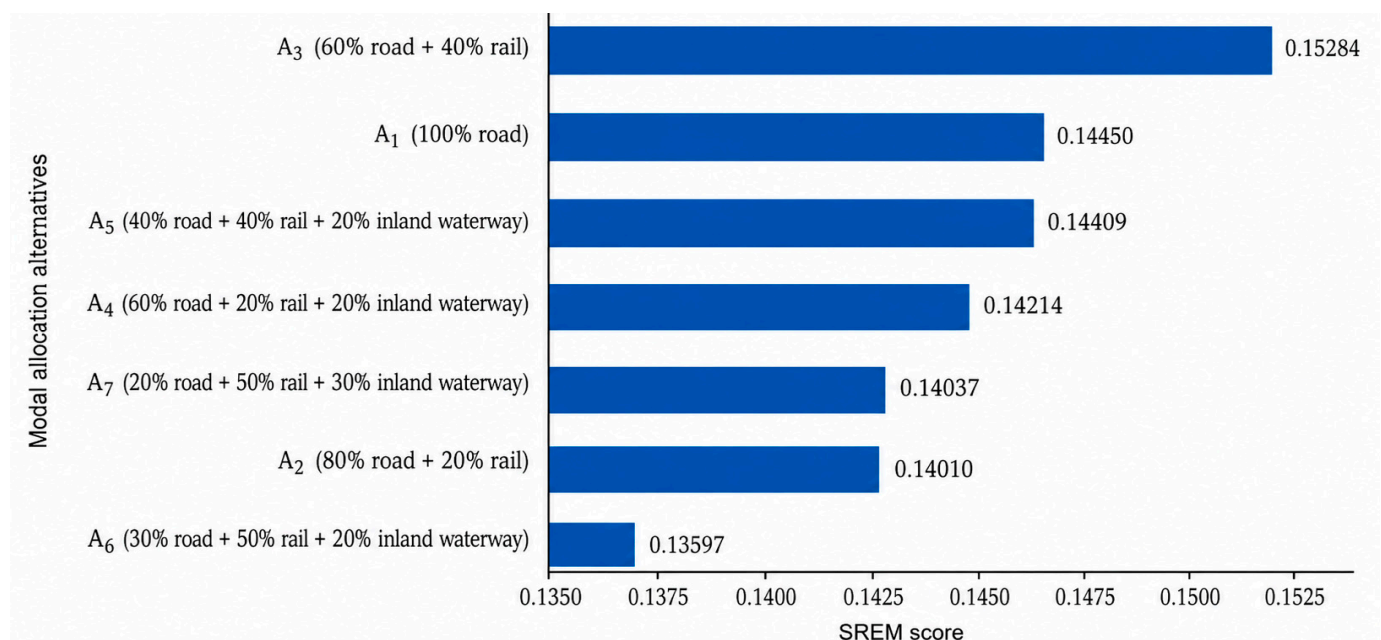


Figure 4. SREM scores and ranking of the freight modal allocation alternatives under baseline conditions ($\alpha = 0.5$).

Figure 4 shows that A₃ (60% road and 40% rail transport) achieves the highest SREM score and is therefore the highest-ranked alternative under the baseline assumptions. The

score differences between A_1 and A_5 (0.00041) and between A_7 and A_2 (0.00027) are small, indicating that their relative positions should be interpreted cautiously. The robustness of the ranking is further examined through the TOPSIS comparison in Section 6.3 and the sensitivity analyses in Section 7.

6.3. Comparative Ranking and Robustness Check Using TOPSIS

To further assess ranking robustness, the TOPSIS method was applied using the same decision matrix (Table 8) and CRITIC weights (Table 9). Vector normalization was employed, with C_1 – C_4 treated as cost criteria and C_5 – C_6 as benefit criteria. The comparative results are presented in Table 10.

Both SREM and TOPSIS identified A_3 (60% road and 40% rail) as the highest-ranked alternative, although differences were observed in the ranking of the remaining alternatives. This comparison provides an additional check of the stability of the preferred alternative with respect to the selected MCDM method. However, it should not be interpreted as empirical validation of the proposed framework or the ANN estimates.

6.4. Interpretation of the Ranking Results

The ranking reflects the trade-off among economic efficiency, operational performance, environmental sustainability, reliability, and capacity-related performance. Under the adopted modelling assumptions, alternatives with higher road shares perform better in terms of transit time and reliability, whereas increasing rail and inland-waterway shares reduces GHG emissions and external costs.

Alternative A_3 achieves the highest baseline score because its 40% rail share reduces direct transport cost, GHG emissions, and external costs relative to the fully road-based alternative, while its remaining road share preserves comparatively favourable transit time and reliability. Alternatives with larger rail and inland-waterway shares provide stronger environmental performance but receive lower performance values for transit time, reliability, and, in some cases, capacity reserve. Under the adopted assumptions and CRITIC weights, A_3 therefore represents the highest-ranked overall compromise.

7. Sensitivity Analysis

The robustness of the ranking produced by the integrated framework is examined through two complementary sensitivity analyses. The first investigates the influence of the SREM balancing coefficient, while the second examines different decision-making priorities by varying the criterion weights. The baseline CRITIC–SREM ranking obtained from the surrogate-estimated decision matrix is:

$$A_3 > A_1 > A_5 > A_4 > A_7 > A_2 > A_6.$$

Under the baseline conditions, A_3 is the highest-ranked alternative, representing a modal structure of 60% road and 40% rail transport.

7.1. Sensitivity to the SREM Balancing Coefficient

The influence of the SREM balancing coefficient α , introduced in Equation (21), was examined by varying its value from 0 to 1. According to the adopted SREM formulation, $\alpha=0$ represents exclusive use of the square-root-transformed component, while $\alpha=1$ represents exclusive use of the squared-transformed component. The results are presented in Table 11.

Table 11. Sensitivity of the SREM ranking to balancing coefficient α .

α	First-Ranked Alternative	Top Three Alternatives
0.00	A ₃	A ₃ > A ₅ > A ₂
0.25	A ₃	A ₃ > A ₅ > A ₄
0.50	A ₃	A ₃ > A ₁ > A ₅
0.75	A ₃	A ₃ > A ₁ > A ₅
1.00	A ₁	A ₁ > A ₃ > A ₅

While Table 11 reports the leading alternatives for selected values of the balancing coefficient, Figure 5 provides a more detailed representation of the SREM-score trajectories over the complete analysed range of α .

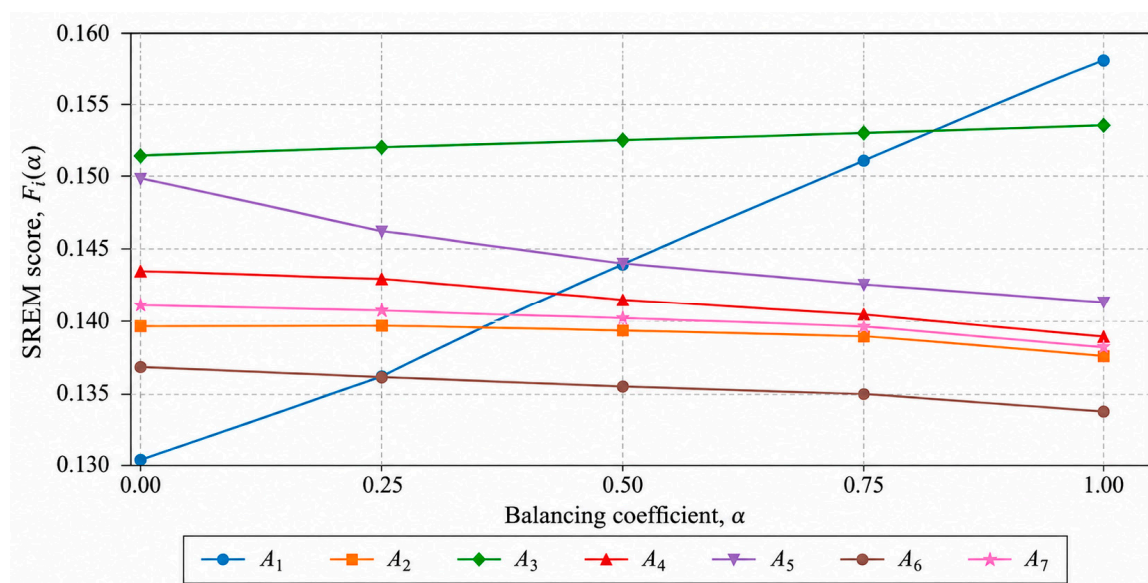
**Figure 5.** Sensitivity of the SREM scores to the balancing coefficient α .

Figure 5 shows that A₃ maintains the highest SREM score for balancing-coefficient values from $\alpha = 0$ to $\alpha = 0.75$. The relative performance of A₁ improves as α increases, and A₁ becomes the highest-ranked alternative at $\alpha = 1$, when the squared-transformed component is used exclusively.

The position of A₁ improves as α increases because the squared transformation strengthens the influence of exceptionally favourable criterion values, primarily transit time and reliability in the case of A₁. Conversely, the square-root transformation produces a more balanced differentiation among the alternatives.

The stability of A₃ over most of the analysed range indicates that its first position is not dependent on the baseline value of the balancing coefficient. However, the selection of A₁ at $\alpha = 1$ shows that the final ranking remains sensitive to the aggregation structure of SREM.

7.2. Sensitivity to Decision-Making Priorities

Alternative decision-priority scenarios were analysed to determine whether the highest-ranked modal allocation changes when greater importance is assigned to economic, operational, environmental, or capacity-related performance.

The criterion weights adopted for the sensitivity scenarios are presented in Table 12. These weights represent illustrative and structured decision-making assumptions rather than empirically elicited stakeholder preferences and are used exclusively to examine

changes in the ranking under different priorities. All criterion-weight scenarios satisfy the weight-normalisation condition defined by Equation (25).

Table 12. Criterion weights used in the decision-priority scenarios.

Scenario	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
Baseline CRITIC weights	0.1361	0.2054	0.1555	0.1565	0.2053	0.1411
Economic priority	0.4000	0.1500	0.1000	0.1000	0.1500	0.1000
Urgent-delivery priority	0.1000	0.4000	0.1000	0.1000	0.2000	0.1000
Environmental priority	0.1000	0.1000	0.3000	0.3000	0.1000	0.1000
Capacity priority	0.1000	0.1000	0.1000	0.1000	0.1000	0.5000
Equal weights	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667

Note: The displayed weights are rounded to four decimal places; unrounded normalised weights were used in the calculations.

The SREM rankings obtained using these criterion-weight scenarios and the baseline value ($\alpha = 0.5$) are shown in Table 13.

Table 13. SREM ranking under different decision-making priorities.

Scenario	First-Ranked Alternative	Top Three Alternatives
Baseline CRITIC weights	A ₃	A ₃ > A ₁ > A ₅
Economic priority	A ₃	A ₃ > A ₅ > A ₂
Urgent-delivery priority	A ₁	A ₁ > A ₂ > A ₃
Environmental priority	A ₇	A ₇ > A ₆ > A ₅
Capacity priority	A ₄	A ₄ > A ₃ > A ₅
Equal weights	A ₃	A ₃ > A ₅ > A ₄

Alternative A₃ remains the highest-ranked alternative under the baseline, economic-priority, and equal-weight scenarios. Under urgent-delivery priority, A₁ becomes the highest-ranked alternative because of its favourable transit time and reliability, whereas environmental priority favours A₇ because of its low GHG emissions and external costs. When capacity reserve receives the highest weight, A₄ becomes the highest-ranked alternative. These results show that the selected modal allocation depends on the decision-making priorities and that no alternative is universally preferred.

Overall, the sensitivity results indicate that the baseline first position of A₃ is relatively robust across the tested settings but is not universal.

The sensitivity analyses assess ranking stability under variations in the SREM balancing coefficient and criterion weights. Although the ANN training dataset incorporates variations in demand, congestion, navigation conditions, and fuel prices, these variations do not constitute a comprehensive probabilistic uncertainty analysis. Therefore, the results remain conditional on the adopted scenario assumptions, while explicit uncertainty propagation and stochastic evaluation are left for future research.

8. Conclusions

An integrated modelling and CRITIC–SREM framework was developed for evaluating sustainable freight modal allocation. The framework combines ANN surrogate estimation of economic, operational, environmental, reliability, and capacity-related criteria with objective CRITIC weighting and SREM ranking. Its application was illustrated

through a scenario-based case study of the Prahovo–Šabac corridor involving road, rail, and inland waterway transport.

Under the baseline assumptions, alternative A₃ (60% road and 40% rail transport) achieved the highest SREM score and provided the highest-ranked compromise among direct transport cost, transit time, GHG emissions, external costs, reliability, and capacity reserve. This result reflects the adopted corridor assumptions and should not be interpreted as a universally optimal modal structure.

The sensitivity analysis showed that the first position of A₃ is relatively robust, but not universal. Alternative A₃ remained highest-ranked for most analysed values of the SREM balancing coefficient and under the baseline, economic-priority, and equal-weight scenarios. However, A₁ became highest-ranked under urgent-delivery priority, while A₇ and A₄ were favoured under environmental and capacity priorities, respectively. The resulting modal allocation therefore depends on the decision-making context and the relative importance assigned to the evaluation criteria.

The principal limitation is the incomplete availability of detailed commercial and operational data. Some transport prices, reliability coefficients, and capacity values were therefore introduced as explicit scenario assumptions. The model also does not explicitly consider terminal handling and transshipment operations, service frequencies, seasonal navigation restrictions, commodity-specific requirements, or uncertainty in infrastructure availability. Consequently, the surrogate estimates remain conditional on the engineering reference model, parameter ranges, and assumptions used to generate the scenario-based dataset.

Future research should validate the framework using observed operator and terminal data and incorporate dynamic freight demand, transshipment costs and times, railway schedules, hydrological conditions, and fuel- and energy-price uncertainty. Stochastic intermodal models demonstrate the importance of jointly accounting for demand and capacity uncertainty when balancing economic, environmental, and reliability objectives [78]. Further developments may include probabilistic ANN models, explainable artificial intelligence, and fuzzy or dynamic MCDM approaches.

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