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Research Article

Orchestrating green ports: An integrated BWM–Fuzzy DEMATEL–ANP–TOPSIS framework for techno-economic prioritization

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Abstract. This study introduces a comprehensive multi-criteria decision-making framework that integrates the Best–Worst Method (BWM), fuzzy DEMATEL, the Analytic Network Process (ANP), and TOPSIS to prioritize green port electrification and operational enhancements. The model reflects complex trade-offs that shape decarbonization plans by asking experts about 20 important techno-economic, environmental, and organizational factors. The most important results show that emission abatement, fuel savings, and pollution reduction had the highest BWM weights. This shows that environmental goals are the most important. Fuzzy DEMATEL research showed that lifecycle replacement risk and labor preparedness were the main factors that affected tariff exposure, operational dependability, and digital integration results. ANP adjusted the weights of the criteria to take into consideration interdependencies, making economic risk and human capital the most important factors in decision-making. The TOPSIS rating found that a hybrid phased deployment option was the best choice for meeting goals for cost, emissions reduction, and operational readiness. It did better than both electric and traditional methods. These results show that the framework may combine expert knowledge, causal structure, and network feedback to make green port techniques more important. The concept goes beyond linear weighing by using cause-and-effect maps and feedback loops. This gives decision-makers a better understanding and more confidence when it comes to allocating resources. The results encourage a balanced growth of capital investments, environmental protection, and the ability of the workforce. This flexible strategy is helpful in gradually combining the renewables, tariff dynamics, and operational data to create strong, low-carbon marine logistics centers.

Keywords: Green port; Techno-economic analysis; Low-carbon marine logistics; Decarbonization plan; Multi-criteria decision-making framework; TOPSIS

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1. Introduction

Worldwide trade volume has seen tremendous growth over recent decades, driving considerable development in seaport infrastructure and maritime shipping operations to ensure the continued global movement of products (Pham *et al.* 2023, 2025). This expansion entails a surge in volumes of raw materials and finished goods transported through increasingly intricate marine corridors, which requires terminals to extend their capacities with additional berths, expanded storage facilities, and enhanced rail and road connections to meet faster and more demanding logistical requirements (Nguyen, Nguyen, and Nguyen 2022; Satta *et al.* 2025). The expansion of ports across Europe and Asia has generated beneficial effects on employment and local economies. However, it has simultaneously escalated fuel consumption by marine vessels and cargo handling equipment, contributing to increased emissions of carbon dioxide, nitrogen oxides, sulfur oxides, particulate pollutants, noise disturbances, and contamination of surrounding waters (Lam and Notteboom 2014; Nguyen, Pham, and Bui 2022; Zhang *et al.* 2024). Among these, carbon dioxide remains a dominant greenhouse pollutant, which imposes stresses on marine and urban ecosystems as well as residents nearby (Hoang *et al.* 2022; Nguyen *et al.* 2021).

The initiative to develop environmentally mindful ports has shifted from abstract ideals to concrete implementations aimed at making environmental protection an integral part of daily port operations, thereby curtailing the anticipated growth of pollution linked to maritime transport (Hua *et al.* 2020). A coordinated mix of actions targets reductions in greenhouse gas emissions within port boundaries, enhancements in energy use efficiency for each operational unit, improved handling of runoff and drainage systems, advances in waste treatment processes, and gradual replacement of conventional equipment and transport modes with cleaner alternatives on docks and connecting roadways (Lin *et al.* 2022). While shipping remains a

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comparatively efficient mode for the bulk movement of goods, carrying large volumes of cargo per voyage reduces emissions per unit of transport when contrasted with many other modalities (Hoang *et al.* 2025; Shahrul Alfian, Zakaria, and Md. Arof 2025). Nevertheless, the heavy dependence on fossil fuels within the sector continually fuels significant atmospheric pollution and global temperature rise, heightening pressure to transition maritime fleets, port infrastructures, and energy systems towards cleaner energy sources sooner rather than later (Hoang *et al.* 2023; Ismail *et al.* 2024).

At the international level, regulatory bodies, led by the International Maritime Organization (IMO), have devised frameworks aiming to steer the shipping industry to achieve net-zero emissions by the middle of the 21st century. These strategic plans incorporate progressively more stringent fuel efficiency standards and emissions caps, alongside economic sanctions on operators surpassing prescribed limits (IMO 2020, 2021). Revenues generated through such enforcement efforts are dedicated to financing advancements in green vessel designs, port infrastructure improvements, and capacity-building initiatives in economically developing regions. The largest ocean-going vessels, which contribute the majority of carbon dioxide released by maritime shipping, are subject to binding reduction commitments with enforcement deadlines set before 2030 (IMO 2023). Complementary regulations focusing on improving operational efficiencies and adopting carbon labeling provoke an environment conducive to broad adoption of cleaner fuel types and operational modifications. These collective efforts are anticipated to propagate through more widespread use of shore-supplied power, optimized vessel design and propulsion tactics, speed regulation in critical zones, and intensified transition towards sustainable fuel usage as supply chain processes mature and improve (Huynh and Tran 2020; Kołodziej and Hoffmann 2024; Le *et al.* 2023; Nguyen *et al.* 2025).

Technological progress in sensor technology, data aggregation, and computational decision-support implementations significantly aid emission and fuel consumption reductions across port and sea operations (Agarwala 2021; Alamoush and Ölçer 2025; Zhang *et al.* 2024). Refinement of berth scheduling, optimization of crane movements, careful balancing of yard work flows, and efficient management of port entry and exit gates collectively reduce fuel-wasting idle times without impairing throughput (Wang, Cheng, and Zhen 2023). At sea, employing navigational path optimization and speed controls could reduce fuel use while maintaining reliable freight arrivals, supported by real-time monitoring systems that highlight energy inefficiencies for immediate intervention, circumventing guesswork. Additionally, experimental adoption of alternative cleaner fuels and shore power systems, transitioning to electric or hybrid cargo handling machinery, and rigorous documentation of operational enhancements solidify sustained environmental and financial improvements. Despite these advancements, strategic decisions about capital expenditures, operational upgrades, energy sourcing, and adherence to evolving regulations remain challenging. Quantitative indices often fail to fully capture all relevant complexities, underscoring the necessity for holistic evaluation frameworks (Gonzalez Aregall, Bergqvist, and Monios 2018; Mansoursamaei *et al.* 2023).

Ports aspiring to reduce their environmental footprints' function amidst a context of growing cargo volumes, increasing regulatory constraints, rapid technological change, and complex logistical interdependencies (Duc and Nguyen 2025; Nguyen *et al.* 2023). Addressing this context requires comprehensive multi-faceted evaluation methodologies that fuse economic, environmental, technical, governance, and human resource perspectives. Multi-criteria decision-making (MCDM) frameworks offer a structured means to appraise options, enabling transparent comparative analysis, effective prioritization, and strategic resource deployment in situations with multifarious, conflicting objectives (Garg, Kashav, and Wang 2023; Perwira Mulia Tarigan *et al.* 2021; Taş and Çakır 2024). MCDM combines economic, environmental, technological, policy, and workforce factors into one decision-making platform. This makes it easier to compare, prioritize, and allocate resources when there are competing or conflicting goals (Emovon and Oghenenyerovwho 2020; Narwane *et al.* 2021). Many MCDM methods can help in these kinds of situations. For example, AHP uses pairwise comparisons to build hierarchical preferences (Alghassab 2022), ANP uses the same logic to deal with mutually dependent criteria (Kar and Jha 2022), BWM uses best-worst scaling to find priorities (Rezaei 2015), and TOPSIS uses geometric similarity to ideal solutions to rank alternatives (Chakraborty 2022). Tools that use fuzzy logic can deal with ambiguities in expert opinion (Büyüközkan and Ifi 2012). Other tools, including MOORA (Dinçer, Yüksel, and Martínez 2019), PROMETHEE (Brans and De Smet 2016; Tang, Liu, and Wang 2025), VIKOR (Rani *et al.* 2020), and ELECTRE (Govindan and Jepsen 2016), let researchers combine inputs in multiple ways to make rankings. Choosing among these strategies depends on how well they can handle the feedback, inconsistency, and ambiguity that come up in real-world port decision-making situations.

Nonetheless, the associated scientific and applied literature reveals research gaps. Many analyses underappreciate interdependent criterion relationships and adopt simplistic linear weighting devoid of feedback or causality recognition. Most studies inadequately address uncertainty scope, and omit multifaceted impacts involving economic, regulatory, technical, societal, and ecological factors. Another important issue is frequent use of narrow criterion subsets or applying a singular MCDM tool, thereby compromising practical relevance and robustness imperatives. To resolve these shortcomings, the present investigation introduces an integrated MCDM schema synergistically combining Best–Worst Method, fuzzy DEMATEL, Analytic Network Process, and TOPSIS. This arrangement consolidates expert insights, delineates causal criterion relationships, incorporates interconnections, and applies context-aware normalization and ranking processes. The process produces reliable priority determination of green port modernization and electrification trajectories attuned to flexible situational parameters. The framework delivers transparent, reproducible, and adaptable decision guidance fostering informed investments, skill development of ports' human capital, and durable operational evolution. Moreover, its extensibility permits assimilation of emergent technological trends, advancing regulatory frameworks, tariff volatility, and dynamic operational feedback, enabling continuous evolution towards environmentally sound, economically justifiable maritime logistics infrastructures in the long term.

2. Methods

2.1 Best–Worst Method

BWM elicits two short vectors of judgments instead of a full pairwise matrix. Following are main steps in BWM implementation (Rezaei 2015):

- Experts select the best (most important) criterion B and the worst (least important) criterion W.

- Best-to-others preference vector $A_B = (a_{B1}, \dots, a_{Bn})$ where $a_{Bj} \in \{1, \dots, 9\}$ expresses how much B is preferred over j.
- Others-to-worst preference vector $A_W = (a_{1W}, \dots, a_{nW})$ where $a_{jW} \in \{1, \dots, 9\}$ expresses how much j is preferred over W.
- Solve the minimax program for weights w and deviation ξ:

Minimize

Subject to, for all j∈C, F

$$\left| \frac{w_B}{w_j} - a_{Bj} \right| \le \xi, \left| \frac{w_j}{w_W} - a_{jW} \right| \le \xi, \quad (1)$$

$$\sum_{j=1}^{n} w_j = 1, w_j \ge 0. \quad (2)$$

A common linear form replaces ratios as

$$| w_B - a_{Bj} w_j | \le \xi, | w_j - \frac{1}{a_{jW}} w_W | \le \xi, \quad (3)$$

which is solved by linear programming. The optimal w gives stable, sparse-burden priorities.

2.2 Fuzzy DEMATEL

Purpose: discover directional influence among criteria and separate "cause" from "effect" groups under uncertainty. The following steps are followed (Akyuz and Celik 2015; Khatun et al. 2023):

- Expert k provides a fuzzy direct-relation matrix $\tilde{D}^{(k)} = [\tilde{d}_{ij}^{(k)}]$ where $\tilde{d}_{ij}^{(k)} = (l, m, u)$ is a TFN rating of the influence of i on j.
- Aggregate across K experts using fuzzy averaging:

$$\tilde{D} = \frac{1}{K} \sum_{k=1}^{K} \tilde{D}^{(k)}. \quad (4)$$

- Normalize using the maximum upper-bound row/column sum:

$$s = max\{ \max_i \sum_j u_{ij}, \quad (5)$$

- Defuzzify elementwise to obtain a crisp normalized matrix N=[n_ij], e.g., centroid:

$$n_{ij} = \frac{l_{ij} + m_{ij} + u_{ij}}{3}. \quad (6)$$

- Computing the total-relation matrix

$$T = N\,(I - N)^{-1}, \quad (7)$$

Provided the spectral radius $\rho(N) < 1$ (enforced by normalization; if needed, damp $N \leftarrow N/\rho(N)$)

- Prominence and relation indices:

$$r_i = \sum_j t_{ij}\ (\textit{influence given}), c_i = \sum_j t_{ji}\ (\textit{influence received}) \quad (8)$$

$\textit{Prominence:}\, p_i = r_i + c_i$, $\textit{Relation:}\, e_i = r_i - c_i$.

Interpretation: $e_i > 0$ implies cause group (drivers), $e_i < 0$ implies effect group (outcomes).

2.3 Analytic Network Process

It will be used to propagate interdependencies into priorities via a supermatrix that preserves feedback. The following steps are involved (Chen et al. 2019; Kheybari, Rezaie, and Farazmand 2020):

- From the (normalized) direct influence among criteria (often use N from DEMATEL), form an unweighted supermatrix W^{un} by column-normalizing the influence columns:

$$W_{ij}^{un} = \frac{n_{ij}}{\sum_k n_{kj}}\ if \sum_k n_{kj} > 0, \quad (9)$$

This makes W^{un} column stochastic.

- For a single criteria cluster, the weighted supermatrix equals the unweighted one:

$$W^{we} = W^{un}. \quad (10)$$

- Limit supermatrix (power method until convergence):

$$W^{(\infty)} = \lim_{k \to \infty} (W^{we})^k. \quad (11)$$

If columns converge, any column of $W^{(\infty)}$ yields the ANP priority vector w^{ANP} (normalize to sum 1).

2.4 TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

TOPSIS is employed to rank alternatives by geometric closeness to an ideal (best) point and remoteness from a nadir (worst) point, given weights and polarity (Chakraborty 2022; Gündoğdu and Kahraman 2018).

- Decision matrix $X = [x_{ij}]$ (rows: alternatives; columns: criteria).
- Vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}. \quad (12)$$

- Weighted normalized matrix:

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

with w taken from ANP (network-consistent) or BWM (if used directly).

- Ideal positive and negative points:

$$v_j^+ = \begin{cases} \max_i v_{ij}, & j \in B \\ \min_i v_{ij}, & j \in K \end{cases}, v_j^- = \begin{cases} \min_i v_{ij}, & j \in B \\ \max_i v_{ij}, & j \in K \end{cases}. \quad (14)$$

- Separation measures (Euclidean):

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad (15)$$

- Closeness, coefficient and ranking:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}, \textit{rank descending by } CC_i. \quad (16)$$

A flow chart depicting integration of BWM–Fuzzy DEMATEL–ANP–TOPSIS for green port is depicted in Figure 1.

2.5 Expert selection and data collection

For this study, a detailed expert survey was conducted involving ten professionals deeply engaged in green port technologies, policy, and operations. These specialists were chosen because they have a lot of expertise in port electrification, maritime logistics, environmental compliance, and techno-economic evaluation (Gazi et al. 2024). In order to show how important each factor was to green port decisions;

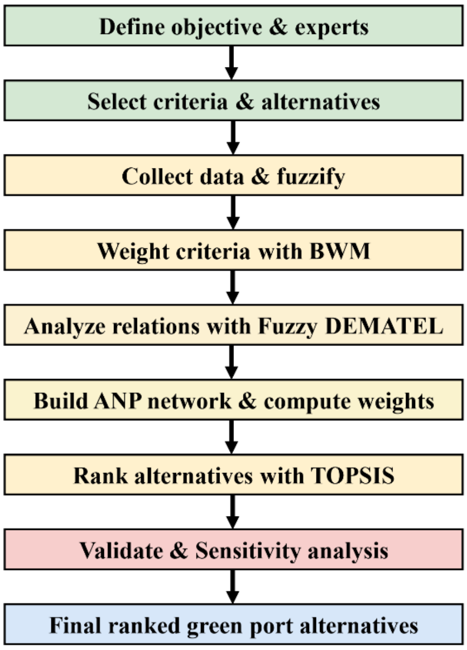

Fig. 1 MCDM Implementation Flowchart

the experts gave their opinions on a carefully chosen set of techno-economic indicators. These included capital expenditures, operational costs, net present value, payback periods, tariff sensitivity, fuel savings, equipment reliability, workforce readiness, carbon abatement potential, and local pollutant reductions. The elicitation was guided by structured tools that were meant to cut down on confusion and inconsistency. These tools used fuzzy logic, including triangular fuzzy numbers, to deal with uncertainty in a strong way. This strategy made it possible to get both qualitative and quantitative information in a single way. The gathered data made it possible to do a thorough Best-Worst weighting analysis, which made sure that the most important criteria were highlighted while keeping the data consistent. The evaluations that were gathered also helped establish a fuzzy DEMATEL model that found causal links between criteria. This was an important step in building an interconnected analytic network process that showed real relationships. This whole data collection and processing pipeline gave the whole multi-criteria analysis a strong base by using real-world expert knowledge. This made it possible to come up with useful suggestions for green port investments.

3. Results and discussion

3.1 Preparation of Aggregate Decision Matrix

The aggregate decision matrix brings together expert opinions on twenty factors that affect investments in green ports. Each criterion, which is shown by its acronym, is put into one of five groups: economic, technical, environmental, policy, or organizational. It is also marked as a cost or benefit to show whether greater values are good or bad. For example, CAPEX (capital expenditure) and OPEX (operating expenditure) are economic expenses with scores of 6.8 and 7.1, respectively. These scores show that there are significant costs up front and over time. Indicators like NPV (7.5) and IRR (6.9) show predicted returns and profits over the medium to long term, which are examples of economic advantages. Technical parameters including throughput gain (TPG, 6.7), utilization factor (UF, 7.2), and availability/reliability (AVR, 7.8), show how suggested innovations are expected to make operations more efficient. Environmental factors, such as emission abatement (EAB, 8.3) and local pollutant reduction (LPR, 7.9), show how much greenhouse gases and dangerous air pollutants are predicted to go down. These are important for the health of the port region and the world. Policy and organizational indicators, such as certification points gain (CPG, 6.3) and workforce and training readiness (WTR, 6.6), show how important compliance and human capital are for effective technology adoption. The aggregation combines several expert opinions into a single, easy-to-understand scoring scale (1–9) that takes polarity into account: as the burden increases, the cost scores go up, and as the expected gains go up, the benefit scores go up. This matrix sets the stage for weighted and causal analyses, making sure that later assessments accurately show the real-world trade-offs that come up when electrifying ports and modernizing logistics, such as the strain on capital, the effect on operations, the benefits to the environment, and the ease of implementation.

3.2 Results of Best Worst Method

The BWM results reflect a weighted hierarchy of criteria symbolizing the experts' consensus on the priorities that matter most in designing and implementing green port technologies. EAB had the largest weight, 0.0740, which shows that experts thought reducing CO_2 and other greenhouse gases was the most important thing to do, perhaps because it directly affects climate objectives. FS came in second with a score of 0.0723, showing how important fuel-saving techniques are for lowering operating emissions. LPR (0.0705) and AVR (0.0696) also did well, showing that cutting down on local pollution and making equipment more reliable and available are important goals that balance environmental and operational advantages. NPV (0.0669) and UF (0.0642) show that economic advantages and how well resources are used are still important elements in making investment decisions. Metrics like IRR and DIL each had weights close to 0.0616, which shows that they have a moderate but nonetheless significant impact on whether an investment is feasible and whether new technology is adopted. Cost-related factors like CAPEX (0.0285) and OPEX (0.0259)

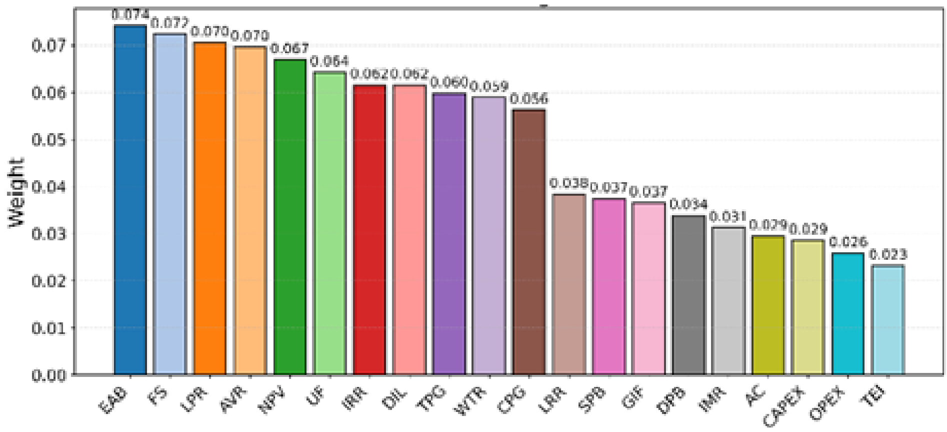

Fig. 2 Barplot of BWM weights

Table 1
Aggregate Decision Matrix

Criterion	Abbreviation	Type	Tag	Aggregated Expert Score (1–9)
Capital Expenditure	CAPEX	Economic	Cost	6.8
Operating Expenditure (annual)	OPEX	Economic	Cost	7.1
Net Present Value (10–25y)	NPV	Economic	Benefit	7.5
Internal Rate of Return	IRR	Economic	Benefit	6.9
Simple Payback	SPB	Economic	Cost	5.8
Discounted Payback	DPB	Economic	Cost	6.2
Tariff Exposure Index	TEI	Economic	Cost	7.4
Fuel Savings (annual)	FS	Economic	Benefit	8.1
Throughput/Productivity Gain	TPG	Econ/Tech	Benefit	6.7
Utilization Factor	UF	Tech	Benefit	7.2
Availability/Reliability	AVR	Tech	Benefit	7.8
Grid Interconnection Feasibility	GIF	Tech	Cost	5.9
Implementation Risk	IMR	Tech/Econ	Cost	6.5
Emission Abatement (tCO2e/yr)	EAB	Tech/Env	Benefit	8.3
Abatement Cost (USD/tCO2e)	AC	Econ/Env	Cost	6.7
Local Pollutant Reduction	LPR	Env/Tech	Benefit	7.9
Certification Points Gain	CPG	Policy	Benefit	6.3
Workforce & Training Readiness	WTR	Org/Tech	Benefit	6.6
Digital Integration Level	DIL	Tech	Benefit	6.9
Lifecycle Replacement Risk	LRR	Tech/Econ	Cost	5.7

had less weight further down the scale. This shows that experts thought long-term profits and benefits were more important than only the initial costs. The low weight of TEI (0.0232) shows that tariff sensitivity was less at the time. These weights take into account complex trade-offs, such as prioritizing reducing emissions, improving fuel efficiency, and making the system available, while also considering costs and risks. This creates a balanced, multi-faceted appraisal that guides future modelling and final rankings.

3.3 Results of Fuzzy DEMATEL method

Figure 3 depicts the scatter plot illustrating the use of fuzzy DEMATEL on the criteria set. It maps each criterion to its computed prominence (total of provided and received influence, r+c) and relation (difference, r–c). The horizontal dashed line shows that points with positive connection scores, such LRR, WTR, IRR, CAPEX, UF, and EAB, are "cause" group factors. These characteristics tend to have a bigger effect on other people in the network, which is why they are the main factors that shape green port priority. For instance, high LRR and IRR figures show that lifetime and investment factors are important to think about when planning improvements. On the other hand, the criteria below the dashed line, TEI, CPG, GIF, AVR, DIL, SPB, DPB, and FS, are in the "effect" group. They are affected by others and usually show results or replies. TEI's position on the far right, with a negative relationship and the highest prominence, shows that tariff exposure is determined by numerous interacting factors instead of being the main one. Criteria that are close to zero on the relation axis, such as LPR, IMR, AC, TPG, NPV, and OPEX, operate as links between other criteria. They give feedback, but they don't clearly dominate or

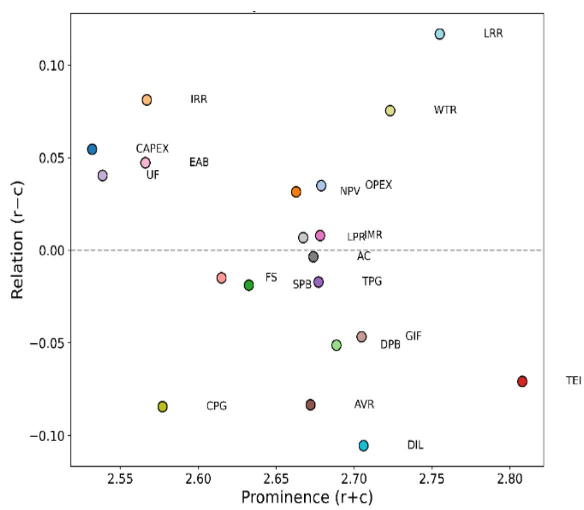

Fig. 3 Scatter plot

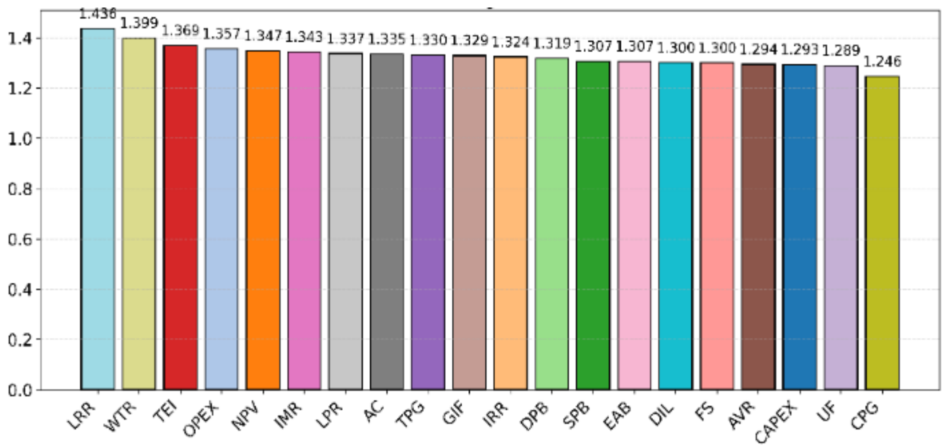

Fig. 4 Fuzzy DEMATEL r value showing given effects

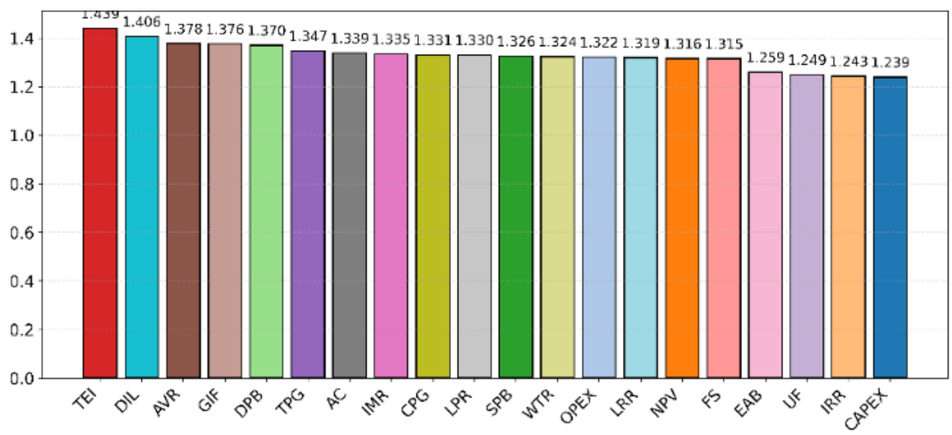

Fig. 5 Fuzzy DEMATEL c value showing received effects

respond. By demonstrating how the function of each criterion varies based on prominence and causation, the display helps decision makers find leverage areas for interventions and predict downstream effects. This helps in deciding which parts to focus on first during electrification or operational upgrades.

The r-values (given effects) from the fuzzy DEMATEL analysis, quantifying the influence exerted by each criterion within the green port evaluation network, are illustrated in Figure 4. The Lifecycle Replacement Risk (LRR) and Workforce & Training Readiness (WTR) scores are the highest, with 1.436 and 1.399, respectively. This means that they are very important factors that impact many other criteria. The Tariff Exposure Index (TEI) and Operating Expenditure (OPEX) also have a big impact, which means that economic risks and costs play a big role in making decisions. Net Present Value (NPV), Implementation Risk (IMR), Local Pollutant Reduction (LPR), and Abatement Cost (AC) are all somewhat less important but still important. This shows that financial rewards, operational risks, environmental benefits, and costs are all important factors in driving change. Criteria with lower r-values, such Availability/Reliability (AVR), Capital Expenditure (CAPEX), Utilization Factor (UF), and Certification Points Gain (CPG), have a modest effect and typically respond to upstream causes. This distribution helps find leverage areas where putting more effort and resources into management can have a ripple effect throughout the network. Figure 4 is important for strategic prioritizing in green port electrification and sustainability planning because it helps decision-makers figure out which criteria spread influence. This lets policymakers and managers deal with the fundamental causes of problems instead of just the symptoms.

Figure 5 displays the “c” scores from fuzzy DEMATEL, quantifying how much influence each criterion receives from all others within the green port evaluation framework. The Tariff Exposure Index (TEI) has the highest c-value at 1.439, followed closely by the Digital Integration Level (DIL, 1.406) and the Availability/Reliability (AVR, 1.378). This means that TEI is very sensitive to upstream causes and tends to take in or reflect the effects of many other decisions, notably those on costs, adopting new technology, or changing how things are done. A high c-value for DIL and AVR means that digitalization and reliable system operation are affected by changes in other parts of the decision network. Criteria such as Grid Interconnection Feasibility (GIF), Discounted Payback (DPB), and Throughput/Productivity Gain (TPG) also show a lot of receptiveness, taking in changes from basic drivers like capital investments, risk, or changes in regulations. Items like IRR, UF, and CAPEX have lower c-values, which means that changes in the economy have less of an effect on their profitability, use, and big costs. Instead, they work more independently or create requirements that other criteria must meet. These differences assist planners figure out which performance factors are the result of system-wide dynamics.

Figure 6 ranks criteria based on prominence (the sum of influences given and received), making it possible to spot which attributes are deeply interactive within the network. It is observed that TEI is the highest with a score of 2.808, which means it has a lot of connections and is affected by many things

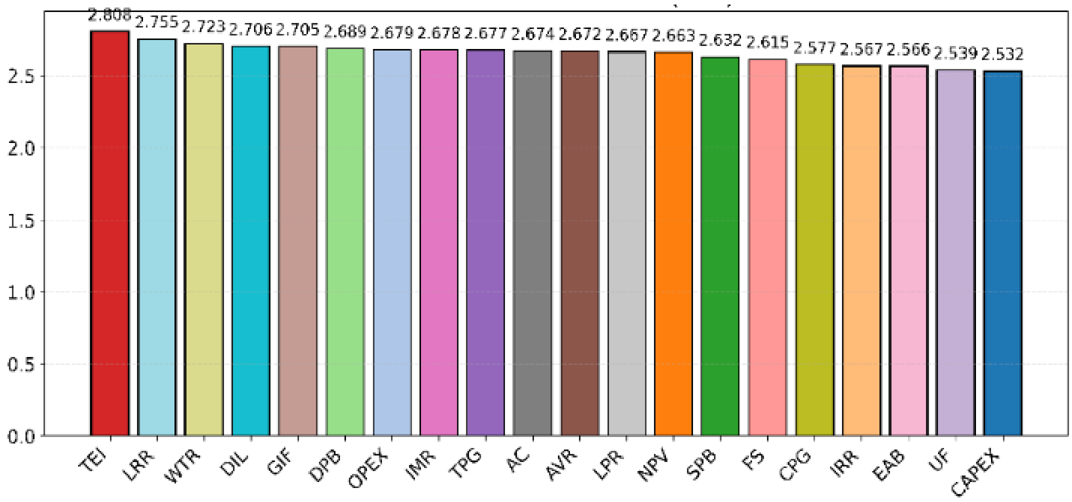

Fig. 6 Fuzzy DEMATEL prominence (r + c)

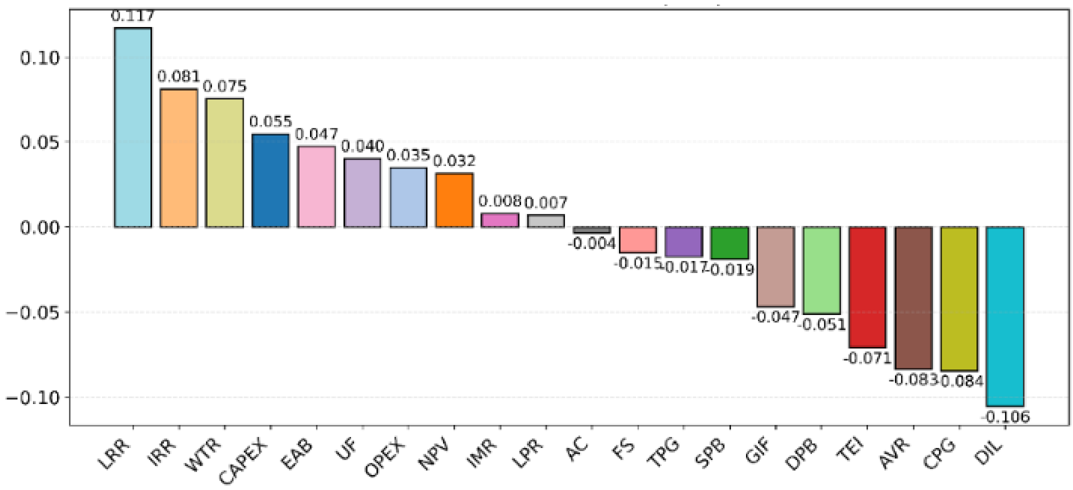

Fig. 7 Fuzzy DEMATEL prominence (r - c)

while simultaneously having a big effect on other criteria. Next are LRR (2.755), WTR (2.723), and DIL (2.706). Each of them is a big part of the overall picture of green port priority and a sensitive receiver. High values here indicate criteria that act as both agents of change and responsive nodes, frequently governing larger dynamics and reacting to changes throughout the system. OPEX, IMR, and TPG are examples of criteria that are in the middle of the table. They show balanced amounts of activity without taking over the network. CAPEX (2.532) and UF (2.539), on the other hand, are less important. They have a more peripheral role in cross-criterion interaction because they impact fewer outcomes and are less likely to cause systemic changes that are started by other factors. Planners may better understand where their efforts to improve performance are more likely to have an effect on the network by looking at this profile. This makes prominence a useful way to deal with the complexity of port transformation.

The relation (r–c) values for the green port criteria, categorizing each as either a root cause or an outcome within the impact network, are depicted in Figure 7. Criteria with positive r–c values, including LRR, IRR, WTR, CAPEX, EAB, and UF, serve as key drivers as these factors exert a greater outward effect than they receive. LRR attains the greatest causative status of 0.117, underscoring lifecycle concerns as the primary determinant influencing subsequent decisions. IRR and WTR indicate how financial appeal and workforce preparedness catalyze subsequent effects. Negative correlation scores, including those for DIL, CPG, AVR, TEI, and DPB, indicate effect criteria as these are predominantly influenced by external factors and are less significant as initiators themselves. DIL possesses the lowest score (–0.106), emphasizing that digital integration results reflect changes within the overarching system. Values proximate to zero, including IMR, LPR, AC, and SPB, indicate bidirectional roles characterized by balanced influence, frequently designating them as connectors or feedback mechanisms between drivers and outcomes. This figure elucidates the variables most suitable for intervention (those with the largest positive r–c), while others act as performance indicators or represent downstream outcomes of network modifications, informing resource distribution and prioritization in green port enhancements.

3.4 Results of ANP-TOPSIS

Figure 8 presents the allocation of ANP-derived criterion weights for the full set of performance indicators considered in this analysis. The analytic network method creates the weighting scheme by changing the relevance of each criterion to take into consideration how all the factors in the decision model are related and how they affect each other. With a weight of 0.054, Lifecycle Replacement Risk (LRR) is at the top of the list. This shows how important the timing and uncertainty of asset replacement are to the overall strategic goals of green port investments. Workforce & Training Readiness (WTR) comes

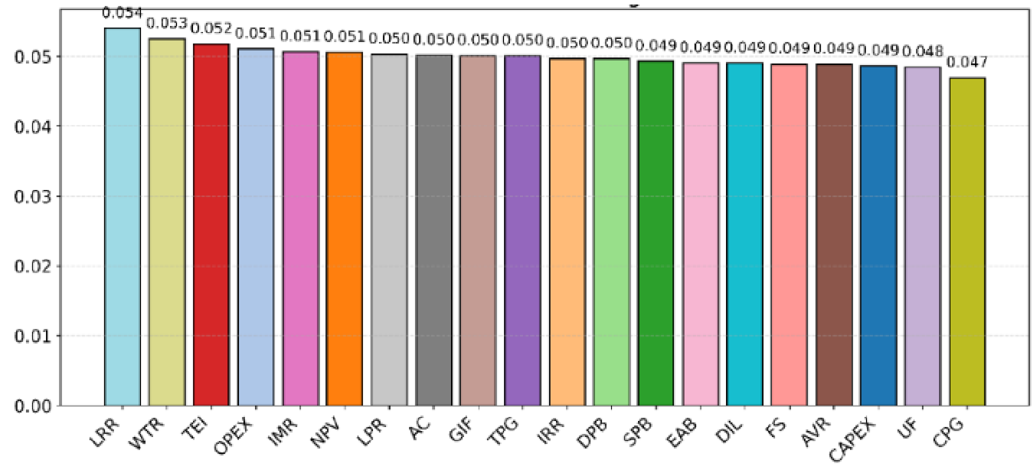

Fig. 8 ANP-derived criterion weights

next with a weight of 0.053, and Tariff Exposure Index (TEI) is almost as important with a weight of 0.052. This shows that human capital and exposure to market-driven costs are key factors in system-wide decision trade-offs. OPEX, IMR, NPV, and LPR all have values close to 0.051, which means that regular spending, implementation weaknesses, net returns, and pollution control all have about the same effect on the system. The wide middle tier, which includes AC, GIF, TPG, IRR, DPB, SPB, EAB, DIL, FS, AVR, and CAPEX, has weights that are very close to 0.049–0.050. This close grouping shows that ANP spreads importance more evenly across the network by taking into account cross-influences, which lessens the value of isolated criterion. UF and Certification Points Gain (CPG) are at the bottom, with weights of 0.048 and 0.047, respectively. This means that their outcomes are more typically caused by upstream factors than by the primary levers themselves.

The trend in Figure 8 supports the scientific idea that in linked, multi-criteria areas like port decarbonization, the most important aspects aren't always clear from a single evaluation. Instead, systemic risk factors (like LRR and WTR) and cost sensitivities (like TEI and OPEX) become more important because changes in these areas have a big impact on the whole network of economic, technological, and environmental priorities, which in turn affects how well modernization and electrification choices work.

The ANP-TOPSIS findings (Table 2) offer a detailed depiction of criterion benchmarks, distinguishing between optimal positive and optimal negative reference values. These benchmarks make it possible to compare project options in a realistic way, considering a wide range of techno-economic and environmental factors. Cost-oriented indicators like CAPEX (ideal positive: 0.0239, ideal negative: 0.0319), OPEX (0.0295, 0.0295), SPB (0.0266, 0.0319), DPB (0.0268, 0.0321), and TEI (0.0282, 0.0329) show that the best solution is to cut costs, improve payback metrics, and limit exposure to tariff changes. Their lower ideal positive values relative to ideal negatives show that a lesser cost is better. On the other hand, economic benefits have the opposite polarity, with NPV (0.0306, 0.0262), IRR (0.0300, 0.0257), FS (0.0333, 0.0208), TPG (0.0305, 0.0254), and UF (0.0280, 0.0280) displaying larger ideal positive values. FS, which stands for fuel savings, has the biggest difference between ideal positive and negative, which shows how important it is as a way to tell options apart. EAB (0.0283, 0.0283) and LPR (0.0313, 0.0279) are examples of environmental standards that balance eastern hopes for lower emissions and better air quality.

AVR (0.0294, 0.0257), WTR (0.0318, 0.0272), and DIL (0.0308, 0.0270) are all examples of technical and organizational

Table 2
TOPSIS ideal points

Criterion	Ideal Positive	Ideal Negative
CAPEX	0.0239	0.0319
OPEX	0.0295	0.0295
NPV	0.0306	0.0262
IRR	0.0300	0.0257
SPB	0.0266	0.0319
DPB	0.0268	0.0321
TEI	0.0282	0.0329
FS	0.0333	0.0208
TPG	0.0305	0.0254
UF	0.0280	0.0280
AVR	0.0294	0.0257
GIF	0.0239	0.0335
IMR	0.0257	0.0308
EAB	0.0283	0.0283
AC	0.0290	0.0290
LPR	0.0313	0.0279
CPG	0.0284	0.0243
WTR	0.0318	0.0272
DIL	0.0308	0.0270
LRR	0.0274	0.0329

elements that show how important operational dependability, workforce preparation, and digital integration are for long-term sustainability. GIF (0.0239, 0.0335) and LRR (0.0274, 0.0329) show a different pattern: their ideal negative values are higher than their ideal positive values, showing that for the best solutions, researchers need to reduce the risks of grid interconnection problems and lifetime replacement. These benchmark values let TOPSIS look at costs, benefits, risks, and operational aspects all at once. This lets it figure out the geometric distances that show how close each option is to the ideal. This analytical methodology respects the complicated relationships between competing criteria and leads to more balanced, useful rankings. It gives decision-makers the tools they need to make the best choices for moving forward with green port electrification and modernization that balance economic viability, environmental stewardship, and technological feasibility.

Figure 9 shows the final alternative rankings that the TOPSIS algorithm came up with. It also shows the closeness coefficients for each scenario that was looked at: AltC, AltB, and AltA. In TOPSIS, closeness shows how close an option is to the best circumstances across all weighted criteria. Higher values mean better overall performance and a better balance between techno-economic and environmental factors. AltC is the most popular choice, with a close score of 0.739. This indicates that

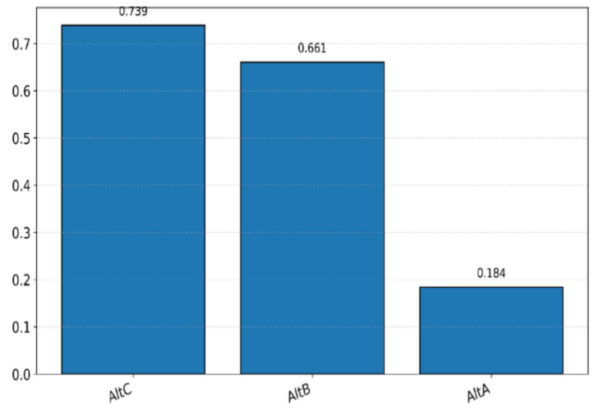

Fig. 9 TOPSIS derived final alternative rankings

it constantly gets scores close to the optimum reference points for the combined set of criteria. This makes it the best-balanced choice among the green port configurations. AltB follows with a rating of 0.661, suggesting that while it nearly approaches the targeted results and displays competitiveness, it falls short of AltC, presumably due to trade-offs in one or more areas where AltC shines (such as integrated environmental and operational qualities). AltA is far behind, with a closeness of 0.184, which shows that it is far from the best mix of benefits and hazards. This big difference shows that one or more problems, maybe more expenses, less emission reduction, or operational weaknesses keep AltA from fulfilling the planned portfolio of goals.

The ranking is the result of rigorous integration across BWM, DEMATEL, ANP, and TOPSIS, with each technique aligning weights, causality, network feedback, and distance measures. The results give clear, useful advice: strategies and investments mapped onto AltC are the best overall fit with the multi-criteria goals set by experts and stakeholders. AltA, on the other hand, can't make up for its larger overall weaknesses compared to the ideal. This rating enables open planning and resource allocation in the goal of green port modernization.

4. Conclusion

This study developed and applied an integrated decision-support scheme blending expert judgment, causal analysis, network weighting, and multi-criteria ranking to prioritize green port establishment with emphasis on techno-economic criteria. The results show that experts care most about reducing emissions, conserving fuel, and making operations more reliable. Lifecycle replacement risk and labor preparedness, on the other hand, are the main factors that affect tariff risk and technology adoption. Network-consistent weights adjusted for the criterion balance, showing that systemic risk and human capital are the most important levers. The hybrid phased electrification option came out on top, showing that a staged investment strategy is superior at balancing costs, environmental effects, operational productivity, and technological readiness than plans that focus on one thing at a time. This shows how important it is to use complex sequencing and balance conflicting goals instead of just relying on simple cost or environmental measures. The framework's modular structure, which includes different areas of knowledge, uncertainty modelling, and feedback loops, makes it a clear, repeatable, and flexible way to make decisions in complicated sustainability situations. It goes beyond simple linear weighing and scoring by showing how things are related and how they depend on each other. This gives policymakers and stakeholders who have to deal with financial limits, regulatory uncertainty, and workforce preparedness at the same time a better understanding of the situation. Future endeavours may enhance the model by integrating real-time operational data, tariff variations, and dynamic renewable integration scenarios, therefore increasing its relevance and responsiveness. Overall, the findings support careful, expert-informed, and multi-dimensional planning for initiatives to change ports to be more environmentally friendly while still protecting their long-term economic and operational sustainability.

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