

An integrated multi-criteria decision analysis framework for comparing inland port transport capabilities in maritime logistics

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Abstract:

Introduction/purpose: Inland ports provide storage, transportation, and customs clearance services for goods moving within inland areas. Ranking and evaluating inland ports are crucial to national logistics, thereby improving management efficiency and optimizing the flow of goods. The current study demonstrates a capacity-focused capability assessment of eight inland ports in Vietnam.

Methods: The comparison is made based on four main parameters: throughput capacity, total area, warehouse area, and maximum exploitation output. Three multi-criteria modelling (MCM) methods, including the Probability Method (PM), objective pairwise adjusted ratio analysis (OPARA), and Root Assessment Method (RAM), were applied to rank the inland ports. The LOPCOW (Logarithmic Percentage Change-driven Objective Weighting) method is used to determine the criteria weights. Rankings from individual methods are aggregated using the Rank Index method (RIM).

Results: The results show that, regardless of the method employed or the criterion weights used, one inland port (A2) performs best among the eight surveyed ports. To assess the stability of the outcome, five scenarios are generated, varying the criterion weights and the ranking of alternatives in each case. The result shows that the outcome is less sensitive to the changes in external conditions.

Conclusion: This study provides transport companies with information to select the optimal inland port based on throughput capacity and warehouse area, supports exporters and importers in optimizing storage and transportation processes, provides the government with data to enhance management, and guides other ports in improving their operating capacity.

Keywords: logistics, inland port, probability method, OPARA, RAM, rank index method, LOPCOW.

Introduction

Vietnam's geographical location is highly favorable for trade and logistics development, with an area of 331,000 km² and a coastline exceeding 3,260 km. Vietnam ranks 10th out of 50 emerging logistics markets, with an average annual growth rate of 14-16% in the logistics sector. The reported total import-export turnover figure for Vietnam was \$732.5 billion in 2022, representing a 9.5% increase compared to 2021. To support and enhance the efficiency of sea import and export, inland ports have been built in inland areas (Rodrigues et al., 2020).

The development and effective management of inland ports not only enhance national logistics capacity but also promote sustainable economic growth (Thao & Tri, 2024). This shows that ranking inland ports plays an important role in developing logistics service policies and investment decisions (Jeevan & Ros, 2019). Moreover, ranking inland ports not only helps the government identify investment priorities and improve infrastructure but also guides provinces in developing and upgrading inland ports to optimize connectivity to seaports (Hervás-Peralta et al., 2019; Price et al., 2018). For transport enterprises, ranking inland ports provides valuable information to select effective dry ports, thereby reducing costs and improving operational efficiency. At the same time, ranking inland ports helps exporters and importers rely on ranking information to optimize the process of storing and transporting goods, ensuring efficiency in the supply chain (Lamii et al., 2020).

In short, ranking inland ports not only helps improve management and investment efficiency but also promotes synchronized development throughout the entire logistics system. However, there is currently no

published document ranking inland ports in Vietnam. This gap motivates this research.

When ranking inland ports, several key factors must be considered, including throughput capacity, total area, warehouse area, maximum exploitation output, infrastructure and equipment, connectivity and traffic, service costs, and others (Lam & Notteboom, 2016; Liu Wang, 2023; Mohan & Naseer, 2022). Besides the economic and transportation criteria mentioned, the ranking of inland ports also needs to evaluate additional criteria related to social aspects, sustainability, and other relevant factors (Mohan & Naseer, 2022; Varese et al., 2022; Beyene et al., 2024). With numerous parameters to evaluate inland ports, it is necessary to rank these parameters to identify those that significantly impact the performance of inland ports before ranking the ports themselves (Senol et al., 2019). Generally, evaluating inland ports is complex due to the diverse criteria. For example, Port A may have better throughput capacity than Port B, but Port B may have better infrastructure and equipment. Or, Port A may have a higher maximum exploitation output than Port B, but its service costs are higher. This complexity shows that ranking inland ports is an MCM task (Kahraman et al., 2023; Setiawan & Pasaribu, 2024).

Many studies have applied MCM methods to rank inland ports or related services in specific geographical areas. The *AHP* and *CODAS* methods have been used to select warehouse locations for inland ports in the Western Balkans (Tadić et al., 2020). The *AHP* method has also been applied to select an inland port for Rijeka Port in Croatia (Bozicevic et al., 2021). The *MARCOS* method was used to evaluate the logistics performance index of Western Balkan regions (Mešić et al., 2022). The evaluation of the logistics performance index of ten countries, including Singapore, Finland, Denmark, Netherlands, Switzerland, Austria, Belgium, Canada, and Hong Kong, was also carried out by applying two methods, *TOPSIS* and *EDAS* (Oguz, 2023). The determination of the location and number of depots, as well as the service area of each depot for a transport company headquartered in Warsaw (Poland), was conducted using the *ELECTRE* method (Zak, 2019). In another work, *ELECTRE* was used to rank ten inland ports in Poland (Zak & Weglinsk, 2024). The *BWM* method was used to rank the challenges of using drones in post operations (Çıkmak et al., 2023). The selection of locations for organizing freight villages (another type of dry port) in Istanbul (Turkey) was done by using the *PROMETHEE* method (Yildirim & Onder, 2014). In other research, the *PROMETHEE* method was used to select locations for inland port construction in Thailand (Komchornrit, 2017).

Thus, it can be seen that the ranking of inland ports by location and capacity using *MCM* methods has been carried out in many countries and territories. Ranking inland ports in Vietnam will contribute valuable resources to this research direction. In this paper, an integrated MCDM framework using three newly developed methods—Probability, OPARA, and RAM—is applied to rank inland ports. These three MCM methods, such as PM, OPARA, and RAM, are all newly discovered methods. PM first appeared in January 2023 (Zheng et al., 2021), the OPARA method first appeared in June 2024 (Keshavarz-Ghorabae et al., 2024), and the RAM method first appeared in September 2023 (Sotoudeh-Anvari, 2023). PM offers a fundamental advantage of considering “simultaneous optimization of multiple indices,” unlike the conventional additive approach followed in MCM methods. PM works on the concept of favourable (“higher is better”) and unfavourable (“lower is better”) probabilities. The advantages of the OPARA method are: a) free from the selection of normalization techniques to avoid any possible information loss; b) use of the concept of pairwise adjusted ratios considering the entire decision matrix for all alternatives. In effect, the potential local superiority of any alternative with respect to its performance values is subject to the influence of the criteria; c) use of adjustment parameters to take into account the effect of range and linearity of the criteria while allowing the decision-maker flexibility make adjustments even with objective data. As a result, the OPARA method helps to circumvent the negative influence of non-linear data and potential bias, making the analysis more equitable. The benefits of using RAM are: a) avoidance of the compensatory effect of superior performance on cost criteria on the inferior performance at profit criteria; b) use of the effect of cost criteria as index and that of profit criteria as radicand. This allows putting a reward for the superior performance on profit-type criteria while penalizing cost-type criteria; c) ability to provide stable and reliable results even with no presence of cost criteria and/or with a large-sized decision matrix.

While the RAM method has been applied in some instances, such as determining the optimal solution for mushroom cultivation (Do et al., 2025), selecting fireproof materials (Trung, 2024), and ranking universities (Do, 2024), the two methods, Probability and OPARA, do not appear to have garnered the attention of scientists. Despite efforts, no documents applying the Probability and OPARA methods have been found. The absence of studies applying the Probability and OPARA methods, as well as the novelty of all three methods, creates an incentive to use them simultaneously in a study. Using all three new methods (Probability, OPARA, and RAM) to rank inland ports in Vietnam further enhances the

novelty and uniqueness of this research. The extant literature shows that the use of multiple MCM helps to rank the alternatives from multiple perspectives comprehensively (ÇalikoğluLuczak, 2024). Therefore, to achieve objective ranking results, each ranking should be performed by at least two different methods (Genç et al., 2024).

To derive the weights of the criteria, this paper employs the LOPCOW method (Ecer & Pamucar, 2022). The LOPCOW method provides several unique advantages, such as: a) use of statistical concepts and logarithmic operators for rational distribution of criteria weights; b) aptness to deal with negative and zero appraisal values of the alternatives in the decision matrix; c) suitability to provide reliable and stable results with a large decision matrix (Biswas et al., 2022a). LOPCOW has been a widely used approach since its inception, applied in various complex problems (Sumanto et al., 2024; Dhruva et al., 2024; Biswas et al., 2022b; Ulutaş et al., 2024; Biswas & Joshi, 2023; Simic et al., 2023; Rong et al., 2024; Biswas & Mukhopadhyaya, 2022; Biswas et al., 2023). While several scholars have employed the LOPCOW method in multiple contexts, there is no instance of its use in conjunction with the PM, OPARA, and RAM methods. This provides another motivation for using LOPCOW in conjunction with the integrated framework presented in this paper. To aggregate the rankings of various MCDM models, we employ a simple approach, such as RIM (Yang et al., 2019). The current study addresses two primary research questions:

RQ1. How can the transport capabilities of the inland ports be scientifically compared to support maritime logistics?

RQ2. How can a reliable and robust hybrid MCDM framework be developed for inland port capability assessment in a real-world maritime logistics context?

The present work offers several contributions to the growing strand of literature, such as:

- a) It offers a multi-criteria-based assessment of the capabilities of inland ports, considering capacity aspects in the context of Vietnam.
- b) The present study widens the scope of applications of PM, OPARA, and RAM.
- c) A novel integrated framework of multiple MCDM models with different philosophies is developed.

In what follows is the description of the organization of the remainder of this paper. Section 2 outlines the theoretical basis and computational steps of various methods used by the current study. Section 3 elaborates on the case study. In Section 4, the application of the LOPCOW-PM-OPARA-RAM framework is exemplified through the ranking of eight inland

ports in Vietnam. Section 5 draws various inferences from the findings and showcases research implications, limitations, and some future scopes for further extension work. Finally, Section 6 concludes with remarks.

Methods

The probability method

What follows are the computational steps of the PM to facilitate the ranking of the alternatives (Zheng et al., 2021).

Step 1: Construct a decision matrix (DM). Let, x_{ij} be the value of option A_i for criterion C_j where $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$. Let w_j be the weight of the j^{th} criterion. Then DM can be represented as

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}_{m \times n} \quad (1)$$

Step 2: For the benefit criteria, denoted as type B criteria, the probability of achieving a favorable outcome in decision-making is calculated according to Eq. (2).

$$P_{ij} \propto x_{ij}, P_{ij} = \alpha_j x_{ij}; i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (2)$$

Here, α_j is the normalization coefficient of the j^{th} benefit criterion, and it is calculated according to Eq. (3).

$$\alpha_j = \frac{1}{\sum_{i=1}^m x_{ij}} \quad (3)$$

Step 3: For the cost criteria, denoted as type C criteria, the probability of achieving a favorable outcome in decision-making is calculated according to Eq. (4).

$$P_{ij} \propto (x_{j\max} + x_{j\min} - x_{ij}), P_{ij} = \beta_j (x_{j\max} + x_{j\min} - x_{ij}) \quad (4)$$

Here, β_j is the normalization coefficient of the j^{th} cost criterion, and it is calculated according to Eq. (5).

$$\beta_j = \frac{1}{m \left(x_{j\max} + x_{j\min} - \frac{\sum_{i=1}^m x_{ij}}{m} \right)} \quad (5)$$

Step 4: Calculate the overall favorable probability of option i subject to the weights of the criteria as given by Eq. (6). The alternative ranked first is the one with the highest overall favorable probability.

$$P_i = \prod_{j=1}^n (P_{ij})^{w_j} \quad (6)$$

The OPARA method

Use the *OPARA* method to determine the ranking of options in the following sequence (Keshavarz-Ghorabae et al., 2024):

Step 1: Follow step 1 of the Probability method.

Step 2: Derive the range-based pairwise adjusted ratio, aka *RPAR*, between option k and option l according to Eq. (7).

$$RPAR_{kl} = \sum_{j \in B} w_j \left(\frac{x_{kj}}{x_{lj}} \right)^{\rho_j} + \sum_{j \in C} w_j \left(\frac{x_{lj}}{x_{kj}} \right)^{\rho_j}, k, l \in \{1, 2, \dots, n\} \quad (7)$$

In Eq. (7), ρ_j is the adjustment coefficient in *RPAR*, which is calculated according to Eq. (8).

$$\rho_j = \begin{cases} \frac{(\alpha - 1) \max(x_{ij}) + \min(x_{ij})}{\alpha(\max(x_{ij}))}; & \text{If } \frac{\max(x_{ij}) - \min(x_{ij})}{\max(x_{ij}) + \min(x_{ij})} > \beta \\ 1, & \text{Otherwise} \end{cases} \quad (8)$$

In Eq. (8), the values of the two quantities α and β are chosen to be 5 and 0.8, respectively (Keshavarz-Ghorabae et al., 2024).

Step 3: Determine the linearity-based pairwise adjusted ratio (*LPAR*) between option k and option l according to Eq. (9).

$$LPAR_{kl} = \sum_{j \in B} w_j \left(\frac{x_{kj}}{x_{lj}} \right)^{\tau_j} + \sum_{j \in C} w_j \left(\frac{x_{lj}}{x_{kj}} \right)^{\tau_j}, k, l \in \{1, 2, \dots, n\} \quad (9)$$

The value of the quantity τ_j in Eq. (9) is determined by the user. When a criterion has a linear nature, τ_j is equal to 1. To increase $LPAR$, choose τ_j greater than 1; conversely, to decrease $LPAR$, choose τ_j less than 1.

Step 4: Calculate the aggregated pairwise adjusted ratios ($APAR_{kl}$) according to Eq. (10).

$$APAR_{kl} = \omega RPAR_{kl} + (1 - \omega) LPAR_{kl} \quad (10)$$

In Eq. (10), $\omega \in [0, 1]$ and is usually chosen to be 0.5.

Step 5: Calculate the scores of the options according to Eq. (11). The option with the highest score is ranked first, and vice versa.

$$S_i = \frac{1}{n} \left(\sum_{l=1}^n \left(\frac{APAR_{il}}{\sum_{k=1}^n APAR_{kl}} \right) \right) \quad (11)$$

The RAM method

The computational steps are as follows (Sotoudeh-Anvari, 2023):

Step 1: Same as the Probability method.

Step 2: Normalize the data according to Eq. (12).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \quad (12)$$

Step 3: Computation of the normalized values according to Eq. (13).

$$y_{ij} = w_j r_{ij} \quad (13)$$

Step 4: Obtain the total normalized scores according to Eq. (14) and (15).

$$S_{+i} = \sum_{j=1}^n y_{+ij}; j \in B \quad (14)$$

$$S_{-i} = \sum_{j=1}^n y_{-ij}; j \in C \quad (15)$$

Step 5: Derive the final appraisal score of each option utilizing Eq. (16). The options are ranked in descending order of their final appraisal scores.

$$R_i = {}^{2+S_{-i}}\sqrt{2+S_{+i}} \quad (16)$$

The LOPCOW method

The procedural steps (Ecer & Pamucar, 2022) are described below briefly:

Step 1. Similar to Step 1 of the Probability method.

Step 2. Do the normalization of the elements of the decision matrix.

By adopting the linear max-min normalization approach, we obtain the elements of the normalized decision matrix (NDM) as demonstrated below.

$$r_{ij} = \begin{cases} \frac{x_{ij} - x_{j\min}}{x_{j\max} - x_{j\min}}; j \in B \\ \frac{x_{j\max} - x_{ij}}{x_{j\max} - x_{j\min}}; j \in C \end{cases} \quad (17)$$

Step 3. For each criterion, obtain the percentage value.

The percentage values subject to various criteria effects are obtained by using Eq. (18) as follows.

$$\xi_j = \ln \left(\frac{\sqrt{\frac{\sum_{i=1}^m r_{ij}^2}{m}}}{\sigma} \right) \cdot 100 \quad (18)$$

σ is the standard deviation of the normalized performance values of the alternatives for each criterion. In effect, step 3 rationalizes the variations in the performance values in the decision matrix to obtain the criteria weights in the next step.

Step 4. Obtain the criteria weights by using percentage values.

The percentage values (obtained at step 3) are used to compute the weight for the j^{th} criterion according to Eq. (19) as follows.

$$w_j = \frac{\xi_j}{\sum_{j=1}^n \xi_j}; w_j > 0, \sum w_j = 1 \quad (19)$$

The Rank Index Method (RIM)

RIM is used to aggregate the results obtained by using various MCDM models (Yang et al., 2019). The method has been used in various situations for aggregation purpose (Kumar et al., 2021; Wakeel et al., 2021; Mahajan et al., 2024). The computational steps are described as follows.

Step 1. Formulate the rank frequency matrix (RFM).

Given that there are m alternatives, the values of the elements of RFM $RF = (\gamma_{ik})_{m \times m}$ are obtained by using Eq. (20).

$$\gamma_{ik} = \sum_{t=1}^t \varphi_{ik}^{(t)} \quad (20)$$

$\varphi_{ik}^{(t)}$ denotes the rank state variable for the i^{th} alternative for a specific rank position k for the t^{th} model ($i = 1, 2 \dots m; k = 1, 2 \dots m; t = 1, 2 \dots t$).

Step 2. Find out the membership degrees of the alternatives.

The membership degree for any particular i^{th} alternative at a specific rank position k is obtained by using Eq. (21).

$$\psi_{ik} = \frac{\xi_{ik}}{t}; \sum_{k=1}^m \psi_{ik} = 1 \quad (21)$$

Step 3. Deduce the final rank index score (RIS).

RIS for the i^{th} alternative is computed as

$$RIS_i = \sum_{k=1}^m k \psi_{ik} \quad (22)$$

The alternative, having at least RIS, is ranked first.

Practical case study

In this section, we briefly describe the case study. Table 1 summarizes the data on eight inland ports in Vietnam (Source: Ministry of Industry and Trade of Vietnam). These eight inland ports are denoted by

options A1-A8. Four criteria are used to evaluate each option: throughput capacity (C1), total area (C2), warehouse area (C3), and maximum exploitable output per month (C4). All these criteria are of type B. The selection of criteria follows the guidelines of the Vietnamese Ministry of Industry and Trade.

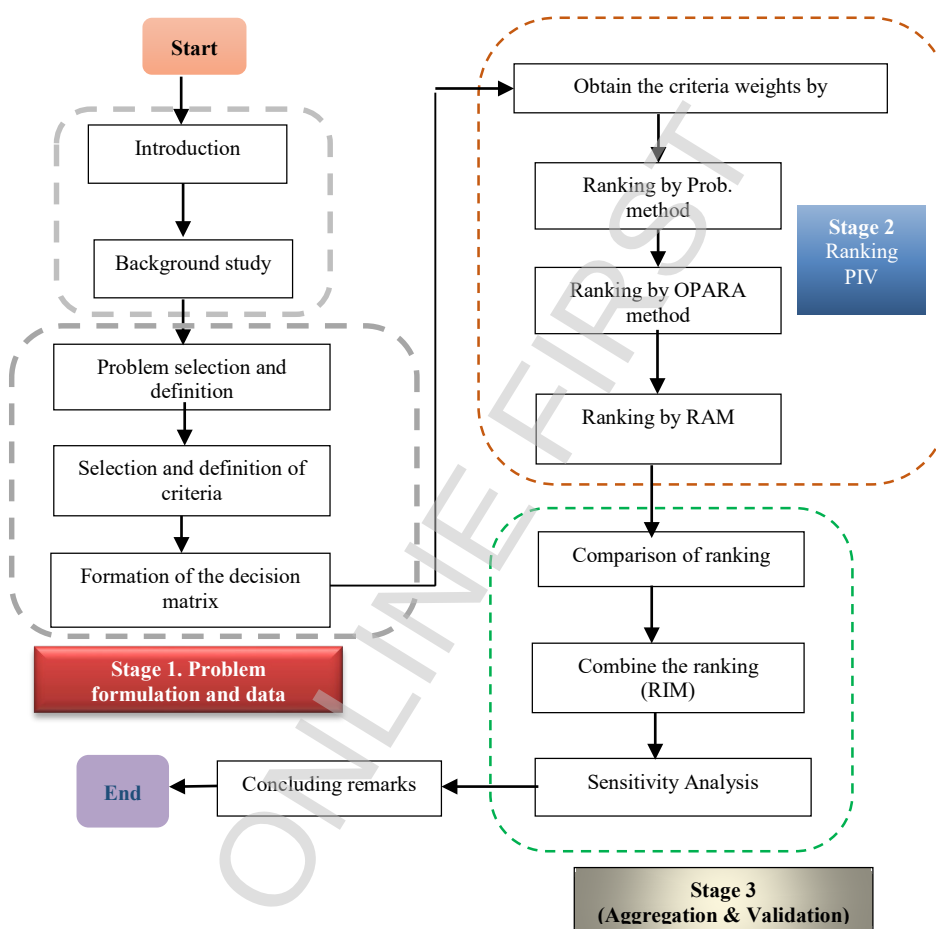


Figure 1 - Research framework

The study examines capacity-based metrics to support the development of operational capability and policy relevance in Vietnam. Critical criteria, including throughput capacity and storage space, are vital for evaluating an inland port's capability to provide maritime operations. These metrics are recorded by the Vietnamese Ministry of Industry and

Trade, guaranteeing data consistency. The study focuses on competence benchmarking rather than comprehensive sustainability evaluations, using capacity measures as preliminary tools for infrastructure design and investment prioritization. The scope may broaden in the future to include operational, environmental, and social factors. Figure 1 shows the flowchart of the research methodology.

Table 1 - Data of inland ports in Vietnam (Source: Ministry of Industry and Trade of Vietnam)

Port Name	Alt.	Throughput Capacity (TEU/year)	Total Area (ha)	Warehouse Area (m ²)	Maximum Exploitable Output (TEU/month)
		C1	C2	C3	C4
Phúc Lộc	A1	100000	10	50000	200
Móng Cái	A2	200000	15	110000	8000
Tân cảng Hà Nam	A3	50000	9.4	11000	350
Tân cảng Quế Võ	A4	105000	10	30000	4500
Hải Linh	A5	65000	5	20000	300
Tân cảng Hải Phòng	A6	120000	15	79000	2000
Đình Vũ	A7	150000	24.5	55000	600
Long Biên	A8	135000	12	50000	1500

Criteria description

What follows is a short description of the criteria used in this case study.

C1- Throughput Capacity (TEU/year): This is an indicator of a dry port's ability to handle cargo in a year. In other words, it shows how much cargo the dry port can receive, process, and dispatch within a specific period. The unit of C1 is TEU (Twenty-foot Equivalent Unit) per year.

C2- Total Area (ha): This is the total land area that the dry port occupies, including the cargo handling area, warehouse, office, and other auxiliary facilities. The unit of C2 is a hectare (ha), which is a unit of land area equivalent to 10,000 square meters.

C3 - Warehouse Area (m²): This is the area specifically designated for cargo storage, including both outdoor and indoor warehouses. The unit of C3 is square meter (m²).

C4 - Maximum Exploitable Output (TEU/month): This is the maximum amount of cargo that a dry port can handle in a month, based on its current capacity and ideal working conditions. The unit of C4 is TEU per month.

It is observed that option A2 has the highest values for three criteria: C1, C3, and C4, compared to the other options. However, the highest value for criterion C2 belongs to option A7. This means that by only observing the data in Table 1, it is not possible to determine which inland port is the best. To select the best inland port, all four parameters must be considered simultaneously, meaning a decision must be made by weighing all four criteria for each option. This task will be carried out by applying the three methods: Probability, *OPARA*, and *RAM* in this study.

Results

The essential task when ranking options using the Probability, *OPARA*, and *RAM* methods is to determine the weights for the criteria. First, we show the calculation of criteria weights using the LOPCOW method. Using Eqs. (17)-(19), the criteria weights are calculated (Table 2).

Table 2 - Calculation of criteria weights (LOPCOW)

Items	C1	C2	C3	C4
Sum of Square	2.2389	1.8372	2.0248	1.3881
Mean Square	0.2799	0.2297	0.2531	0.1735
Standard Deviation	0.3179	0.2971	0.3258	0.3529
Percentage Values	50.9135	47.7969	43.4379	16.5714
Criteria Weights	0.3208	0.3011	0.2737	0.1044

Table 2 indicates that throughput capacity (C1) and total area (C2) are assigned the greatest weights, signifying their predominant role in distinguishing inland ports. The maximum exploitable output (C4) is assigned the lowest weight because of its lower variability among options. This distribution indicates that LOPCOW objectively highlights factors with greater discriminative power, thereby enhancing the legitimacy of the weighing procedure.

Now, we use the calculated weights to rank inland ports using three MCDM methods following a step-by-step approach. Table 3 summarizes the findings, including appraisal scores and ranks.

The *OPARA* methodology employs parameters (α , β , γ) that correspond with its foundational framework to support theoretical coherence and outcome comparability. α and β regulate the sensitivity of range-based adjustments, whereas γ mediates the compromise between range-based and linearity-based ratios. The investigation used parameter values suggested by *OPARA* developers, which have been empirically shown to optimize stability and discriminatory power. This constrains subjectivity and prevents overfitting to an individual case study.

Table 3 - Ranking of alternatives using various methods

Method	PM		OPARA		RAM	
Alternative	Pi	Rank	Si	Rank	Ri	Rank
A1	0.0864	6	0.7339	6	1.4490	6
A2	0.2224	1	2.0146	1	1.4954	1
A3	0.0476	8	0.4228	7	1.4335	7
A4	0.1056	5	1.0262	4	1.4538	5
A5	0.0496	7	0.4073	8	1.4328	8
A6	0.1492	2	1.1907	3	1.4669	3
A7	0.1484	3	1.2230	2	1.4717	2
A8	0.1240	4	0.9814	5	1.4579	4

Table 3 shows robust agreement among the three MCDM methodologies. Inland port A2 is continuously ranked #1 across all methodologies, whilst A3 and A5 constantly hold lower rankings. Minor rank fluctuations among intermediate options indicate methodological discrepancies rather than volatility. This convergence reinforces the resilience of the integrated architecture and substantiates the use of various ranking methodologies.

We proceed to examine the consistency among the rankings of alternatives provided by various methods. By applying Spearman's rank correlation test (Table 4), we observe that PM, OPARA, and RAM are highly correlated with each other. It suggests that these methods are in harmony and, hence, an integrated MCDM framework is possible to rank the alternatives. However, all these methods provide different ranges of appraisal scores for the alternatives (Figure 2).

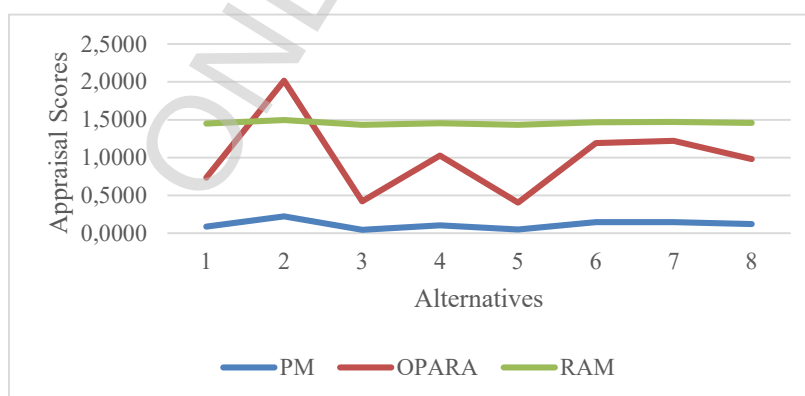


Figure 2 - Distribution of appraisal scores of alternatives (provided by various methods)

Table 4 presents significantly high Spearman correlation coefficients (>0.9), highlighting robust concordance among PM, OPARA, and RAM. The statistical consistency validates that the techniques, despite varying computational philosophies, identify consistent performance patterns, thereby enhancing trust in the resultant rankings.

Table 4 - Association among ranking of PM, OPARA and RAM

Coefficient	Method	PM	OPARA	RAM
Spearman's rho	PM	1		
Spearman's rho	OPARA	.929**	1	
Spearman's rho	RAM	.952**	.976**	1

** Correlation is significant at the 0.01 level (2-tailed).

Figure 2 illustrates that although the ranges of evaluation scores vary among techniques, the relative ranking of alternatives stays consistent. RAM demonstrates score compression, indicative of its conservative and non-compensatory characteristics, while OPARA offers enhanced score dispersion. These discrepancies underscore methodological consistency.

Next, the ranking results provided by PM, OPARA, and RAM are aggregated by using the procedural steps of RIM. Using Eq. (20), we obtain the RFM, and then, by applying Eq. (21) and Eq. (22), the membership degrees and RIS are found to arrive at the final ranking of the alternatives (Table 5). A2 retains its position as the premier inland port, succeeded by A7 and A6. The aggregate verifies that dominance is independent of the strategy employed and that the integrated approach reduces bias inherent in separate models.

Table 5 - Final ranking of the alternatives (RIM)

Alternatives	Rank positions								Score	Final Rank
	1	2	3	4	5	6	7	8		
A1	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	6.00	6
A2	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1
A3	0.00	0.00	0.00	0.00	0.00	0.00	0.67	0.33	7.33	7
A4	0.00	0.00	0.00	0.33	0.67	0.00	0.00	0.00	4.67	5
A5	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.67	7.67	8
A6	0.00	0.33	0.67	0.00	0.00	0.00	0.00	0.00	2.67	3
A7	0.00	0.67	0.33	0.00	0.00	0.00	0.00	0.00	2.33	2
A8	0.00	0.00	0.00	0.67	0.33	0.00	0.00	0.00	4.33	4

Table 6 exhibits the correlation among the aggregated ranking (provided by RIM) and the MCDM methods like PM, OPARA, and RAM. It is evident that all methods maintain a high correlation with the aggregated ranking.

Table 6 - Correlation among various methods and final ranking

Coefficient	Method	PM	OPARA	RAM
Spearman's rho	RIM	.952**	.976**	1.000**

** Correlation is significant at the 0.01 level (2-tailed).

Comparison of MCDM methods

There are several MCDM methods. These MCDM methods have different underlying conditions to arrive at the appraisal scores of the alternatives for ranking them (Komatina, 2025; Chakraborty & Saha, 2024). Therefore, it is essential to compare the results of various MCDM methods to examine the reliability of a specific model (Wardany & Zahedi, 2024; Pramanik et al., 2021; Biswas et al., 2025). In this work, we compare the ranking results of PM, OPARA, and RAM methods with other models like CRADIS, MABAC, ARAS, and SAW by applying Spearman's rank correlation test (Table 7). The values of Spearman's rho coefficient suggest that all methods are consistent with each other. Figure 3 shows the distribution of the ranking of the alternatives provided by various methods. It is evident that there is no significant variation in the ranking.

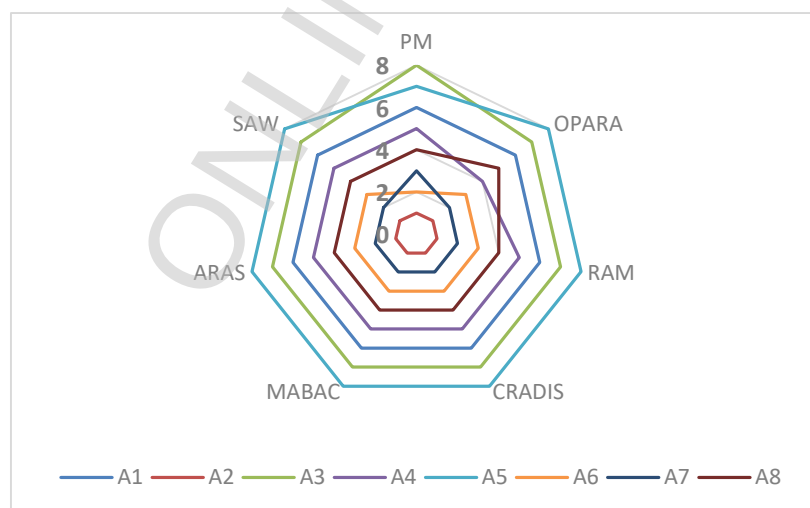


Figure 3 - Distribution of ranking of alternatives (provided by various methods)

Table 7 - Association among the ranking of various methods

Coefficient	Method	CRADIS	MABAC	ARAS	SAW
Spearman's rho	PM	.952**	.952**	.952**	.952**
Spearman's rho	OPARA	.976**	.976**	.976**	.976**
Spearman's rho	RAM	1.000**	1.000**	1.000**	1.000**

** Correlation is significant at the 0.01 level (2-tailed).

Sensitivity analysis

MCDM models are susceptible to changes in the external conditions, which arise due to the inclusion/exclusion of criteria and alternatives, changes in criteria weights, variations in the aggregation parameters, alterations in normalizations, and others (Więckowski & Sałabun, 2025; Stević et al., 2024; Biswas et al., 2025a). To ascertain the stability of the final outcome, sensitivity analysis is carried out (Görçün et al., 2023; Özekenc, 2025; Mishra et al., 2025). Accordingly, in this paper to ensure that the evaluation results of the inland ports are objective, the weights of the criteria have been determined in five different scenarios. In the first scenario (S1), the weights of the criteria are chosen to be equal, i.e., 0.25. In the remaining four scenarios (from S2 to S5), the weight of one criterion is chosen to be twice the weight of the other criteria. For example, in scenario S2, w_1 is chosen to be 0.4, while the values of w_2 , w_3 , and w_4 are all 0.2. For for scenario S3, w_2 is chosen to be 0.4, while the values of w_1 , w_3 , and w_4 are all 0.2, etc. The values of the weights in the scenarios are summarized in Table 8.

Table 8 - Different scenarios for the weights of the criteria

Scenario	w_1	w_2	w_3	w_4
S1	0.25	0.25	0.25	0.25
S2	0.4	0.2	0.2	0.2
S3	0.2	0.4	0.2	0.2
S4	0.2	0.2	0.4	0.2
S5	0.2	0.2	0.2	0.4

Applying the procedural steps of the MCDM methods described in Section 2, the inland ports have been ranked using different methods in various scenarios. The data has been summarized in Table 9.

It has been found that, across all five scenarios surveyed and using all three MCDM methods, the ranking of the inland ports does not change significantly. Notably, in all surveyed cases, A2 is ranked 1st, A1 is ranked 6th, and A3 and A5 alternate between 7th and 8th. For other options, the

change in ranking is also not significant. To comprehensively evaluate changes in the options across different ranking methods and scenarios, the Spearman's rank correlation coefficient was used. This coefficient is calculated according to Eq. (23) (Thien & Son, 2024; Aazagreyir et al., 2024), where R_i denotes the difference in the ranking of option i across different methods/scenarios.

$$\rho = 1 - \frac{6R_i^2}{m(m^2 - 1)} \quad (23)$$

Because it is limited by the framework of the data table, the notation of the combination of weighting scenarios with *MCDM* methods is done as follows. For example, in scenario *S1*, *S1-P*, *S1-O*, and *S1-R* represent the ranking results of alternatives using Probability, *OPARA*, and *RAM* methods; in scenario *S2*, *S2-P*, *S2-O* and *S2-R* also represent the ranking results of alternatives using Probability, *OPARA* and *RAM* methods; etc. The value of the Spearman coefficient has been calculated and summarized in Table 10.

Table 9 - Ranking of inland ports

Scenario	Method	A1	A2	A3	A4	A5	A6	A7	A8
S1	Probability	6	1	8	3	7	2	5	4
	OPARA	6	1	7	2	8	3	4	5
	RAM	6	1	7	4	8	2	3	5
S2	Probability	6	1	8	5	7	2	3	4
	OPARA	6	1	8	2	7	3	4	5
	RAM	6	1	8	4	7	3	2	5
S3	Probability	6	1	7	5	8	2	3	4
	OPARA	6	1	7	2	8	4	3	5
	RAM	6	1	7	4	8	3	2	5
S4	Probability	6	1	8	5	7	2	3	4
	OPARA	6	1	8	3	7	2	4	5
	RAM	6	1	8	4	7	2	3	5
S5	Probability	6	1	7	2	8	3	5	4
	OPARA	6	1	7	2	8	3	5	4
	RAM	6	1	7	2	8	3	4	5

It is observed that the Spearman correlation coefficients between the methods/scenarios are all very high, with the smallest being 0.81. This indicates that the rankings of the options show very little difference when ranked by different methods/scenarios (Keshavarz et al., 2016). Additionally,

many Spearman correlation coefficient values are very close to 1, and there are even values where the Spearman correlation coefficient is 1 (between *S1-O* and *S5-R*, between *S2-P* and *S4-P*, and between *S5-P* and *S5-O*), further demonstrating a very high level of consistency in the rankings of the options when ranked by different methods in different scenarios.

Table 10 - Spearman rank correlation test among ranking under experimental cases

	S1-P	S1-O	S1-R	S2-P	S2-O	S2-R	S3-P	S3-O	S3-R	S4-P	S4-O	S4-R	S5-P	S5-O	S5-R
S1-P	1	0.93	0.9	0.9	0.95	0.86	0.88	0.86	0.83	0.9	0.98	0.93	0.95	0.95	0.93
S1-O		1	0.93	0.83	0.98	0.88	0.86	0.98	0.9	0.83	0.95	0.9	0.98	0.98	1
S1-R			1	0.95	0.9	0.95	0.98	0.9	0.98	0.95	0.95	0.98	0.88	0.88	0.93
S2-P				1	0.86	0.95	0.98	0.81	0.93	1	0.93	0.98	0.81	0.81	0.83
S2-O					1	0.9	0.83	0.95	0.88	0.86	0.98	0.93	0.95	0.95	0.98
S2-R						1	0.93	0.9	0.98	0.95	0.93	0.98	0.81	0.81	0.88
S3-P							1	0.83	0.95	0.98	0.9	0.95	0.83	0.83	0.86
S3-O								1	0.93	0.81	0.9	0.88	0.93	0.93	0.98
S3-R									1	0.93	0.9	0.95	0.83	0.83	0.9
S4-P										1	0.93	0.98	0.81	0.81	0.83
S4-O											1	0.98	0.93	0.93	0.95
S4-R												1	0.86	0.86	0.9
S5-P													1	1	0.98
S5-O														1	0.98
S5-R															1

(all coefficients are statistically significant at 0.05 level, two-tailed)

Discussion

The above results show that confirming A2 is the best option is an assertion that ensures very high accuracy. This conclusion creates an opportunity for transportation businesses to have a basis for choosing inland ports for their purposes. Furthermore, the ranking results of inland ports in Table 3 also help managers make appropriate policies for exploiting the potential of high-ranking ports and taking measures to upgrade existing dry ports. This ranking also helps inland ports themselves see their true capacity to have appropriate upgrading solutions, creating a healthy competitive environment among inland ports.

The persistent top ranking of inland port A2 across all methodologies and weighting scenarios is currently seen as indicative of its structural capacity superiority, particularly in throughput, warehousing space, and

maximum exploitable output. This suggests that the competitiveness of inland ports in Vietnam is primarily driven by scalable handling capacity rather than land availability alone, while ports with greater total acreage (e.g., A7) do not always achieve superior overall performance.

The strong correlation among PM, OPARA, and RAM rankings indicates latent performance uniformity across mid-ranked ports, suggesting that small capacity improvements—rather than extensive expansion—could substantially modify their relative standings. The observed stability in rankings during sensitivity analysis indicates infrastructure-driven resilience, suggesting that policy decisions derived from the proposed framework are unlikely to be influenced by mild fluctuations in preferences.

The RAM framework demonstrates a non-compensatory, conservative evaluation of alternatives, designed to minimize excessive score fluctuations. It imposes penalties for cost performance while incentivizing superior benefit performance, using benefit-oriented criteria that yield narrower score distributions. This approach improves decision reliability by reducing dominance stemming from negligible performance disparities. Significantly, RAM reliably preserves rank ordering, which is essential for comparative decision-making.

Research implications

The present research offers a number of significant implications.

- a) First, the current work provides a capacity-focused capability analysis of inland ports. Maritime logistics is an important area for supply chain and logistics decision-makers. To strategize an effective logistics delivery chain in the country, while connecting the global market, inland ports play critical roles. In this regard, the present work demonstrates a novel decision-making framework.
- b) Secondly, from the point of view of an emerging economy like Vietnam, the current study is a crucial one for strategic decision-making and policy formulation, resource mobilization, and infrastructure development while deciding the investment requirements directed towards enhancing the most promising ports.
- c) Thirdly, the current work sheds light on an important aspect of the assessment of overall operational efficiency of inland port-based logistics operations. The findings of this work contribute notably to enhancing supply chain and logistics performance.
- d) Fourthly, the framework used in the ongoing work contributes to the development of competitive benchmarking for performance

assessment of inland ports, which stimulates the ports to adopt best practices and invest in improvements.

- e) Fifthly, the present research provides a novel integrated MCDM framework with objective information that may act as a robust technique to solve various other complex issues of logistics and supply chain management and, eventually, can be applied to several other real-life issues.

Limitation and future scope

While the current work offers numerous benefits and implications for strategic and operational decision-making and data analysis, the ongoing work is limited to crisp information only. Furthermore, a limited set of criteria undermines the generalizability of the results. The analysis is confined to capacity-based criteria, which, although objective, fail to encompass operational efficiency, service quality, or sustainability aspects. Secondly, the study relies on precise quantitative data, limiting its ability to capture the uncertainty and ambiguity inherent in real-world logistics systems. Third, the absence of expert opinion limits stakeholder-driven preference modeling.

There are a number of scopes for further extensions in the near future.

- a) First, the present work is limited to a few criteria only. Future work may consider a more general approach by considering strategic, operational, social, and sustainability aspects. This in turn helps to develop a comprehensive framework for assessing the efficiency and effectiveness of inland ports.
- b) Second, future work may extend the scope of the present model for assessment of multi-modal maritime logistics.
- c) Third, technology and analytics play a critical role in shaping the performance of logistics. The ongoing work has not considered the technological capability analysis of inland ports and its impact on operational efficiency and capacity. Future work may address this aspect.
- d) Fourth, the current work provides a comparative analysis of capacities. However, a further extension may attempt to optimize inland port efficiency based on capacity parameters.
- e) Fifth, in this present work, we have not considered experts' opinions. A future work may be conceptualized to synthesize experts' opinions and operational performance together to develop a multi-faceted framework.

- f) Sixth, in this paper we have used a crisp information-based MCDM framework of very recently developed methods that can be extended with fuzzy and rough numbers for uncertain modelling purposes.
- g) Future work may also concentrate on developing a hybrid machine learning- and MCDM-based approach (e.g., Tešić, 2025) for uncertainty prediction and optimization.
- h) Future work may investigate the causal relationships among various factors influencing inland port performance in maritime logistics by utilizing the frameworks such as DEMATEL in an uncertain environment (e.g., Appasamy, 2026).
- i) The current study uses a standalone normalization approach, which may not accurately reflect the true differentiation among the alternatives in dynamic, changing situations. Scholars (e.g., Biswas et al., 2026) have argued for using multiple normalizations to effectively represent the initial decision matrix. This highlights a new scope for further extension of our work.

Conclusion

This study presents a novel multi-criteria decision-making (MCDM) framework for evaluating and ranking the transport capabilities of inland ports in Vietnam, marking a significant advancement in the field of logistics and transportation management. By employing three distinct MCDM methods—Probability, OPARA, and RAM along with RIM and LOPCOW, the ranking of eight inland ports in Vietnam is carried out for the first time in this study. This is also the first research to use all three methods, Probability, OPARA, and RAM simultaneously in one study. Notably, this is also the first study to use the Probability and OPARA methods since they were proposed until now. Although there are many novelties mentioned in this study, the findings reveal that one inland port (A2) consistently ranks as the top performer, highlighting its superior capabilities in terms of throughput capacity, total area, warehouse area, and maximum exploitable output. The present work shows a capacity-focused capability analysis of inland ports that helps decision-makers with benchmarking the best performances.

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Integrirani okvir za višekriterijumsku analizu odlučivanja za poređenje transportnih kapaciteta unutrašnjih luka u pomorskoj logistici

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Sažetak:

Uvod/cilj: Unutrašnje luke pružaju usluge skladištenja, transporta i carinjenja robe koja se kreće na kopnu. Rangiranje i evaluacija unutrašnjih luka od ključnog su značaja za nacionalnu logistiku, jer unapređuju efikasnost upravljanja i optimizuju tok robe. Ovaj rad predstavlja procenu sposobnosti orijentisanu na kapacitete osam unutrašnjih luka u Vijetnamu.

Metode: Poređenje se vrši na osnovu četiri glavna parametra: kapaciteta pretovara, ukupne površine, površine skladišta i maksimalnog eksploatacionog učinka. Tri metode višekriterijumskog modeliranja (eng. MCM), uključujući Metodu verovatnoće (eng. PM), objektivnu analizu parno prilagođenih odnosa (eng. OPARA) i Metodu procene korena (eng. RAM), primenjene su za rangiranje unutrašnjih luka. Metoda LOPCOW (eng. Logarithmic Percentage Change-driven Objective Weighting) koristi se za određivanje težina kriterijuma. Rangiranja dobijena pojedinačnim metodama objedinjuju se primenom metode indeksa ranga (RIM).

Rezultati: Rezultati pokazuju da, bez obzira na primenjeni metod ili težine kriterijuma, od osam posmatranih unutrašnja luka jedna luka (A2) ostvaruje najbolji rezultat. Radi procene stabilnosti rezultata, formirano je pet scenarija u kojima se menjaju težine kriterijuma i rangiranje alternativa. Rezultati pokazuju da je ishod manje osetljiv na promene spoljašnjih uslova.

Zaključak: Ova studija pruža transportnim kompanijama informacije za izbor optimalne unutrašnje luke na osnovu kapaciteta pretovara i površine skladišta, podržava izvoznike i uvoznike u optimizaciji procesa skladištenja i transporta, pruža državnim organima podatke za unapređenje upravljanja i usmerava druge luke ka poboljšanju svojih operativnih kapaciteta.

Ključne reči: logistika, unutrašnja luka, metoda verovatnoće, OPARA, RAM, metoda indeksa ranga, LOPCOW.

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