Lecture Notes in Intelligent Transportation and Infrastructure
Series Editor: Janusz Kacprzyk

Olegas Prentkovskis ·
Irina Yatskiv (Jackiva) · Mykola Karpenko ·
Kamilė Taujanskaitė · Paulius Skačkauskas ·
Michał Stosiak *Editors*

TRANSBALTICA XVI: Transportation Science and Technology

Proceedings of the 16th International Conference TRANSBALTICA, September 18–19, 2025, Vilnius, Lithuania

Springer

Development of a Procedure for Ranking of Innovative Technologies for Decarbonization of Rail Transport

Oleksandr Rohovyi[1], Valerii Samsonkin[1], Oksana Yurchenko[1](✉), Gintautas Bureika[2], and Iuliia Bulgakova[1]

[1] National Transport University, 1, M. Omelianovycha-Pavlenka Str., Kyiv 01010, Ukraine
yurchenko_og@gsuite.duit.edu.ua

[2] Vilnius Gediminas Technical University, 25, Plytinės Str., 10105 Vilnius, Lithuania
gintautas.bureika@vilniustech.lt

Abstract. The article considers the tools for comprehensive assessment of railway transport decarbonization strategies in the context of European climate policy. A methodological combination of full life cycle assessment, hierarchical analysis of priorities and a method for choosing the solution closest to ideal is proposed. Using the example of four options: full electrification, hydrogen traction, battery traction and biofuel, a multi-criteria comparison is carried out according to environmental, economic, technical, capital and social indicators. The results of the calculations show the advantage of electrification according to the integral rating, although under certain conditions (decreasing the price of hydrogen and increasing capital costs for the contact network). Hydrogen traction demonstrates potential only under conditions of significant reduction in the cost of "green" hydrogen. Battery traction is appropriate on short routes, and biofuel is inferior in all main criteria. The developed approach allows integrating quantitative and qualitative indicators into a single system for forming transparent and reproducible management decisions in the field of sustainable development of railway transport by implementation of innovations.

Keywords: Railway transport · Innovations · Decarbonization · Multi-criteria decision-making · Life cycle assessment · Hydrogen traction · Railway Electrification

1 Introduction

Decarbonization of rail transport is currently one of the highest priorities of European policy [1]. The adoption of the Green Deal and the Fit for 55 package [2] requires a 55% reduction in greenhouse gas emissions by 2030 and the achievement of climate neutrality in the middle of the 21st century [3, 13]. For railways, it should be noted that they already have the lowest specific emissions among transport modes, but fulfilling such commitments requires a profound change in existing practices, namely: large-scale electrification, deployment of hydrogen and battery-powered multi-units, digitalization of traffic control systems, formation of flexible financial and regulatory incentives, etc.

O. Prentkovskis et al. (Eds.): TRANSBALTICA 2025, LNITI, pp. 1025–1035, 2026.
https://doi.org/10.1007/978-3-032-18771-0_93

Today, numerous decarbonization solutions exist, especially in transport, forming a complex multi-criteria landscape where each option is assessed by environmental, economic, technological, and social indicators. Gains in one area are often offset by drawbacks in others. Traditional single-criteria or financial approaches fail to capture this complexity, prompting wider use of multi-criteria decision-making (MCDM) methods. The literature cites over two dozen such methods, including AHP, TOPSIS, VIKOR, PROMETHEE, ELECTRE, and others. The tool selection depends on specific conditions.

The aim of this research work is to substantiate and consider, using an example, the most suitable tools for comprehensive evaluation of railway decarbonization strategies.

2 Methodology

To assess railway decarbonization strategies effectively, a structured methodological approach is required. This section presents the main groups of analytical tools used in recent studies – from basic statistics to advanced multi-criteria and strategic methods.

2.1 Methodological Spectrum for the Evaluation of Railway Decarbonization Innovations

At the initial level, primary statistical analysis is used: means, medians, variances, histograms. This enables the identification of distribution patterns, detection of anomalies, and formulation of preliminary hypotheses. Correlation analysis establishes the direction and strength of relationships between parameters (for example, electrification and specific CO_2 emissions). Regression modeling (linear and nonlinear) quantitatively describes these relationships and checks the significance of factors.

For system analysis, the tools are divided into five blocks (in Table 1), which cover the full cycle – from statistical data processing to strategic policy evaluation.

The following abbreviations are used in Table 1: σ – standard deviation; AHP – Analytic Hierarchy Process; ANP –Analytic Network Process; ARIMA – AutoRegressive Integrated Moving Average; CBA – Cost-Benefit Analysis; Delphi – expert judgment method; ELECTRE – ELimination Et Choix Traduisant la REalité; ETS – Exponential Smoothing; GLM – Generalized Linear Model; LCA – Life Cycle Assessment; LSTM-NN – Long Short-Term Memory Neural Network; OLS – Ordinary Least Squares; PESTEL – Political, Economic, Social, Technological, Environmental, and Legal analysis; PROMETHEE – Preference Ranking Organization METHod for Enrichment Evaluation; SWOT – Strengths, Weaknesses, Opportunities, Threats analysis; TCO – Total Cost of Ownership; TOPSIS – Technique for Order of Preference by Similarity to Ideal Solution; VIKOR – Multi-Criteria Optimization and Compromise Solution.

If the analysis extends beyond description and transitions into forecasting, it becomes rational to apply time series methods. Simple and weighted moving averages smooth fluctuations; exponential smoothing gives more weight to recent data; ARIMA models and neural networks capture nonlinear traction energy demand dynamics and can extrapolate trends beyond historical data. At the strategic level, scenario-based methods are used – classic "what-if" analyses to system dynamics, which model interactions between

Table 1. Classification of methods used for railway decarbonization studies.

Method block	Main tools	Key purpose	Typical examples from literature
Descriptive and Correlation – Regression	means, σ, histograms, correlation, OLS / GLM regressions	primary data structure, identification of emission drivers	abatement cost curves [4]; elasticity "electrification → CO_2" [5]
Time Series and Forecasting	simple/weighted moving averages, ETS, ARIMA, LSTM-NN	short- and medium-term forecasts of energy consumption, formation of discounted cost	IEA Net Zero scenarios [6]; LSTM-NN for Short-Term Passenger Flow Prediction [7]
Full Life Cycle and Economics	LCA (ISO 14040), TCO, CBA	comparison of alternatives by CO_2 emissions and cost per t*km over a 25 to 30 year horizon	LCA Coradia iLint vs DMU [8]; CBA Green-Hub FS Italiane
MCDM	AHP, TOPSIS, VIKOR, PROMETHEE, ELECTRE, fuzzy extensions	integrated ranking of technologies using 3 + diverse criteria	AHP-TOPSIS for route electrification [9]; Fuzzy-VIKOR for routes [10]
Expert, Scenario-Based, and Strategic	Delphi, ANP, system dynamics, SWOT, PESTEL	consensus-building, comprehensive strategic assessment, risks	SWOT of country electrification [11]

investments, tariffs, energy mix, and transport volumes. Environmental and economic efficiency is evaluated using life cycle assessment (LCA), cost-benefit analysis (CBA), and total cost of ownership (TCO). LCA accounts for emissions across all stages, while TCO and CBA convert environmental impacts into monetary terms, considering capital and operating costs, tax incentives, and externalities.

To compare alternatives optimal under different criteria, multi-criteria decision-making (MCDM) methods are applied. Literature references over two dozen such methods. AHP structures problems hierarchically and weights criteria; TOPSIS compares alternatives with ideal and anti-ideal solutions; VIKOR balances maximum and minimum deviations; PROMETHEE and ELECTRE use pairwise comparisons. DEA is useful for evaluating fleet and route efficiency, as it considers multiple inputs (e.g., fuel, staff, infrastructure) and outputs (e.g., passengers, distance, emission cuts). It requires no predefined weights and identifies the most efficient option for a given setup. Most methods have fuzzy, probabilistic, or rough-set variants, improving robustness when data are incomplete or expert judgments unclear. For consensus building, expert techniques like Delphi and ANP collect and align expert views through multiple rounds.

At the final stage, when a pool of scenarios and a package of policy measures have been formed, decision support tools and comprehensive business analytics instruments are applied. These integrate regression models, the results of MCDM calculations, as well as SWOT and PESTEL matrices into a unified information environment for managers and regulators.

2.2 Analysis of Factors Influencing the Choice of Decarbonization Strategies

The choice of a strategy selection tool depends on several interrelated factors. The first – data availability and structure: extensive datasets suit classical regression or ARIMA models; fragmented or expert-based data favor hierarchical analysis and fuzzy MCDM methods. The second – the number of criteria: when many diverse criteria are involved, multi-criteria approaches are preferable to single-metric financial ones. The third – uncertainty level: long-term forecasts benefit from combining scenario models with fuzzy or probabilistic MCDM to ensure result robustness under varying assumptions.

Equally important is the tolerance of stakeholders toward "complex" mathematics. In communication with authorities or the public, transparency in ranking and explainable weighting are valued, making AHP a popular tool in transport policy. Pairwise comparisons generate intuitive weights, and consistency is statistically validated. Based on these considerations, the most suitable approach for selecting innovations in railway decarbonization is an integrated "LCA + AHP + TOPSIS" model. LCA offers an environmental baseline, AHP ensures priority consistency, and TOPSIS delivers clear, actionable outputs. Among the many available methods, those combining hierarchical weighting and proximity-to-ideal solutions are the most applicable to decarbonization tasks.

2.3 Research Results

This section considers the application of the integrated approach "LCA + AHP + TOPSIS" to four possible alternatives for the decarbonization of rail transport: full electrification (EL), hydrogen fuel cell traction (H_2), battery-electric traction (BAT), and diesel multi-units powered by biofuel (B100 – biodiesel of class B100, containing 100% bioester without any mineral diesel fuel).

Input Data and LCA Boundaries. For each of four technologies, a complete life cycle was constructed using the Ecoivent 3.9 database (an international life cycle inventory database) and GREET 2023 (Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies).

Key assumptions: 65% of electricity is sourced from renewable energy; "green" hydrogen requires 55 kWh/kg; lithium-ion batteries are replaced on average every 10 years; and polymer electrolyte fuel cells are regenerable.

Statistical modeling using the Monte Carlo method (with 2,000 iterations, in accordance with typical parameters of verified LCA models in the Ecoinvent database and ISO 14044 guidelines) produced an empirical 95% confidence interval of 0.011 to 0.015 kg CO_2/tkm – the range within which the result lies with 95% probability. The sample standard deviation σ is 0.0017 kg/tkm.

The notations were introduced for the cost components of the alternatives:

I. CRS – cost of a single multi-unit (thousands of euros per multi-unit);

II. CEL = €8 to 10 million – cost of 1 km of catenary infrastructure (considered only in specific scenarios).

For the H_2 alternative, the initial discounted cost of hydrogen (LH, €/kg) was converted into the equivalent cost of traction energy – EH (€/kWh-eq). The designation "kWh-eq" (from equivalent) refers to the actual traction energy effectively delivered to the multi-unit from the chemical energy of hydrogen, accounting for conversion efficiency. In other words, this is not the thermal energy of the fuel, but the net electrical energy supplied to the drivetrain – factoring in the fuel cell efficiency, inverter losses, and auxiliary systems.

The equivalent cost of traction energy is calculated using the following formula:

$$E_H = \frac{(L_H + \alpha)}{(H_H \cdot \eta)}, \quad (1)$$

where H_H – higher heating value (HHV) of hydrogen equal to 33.3 kWh/kg –, η – 0.55 – efficiency coefficient of the fuel cell, α – plus €0.9/kg accounts for compression, storage, and delivery of hydrogen to the refueling station.

It should be noted that the chosen value of $\eta = 0.55$ represents the upper limit for modern polymer electrolyte fuel cells. At the same time, technical reviews of the Alstom Coradia iLint hydrogen multi-unit indicate that the efficiency of the fuel cell is typically around 55%, and when accounting for losses in the traction system (energy conversion, storage, drivetrain), the overall system efficiency does not exceed (45 to 50%).

This means that a significant portion of hydrogen energy is lost at intermediate stages, increasing the cost of traction energy. Accordingly, the parity threshold – that is, the price at which hydrogen traction becomes economically competitive with conventional electrification – may increase from €0.1/kg to €0.2/kg compared to the baseline scenario, in which $\eta = 0.55$ and electrification is assessed at an average rate excluding externalities.

Similarly, the assumption of lithium-ion battery replacement every 10 years is an average estimate, as in series such as the Stadler FLIRT Akku, the manufacturer's warranty is limited to 8 years or 15,000 cycles, which under daily operation corresponds to an actual service life is (6 to 7) years. This may impact on the life cycle of capital expenditures (CAPEX) for battery-electric traction (BAT alternative).

The mean time between failures (MTBF) for hydrogen multi-units has been partially estimated through multiple imputation, since publicly available technical records cover less than 20,000 h of actual operation. A complete reliability assessment is only be possible after several years of monitoring under real operating conditions.

Application of the AHP Method: Criterion Weights. Five harmonized criteria (environmental, economic, capital, technical, social) are assigned weighting coefficients calculated as average values based on four recent LCA-MCDM studies: [4, 8–10, 12], as shown in Table 2.

Ar.mean – arithmetic mean of the normalized statistics; σ – standard deviation of the normalized statistics. The normalization process involves converting values to a dimensionless form, with the sum of all five ar.mean values equal to one. For the criterion "cost of one multi-unit," only the rolling stock cost is considered, excluding infrastructure costs, which are addressed in a scenario-based manner.

Table 2. Criterion Weight.

Criterion	Description	ar.mean ± σ	Weight
Environmental	Amount of CO_2 emissions per tonne-kilometer of transport. Indicator: lower is better (↓)	0.30 ± 0.02	0.3
Economic	Average discounted cost of traction energy (i.e., cost per kWh of energy actually used for motion). Indicator: lower is better (↓)	0.24 ± 0.03	0.24
Capital	Initial capital cost per multi-unit. Indicator: lower is better (↓)	0.18 ± 0.02	0.18
Technical (reliability)	Mean time between failures. Indicator: higher is better (↑)	0.15 ± 0.02	0.15
Social	Number of works created and level of public support for the technology. Indicator: higher is better (↑)	0.13 ± 0.01	0.13

In Table 2, the values in the third and fourth columns are averaged across four studies that combine life cycle assessment with multi-criteria analysis [4, 9, 10, 12]. All sources provide weighting coefficients for the same five criteria. For each criterion, the coefficient of variation was below 8%, indicating low dispersion and allowing the mean value to be considered representative for further calculations in the TOPSIS method. The four referenced studies contain harmonized weights for the same five criteria, with only minor differences: the standard deviation for each criterion does not exceed 0.03. This makes it possible to use the arithmetic mean as the operational value for subsequent ranking within the TOPSIS method.

Consider the base case scenario TOPSIS, as shown in Table 3.

Table 3. Input Data and Criterion Scores of Decarbonization Alternatives for the TOPSIS Method.

Alternative	Criterion / Indicator				
	1 Environmental (↓)	2 Economic (↓)	3 Capital (↓)	4 Technical (↑)	5 Social (↑)
1. EL	0.013	0.10	900	72	0.68
2. H_2	0.025	0.25	1150	65	0.64
3. BAT	0.020	0.22	1050	60	0.70
4. B100	0.045	0.26	820	55	0.55

The indicators in Table 3 are interpreted as follows: "↓" – the lower, the better; "↑" – the higher, the better.

To compare alternatives, an AHP → TOPSIS combination is used. AHP determined the weights of five key criteria (environmental, economic, capital, technical, social), while TOPSIS ranked technologies by their proximity to the ideal and distance from the anti-ideal solution. This approach provides transparent, reproducible rankings and allows rapid scenario testing (e.g., changes in hydrogen prices or CAPEX).

The TOPSIS algorithm followed five steps: normalization, weighting, identification of ideal and anti-ideal solutions, distance calculation, and closeness index computation.

Let us represent Table 3 as a matrix. $\boldsymbol{X} = \{x_{ij}\}$, $i = 1, 2, 3, 4; j = 1, 2, 3, 4, 5$.

Let us define the normalized matrix. $\boldsymbol{X}^1 = \{x_{ij}\}$, $i = 1, 2, 3, 4; j = 1, 2, 3, 4, 5$. The elements of the normalized matrix $\boldsymbol{X}^1$ are determined using the following formulas:

$$x_{ij}^{'} = \frac{min(x_j)}{x_{ij}}, \tag{2}$$

for $j = 1, 2, 3$; and

$$x_{ij}^{'} = \frac{x_{ij}}{\max(x_j)}, \tag{3}$$

for $j = 4, 5$.

Next, the weighted normalized matrix $\boldsymbol{V} = \{v_{ij}\}$, $i = 1, 2, 3, 4; j = 1, 2, 3, 4, 5$ is constructed, whose elements are calculated using the following formula:

$$v_{ij} = w_j \cdot x_{ij}^{'}, \tag{4}$$

where w_j – is the weight of criterion j from Table 2.

The values of the matrix $\boldsymbol{V} = \{v_{ij}\}$, are presented in Table 4.

Table 4. Values of the elements of the weighted normalized matrix $\boldsymbol{V}$.

Decarbonization Technology	Criterion					Σ
	1 Environmental (↓)	2 Economic (↓)	3 Capital (↓)	4 Technical (↑)	5 Social (↑)	
1. EL	0.30	0.24	0.164	0.150	0.126	0.98
2. H_2	0.156	0.096	0.128	0.135	0.119	0.634
3. BAT	0.195	0.109	0.141	0.125	0.130	0.700
4. B100	0.087	0.092	0.180	0.115	0.102	0.576

Note: Arrows indicate optimization direction – (↓) for minimization, (↑) for maximization

The ideal (the best) and anti-ideal (the worst) solutions are presented in Table 5.

The calculations of the distance to the ideal and anti-ideal values for each criterion are performed using formula (5), (6):

$$D_i^+ = \sqrt{\sum\nolimits_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2}, \tag{5}$$

$$D_i^- = \sqrt{\sum\nolimits_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{6}$$

Table 5. Ideal and anti-ideal values for each criterion.

Value	Criterion / Indicator				
	1 Environmental (↓)	2 Economic (↓)	3 Capital (↓)	4 Technical (↑)	5 Social (↑)
Ideal (V^+)	0.30	0.24	0.18	0.15	0.13
Anti-Ideal (V^-)	0.087	0.092	0.128	0.115	0.102

And the closeness index to the ideal solution is determined using the following formula:

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{7}$$

The results of the TOPSIS baseline scenario are presented in Table 6.

Table 6. Results of using TOPSIS.

Alternative	D^+ (Distance to Ideal)	D^- (Distance to Anti-Ideal)	S_i (Closeness Index)	Rank
EL	0.016	0.265	**0.942**	1
BAT	0.174	0.114	0.396	2
H_2	0.210	0.074	0.261	3
B100	0.263	0.052	0.164	4

Thus, the TOPSIS calculation data (Table 6) confirm the strategic precedence of electrification (EL). Hydrogen traction (H_2) only approaches it under the simultaneous fulfillment of two critical thresholds: the discounted cost of "green" hydrogen is approximately €2.1/kg and an increase in catenary infrastructure costs more than 30%.

BAT remains economically viable for routes up to 150 km with no more than two battery charging cycles per day; however, in none of the tested parameter combinations does it emerge as the leading option. Option B100 demonstrates the lowest overall ranking due to its higher environmental impact and the high price volatility of its feedstock.

3 Discussion

The aggregated modeling results align with real-world pilot projects in Europe. Full electrification, ranked the highest by TOPSIS, is only partially confirmed by data from the Coradia iLint: despite hydrogen multi-units covering over 200,000 km and reducing emissions by 55 tonnes of CO_2 per unit annually, their capital cost remains ~ 25% higher than diesel multi-units. This supports proposed model, where hydrogen is penalized due to high Levelized Cost of Energy and CAPEX. Similarly, FLIRT Akku battery units operating up to 150 km show cost parity with diesel, validating their second-place ranking, driven by minimal infrastructure needs. Integrated hubs like Green Hub FS Italiane in Verona reduce NO_x emissions by 25% and peak energy demand by 20%, illustrating electrification's bene-fits where catenary investment is feasible or supported by on-site renewables.

Among analytical methods, the LCA + AHP + TOPSIS combination offers the best balance between depth and practical usability. Descriptive-regression tools reveal trends but fail to capture the complexity of strategic decisions. Time series and neural models aid in forecasting but miss environmental impacts. Classical financial tools (TCO, CBA) focus on costs while ignoring carbon footprint. In contrast, the proposed approach synchronizes environmental, economic, technical, and social indicators, allowing transparent ranking and reproducible results – all within (1 to 2) weeks, while fuzzy logic requires more time and complexity.

This study has several limitations. The first, the MTBF for hydrogen multi-units is based on limited data and needs revision post-2025. The second, all price thresholds reflect average European conditions and may differ elsewhere. The third, the social criterion combines public support and job creation; a more de-tailed breakdown may be needed in specific contexts. Finally, emerging technologies like synthetic fuels and inductive charging are excluded and warrant separate research.

Future work includes implementing dynamic TOPSIS, with automatically up-dated weights based on current energy prices, and developing a business intelligence dashboard for integrating rankings with EU funding tools. Preliminary route segmentation using DEA will also be conducted. These steps will enhance regional relevance, responsiveness to market shifts, and more targeted decarbonization strategies.

4 Conclusions

The proposed framework "LCA + AHP + TOPSIS" effectively supports strategic decisions in railway decarbonization by synchronizing environmental, economic, technical, and social indicators in a single decision matrix. This enables reproducible rankings of alternatives within (1–2) weeks. Under baseline assumptions, full electrification option scores are the highest ($S \approx 0.94$) due to minimal Global Warming Potential and the lowest energy cost. Battery traction option is ranked as the second, benefiting from existing infrastructure on routes smaller than 150 km, though lifecycle cycle of capital expenditures (CAPEX) rises due to battery replacements. Hydrogen option is ranked as the second only if two conditions are met: "green" hydrogen cost is lower than €2.1/kg and electrification CAPEX rises more than 30%. Biodiesel option remains the lowest viable due to high emissions and fuel price volatility.

Compared to classical Total Cost of Ownership models or fuzzy Multi-criteria Decision-making methods, proposed approach offers an enhanced balance of analytical depth and responsiveness. Its practical value lies in clear financial benchmarks for the "Fit for 55" pro-gram: support should target reducing "green" hydrogen cost to €2/kg or lowering electrification costs in difficult terrains. The method suits rapid feasibility studies for new railway corridors.

Acknowledgment. Authors express the sincere gratitude to the European Rail Joint Undertaking (EU-Rail JU) for their support and the opportunity to participate in important research aimed at developing Europe's railway infrastructure.

Project PhDs EU-Rail (Grant number: 101175856). Funded by the European Union, Europe's Rail Joint Undertaking. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or Europe's Rail Joint Undertaking. Neither the European Union nor the granting authority can be held responsible for them.

References

1. Samsonkin, V., Yurchenko, O., Sorochynska, O., Rohovyi, O., Bureika, G.: Decarbonizing strategy of ukrainian transport sector. In: Slavinska, O., Danchuk, V., Kunytska, O., Hulchak, O. (eds.) Intelligent Transport Systems: Ecology, Safety, Quality, Comfort. ITSESQC 2024. LNNS, vol. 1335, pp. 109–119. Springer, Cham (2025). https://doi.org/10.1007/978-3-031-87376-8_10
2. European Union Agency for Railways: All aboard! 2024 Rail Environmental Report. ERA, Brussels (2024)
3. Sladkowski, A., Bureika, G., Matijošius, J., Rimkus, A. et al.: Ecology in Transport: Problems and Solutions: Monograph, p. 563. Springer, Cham (2020)
4. Hernandez, A., et al.: Abatement cost curve analysis of freight rail decarbonization alternatives. Transp. Res. Part D **129**, 104341 (2024)
5. Tian, A.-Q., et al.: Multi-objective optimization model for railway heavy-haul traffic. Energy **294**, 130927 (2024)
6. International Energy Agency: CO_2 emissions from rail in the Net Zero Scenario, 2010–2030. IEA (2023)
7. Zhang, Y., Zhang, M.: Enhancing intelligent mobility: LSTM neural networks for short-term passenger flow prediction. In: Proceedings of 11th International Conference on Data Science and Advanced Analytics (ICDSA 2024), pp. 201–208. ScitePress (2024). https://doi.org/10.5220/0012797600003685
8. Marjani, S.R., et al.: Assessing hydrogen as an alternative fuel for rail transport. Sci. Rep. **15**, 6449 (2025)
9. Chamaret, A., et al.: Analysis, trends and expectations for low-carbon railway. Transp. Res. Procedia **72**, 2684–2691 (2023)
10. Kapetanović, M., et al.: Energy use and GHG emissions of traction alternatives for regional railways. Energy Convers. Manag. **303**, 118202 (2024)
11. Trafikverket: Elektrifiering av kvarvarande dieselliinjer – samhällsekonomisk analys [Electrification of remaining diesel traction lines – socio-economic analysis.]. Internal memo, 15 Dec 2022. Available via Altinget.se (accessed 2023/06/24). https://www.trafikverket.se [in Swedish]

12. Ahsan, N., et al.: A critical review of sustainable rail technologies. Renew. Sustain. Energy Rev. **185**, 113621 (2023)
13. Sladkowski, A., et al.: Modern Trends and Research in Intermodal Transportation: Monograph, p. 559. Springer, Cham (2022)