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PAPER

A multi-criteria assessment of decarbonization pathways for heavy-duty trucks

Aybike Esra Şahin* and **Şeyma Özekinci**

Faculty of Economics, Administrative and Social Sciences, Logistics Management (English) Department, Istanbul Gelisim University, Avcılar, Istanbul 34310, Türkiye

* Author to whom any correspondence should be addressed.

E-mail: aesahin@gelisim.edu.tr and sozekinci@gelisim.edu.tr

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Abstract

Despite growing interest in alternative heavy-duty truck (HDT) powertrains, limited research has evaluated their techno-economic competitiveness across major freight markets while explicitly considering logistics and transportation cost structures. This study examines whether diesel, BEVs (battery electric vehicles), and FCEVs (fuel cell electric vehicles) are market-competitive for freight trucks in the US, EU, and China by assessing the competitiveness of these powertrains, taking into account logistics and transport costs such as vehicle purchase price, maintenance and insurance costs, payload, infrastructure investment and operation costs and policy-related cost exemptions to ease the relative competitiveness assessment of alternative HDT powertrains, a three-stage multi criteria decision making method approach is proposed in the first stage of the framework, the key techno-economic evaluation criteria are identified and their relative weights are computed using the criterion impact loss method second, the diesel, BEV and FCEV alternatives are ranked by applying the weighted criteria using two ranking techniques: namely, the measurement of alternatives and ranking according to compromise solution and the combined compromise solution approaches finally, a robustness analysis is performed using the evaluation based on distance from average solution approach The results indicate that diesel trucks are the most cost-competitive in the United States and the EU, due to lower cost volatility and established logistics infrastructure BEVs are also cost-competitive in certain regional and methodological settings, particularly in the EU In China, the relative competitiveness of powertrain technologies varies across methods, with no single technology consistently dominating. FCEVs generally rank as the least competitive option across regions. Infrastructure readiness, energy pricing, regulatory incentives, and logistics cost structures strongly influence HDT powertrain competitiveness. Incorporating logistics cost considerations into techno-economic assessments provides more realistic insights for policymakers and industry stakeholders when designing freight transport decarbonization strategies and investment priorities.

1. Introduction

The heavy-duty transportation sector constitutes a major leverage point for reducing logistics-related emissions. Road freight transport exhibits a disproportionate contribution to global emissions, accounting for nearly 40% of life-cycle road transport GHG emissions despite representing less than 10% of the vehicle stock (Aryanpur and Rogan 2024). Recent evidence from California indicates that nearly 8% of statewide greenhouse gas emissions stem from heavy-duty vehicles (HDVs), underscoring the strategic importance of this segment for decarbonizing freight transport systems (Hennessy *et al* 2024). Electrifying passenger automobiles progresses rapidly, yet decarbonizing heavy-duty road transport, especially long-haul trucking, is a difficult area of the global energy transition. Heavy-duty diesel internal-combustion engine vehicles (ICEVs) dominate long-haul trucking, generating a disproportionate amount

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of transport GHG emissions and local air pollution. While zero-emission vehicle sales mandates are a central policy instrument, they are insufficient on their own to decarbonize HDV fleets within policy-relevant time horizons. Hennessy *et al* (2024) demonstrate that even a full transition to ZEV sales by 2025 fails to deliver fleetwide zero emissions by 2045, highlighting the constraining role of slow fleet turnover. An important part of the global freight transportation fleet will need to be converted to non-customary powertrains that comply with climate goals. Whether battery-electric vehicles and fuel-cell electric vehicles can be techno-economically viable will vary according to energy prices, infrastructure readiness, industry policies, and different regions' characteristics.

While battery electric vehicle (BEV)s benefit from superior energy efficiency, fuel cell vehicles offer operational advantages such as extended range and refueling times comparable to conventional trucks, making the technology choice context-dependent (Aryanpur and Rogan 2024). Technology maturity and cost disparities between the United States, the European Union, China, and other countries are described in international publications. International papers also detail variations in the cost of power, the supply chains for hydrogen, and the availability of infrastructure for charging and refueling. The International Energy Agency's (IEA) Global EV (electrical vehicle) Outlook 2025 serves as one illustration. These asymmetries affect the total cost of freight transport, as well as diesel, BEV and fuel cell electric vehicle (FCEV) truck competitiveness in economies that differ from each other in both the sources and quantities of freight. BEVs offer increased energy efficiency and lower costs, whilst FCEVs have much longer ranges and much shorter refueling times, but only through greatly higher capital and infrastructure costs. Diesel is well established and low cost to operate in the short term but is coming under increasing regulatory pressure (Bai *et al* 2024, Liang *et al* 2024, Mansour *et al* 2025). Recent evidence also indicates that battery-electric heavy-duty trucks (HDTs) still face higher private costs in long-haul applications despite their substantial environmental and societal benefits (Porzio *et al* 2026).

In consequence, an integrated assessment framework is needed to consider different economic, operational, technical, and regulatory aspects that influence the selection of the best-suited powertrain variant. Traditional cost-comparison methods often fail to capture multidimensional trade-offs or regional variations. Moreover, heavy-duty freight decisions involve conflicting objectives; minimizing capital and operating costs, maximizing payload capacity, and ensuring compatibility with existing infrastructure. Multi-criteria decision-making (MCDM) methods provide a systematic and transparent way to evaluate such trade-offs and are increasingly used in sustainable transport and energy policy research. These findings align with previous studies indicating that no single powertrain dominates across all scenarios and that competitiveness depends on operational conditions such as range, vehicle class, energy prices, and infrastructure availability (Liang *et al* 2024, Mu *et al* 2024 Syré *et al* 2025). These studies, while growing in number, have two main weaknesses in terms of generalizability arising from their limited geographical scope: they have focused heavily on specific countries or regions. Most techno-economic analyses are limited to national or regional boundaries, making it difficult to compare the findings on a global scale. (Bai *et al* 2024, Liang *et al* 2024, Magnino *et al* 2024, Mu *et al* 2024, Mansour *et al* 2025, Syré *et al* 2025). Second, when comparing powertrains, many studies create a single MCDM model leading to results sensitive to these assumptions. A small number of studies compare vehicle powertrains in major global freight markets using different MCDM methods and robustness analysis. Previous studies do not consider the effects of local policies such as mass exemptions for zero-emission trucks, affecting effective payload and competition. They also focus on freight decarburization in single sectors, and often do not consider systems interactions between vehicle technologies, energy system, energy carrier supply, and the availability of supporting infrastructure (Aryanpur and Rogan 2024).

To address this research gap, this paper investigates the techno-economic competitiveness of alternative HDT powertrains regarding the structure of logistics costs in the leading freight markets. The techno-economic competitiveness of diesel, BEV, and FCEV is tested in the US, EU, and China to evaluate the most cost-effective powertrains for freight transportation across the three regions.

A relative comparative MCDM framework is proposed for this purpose. Criterion impact loss (CILOS) is applied to determine the relative weights of the evaluation criteria, while the alternatives are evaluated and ranked according to the measurement of alternatives and ranking according to compromise solution (MARCOS) and combined compromise solution (COCOSO) methods. The robustness of these results is verified through a sensitivity analysis using the distance from average solution (EDAS) method.

By comparing the three largest freight markets, this research contributes to the sustainable freight literature and informs policymakers of which technologies should be prioritized to decarbonize HDT.

2. Literature review

2.1. Decarbonization pathways in heavy-duty freight transport

The HDTs sector contributes 50% of the road transport energy consumption and GHG emissions in China although it only makes up ∼10% of the total on-road vehicle stock (Xue *et al* 2023), owing to the longer distances, heavier loads and higher energy consumption intensity. Given the role of HDTs in the logistics sector, there has been growing interest in decarbonization research. The study by Hennessy *et al* (2024) employs detailed fleet turnover and air quality models to analyze the evolution of California's HDV fleet. The findings indicate that, although zero-emission vehicle sales mandates are effective, they are unlikely to be sufficient on their own to achieve fleetwide zero emissions by 2045. Achieving carbon neutrality requires a combined policy approach, including both ZEV sales mandates and accelerated vehicle retirement strategies. According to Sun *et al* (2024), the TCO (total cost of ownership) assessment considers the cost of vehicle purchase, operation, maintenance, disposal, energy use, infrastructure, and the environment. The analysis is based on fleet data, expert interviews, and publicly available datasets, and includes both sensitivity and scenario analysis of the main parameters and investments, enabling an informed assessment of the economic feasibility of zero- or near-zero-emission heavy-duty freight vehicles. These results indicate that battery, fuel cell, and hydrogen-based technologies should achieve cost parity with diesel between 2030–2040 with this opening the door to heavy-duty freight sector decarbonization. Briand *et al* (2026) apply deep decarbonization pathways for development of decarbonization strategies for national freight transport in Brazil, India, and South Africa, based on storyline development, quantified pathways, and iterative backcasting. The resulting strategies show that 60% to 100% cuts to GHG emissions per ton-kilometer (tkm) by 2050 can help energy efficiency and national carbon neutrality goals. According to Syré and Göhlich (2025) for battery electric trucks on an electric road network in Germany from 2023 until 2050, LCA (life cycle assessment) and TCO (total cost of ownership) analysis concluded the lowest life cycle GHG emissions of 21 Mt CO_2e and the lowest TCO of 45 billion euros and the lowest life cycle GHG emissions and TCO in comparison with diesel trucks (54%–62% lower). Trucks powered by on-site hydrogen fuel cells have the most GHG emissions (65 Mt CO_2e) and the highest TCO (EUR 69 billion) compared to other trucks, with operational costs dominating total costs. Infrastructure capacity should be matched to vehicle-to-infrastructure ratios, transport performance and range. While prior life cycle assessment studies provide valuable insights at the vehicle level, they often fail to capture fleet-scale dynamics, particularly vehicle turnover rates, which critically determine the effectiveness of decarbonization strategies in the heavy-duty transport sector (Xue *et al* 2023).

Prussi *et al* (2022) use a Well To Wheels approach, and a LCA, to study the use of electricity and e-fuels in heavy duty freight decarbonization, and conclude that direct use of very low-carbon-intensity electricity in trucks can reduce greenhouse gas emissions by up to 98% compared to fossil fuel trucks. The emissions are calculated for the full fuel lifecycle assuming a reference truck. For the carbon intensity, an internal Excel tool was used following the International Organization for Standardization and JEC (JRC–EUCAR–CONCAWE) v5 methodology. It further shows that both electrification and e-fuels can lead to meaningful decarbonization in trucks. Hoehne *et al* (2023) used the Transportation Energy & Mobility Pathway Options model to project decarbonization of U.S. passenger and freight transport. These pathways specifically assume rapid adoption of BEVs and FCEVs and a decarbonized electric supply. Thirty-four pathways with 51 inputs are modeled, including 222 technology cost, consumer behavior, and policy drivers, and sensitivity analysis with both univariate and multivariate scenarios. A 69% ZEV truck market share by 2030 and 100% by 2040 would reduce GHG emissions by up to 89% by 2050. Electricity demand could reach up to 3000 TWh by 2050. Sustainable biofuels and travel demand management could complement ZEV strategies, accelerate decarbonizing HDT traffic even further.

The HDT sector is both energy-intensive and cost-intensive, making near-term greenhouse gas abatement particularly challenging, as alternative powertrain solutions must offer comparable range, payload, durability, and refueling convenience to conventional diesel trucks (Xue *et al* 2023). Khanna *et al* (2021) use the China 2050 Demand Resource Energy Analysis Model, a bottom-up energy end-use model, to estimate that early deployment of BEVs and FCEVs, together with power sector decarbonization, could reduce diesel demand and CO_2 emissions in China by 94% and 235 Mt by 2050. Near-term strategies such as efficiency improvements and LNG use could achieve a 50% reduction. Historical calibration, scenario analysis, and a sensitivity analysis show reductions across all scenarios considered, reference, short-term, NEV early adoption (EAP), and NEV late adoption (LAP). Fleet turnover and NEV deployment early on are key to maximizing the benefits in the short-term and longer-term.

2.2. Comparative studies on diesel, battery electric, and fuel cell trucks

Several studies have analyzed the techno-economic performance of diesel, battery electric and hydrogen fuel cell heavy trucks in the major markets with cost-based analysis tools such as TCO, levelized cost of transportation, levelized cost of driving, and in some cases life cycle assessment. (Gunawan and Monaghan 2022, Burke *et al* 2023, Bai *et al* 2024, Liang *et al* 2024, Magnino *et al* 2024, Mu *et al* 2024, Mansour *et al* 2025, Syré and Göhlich 2025, Xue *et al* 2025, Maggini *et al* 2026) Techno-economic assessments of alternative truck technologies in the fragmented freight markets of the US, China, Germany, and Finland suggest that operational parameters such as truck weight class, driving range, energy prices, and refueling/recharging infrastructure availability determine the competitiveness of alternative truck technologies (Liang *et al* 2024, Mansour *et al* 2025, Syré and Göhlich 2025).

The literature also highlights range-dependent technology advantages. Battery electric trucks are more cost-competitive for freight transport over short distances (400–700 km d^{-1}), while hydrogen fuel cell trucks are typically more cost-competitive for longer distances (750–1100 km d^{-1}) (Bai *et al* 2024, Liang *et al* 2024, Magnino *et al* 2024). In addition, payload is another limitation, particularly for battery-electric trucks, where the battery weight reduces the available payload. However, hydrogen power may relieve weight penalties in some long-haul trucking applications. (Mu *et al* 2024, Syré and Göhlich 2025). Most studies concluded that there is no one-best technology for all freight applications. The optimal freight truck powertrain technology is likely to be context sensitive, depending on the interaction of the trucking application, the infrastructure and logistics environment and potential future energy prices (Burke *et al* 2023, Mansour *et al* 2025).

Goulet *et al* (2025) conducted an analysis of the TCO and carbon emissions of heavy-duty battery electric, fuel cell and diesel trucks at the regional (zip code) level in the US. The Regional Readiness Framework identifies regions that are more likely to adopt alternative powertrains, and those that require more investment to ease adoption. The research indicates that BEVs already have lower carbon life cycle emissions than FCEVs and a diesel truck, so infrastructure remains key to unlocking the potential of low carbon heavy-duty transport solutions.

Xue *et al* (2025) published a life cycle economic and environmental assessment of BEV, fuel cell electric truck (FCET) and hydrogen combustion engine truck powertrains in China in 2025. They used an integrated vehicle dynamic simulation and life cycle assessment model to compare energy use, GHG emissions, and total cost of ownership differences for various driving ranges and duty cycles. These include BEVs for regional freight, fuel cell trucks for long-distance travel, or hydrogen-combustion engines for high-demand applications, providing options for low-carbon freight transport by 2035.

A study by Cunanan *et al* (2021) compared the advantages and disadvantages among the different powertrain options for HDTs: diesel trucks, battery electric trucks, and hydrogen FCETs. Several characteristics such as tailpipe emissions, fuel consumption, range, refueling time, and energy-efficiency were compared. The study finds that diesel trucks are currently cost-competitive due to existing diesel refueling infrastructure, but zero-emission technologies are much lower-emitting and more sustainable in the long run. Battery electric trucks have the best tank-to-wheel energy efficiency and both fuel cell and BEVs can be cost-competitive with diesel trucks if battery and fuel cell cost targets are met (around US$100/kWh).

Zhang *et al* (2022) performed a techno-economic analysis of electric truck scenarios in China's trucking sector through 2040, comprising diesel, battery electric, plug-in hybrid (PHEV), hydrogen fuel cell and battery electric catenary trucks. It analyzed a full-cost and life-cycle emissions framework for CO_2, NO_x, and $PM_{2.5}$ that captures vehicle purchase prices, operating costs, infrastructure costs, and externalities. The authors found that slow charging PHEVs have the lowest TCO and CO2 emissions whereas hydrogen FCEVs have the lowest NO_x and particulate emissions. The authors conclude that if cost is the main constraint, PHEVs are the best option in the short term, whilst BEVs and hydrogen FCEVs are better options for long term emission reductions.

In their global comparison of sustainable vehicles for freight transport, Jaller and Otay (2021) applied a hybrid Stochastic Fuzzy Analytic Hierarchy Process–technique for order preference by similarity to ideal solution (TOPSIS) approach to evaluate Compressed Natural Gas (CNG), renewable natural gas, hybrid electric, battery electric, and hydrogen freight vehicles. In the multi-criteria comparison of freight vehicles, five main criteria were considered: financial, business and market, environmental and legal, maintenance and repair availability, and safety and performance of the vehicle. In addition, 21 sub-criteria were analyzed. The results showed that BEVs or fuel-cell vehicles were the most sustainable option in the long-term. Both hybrid and CNG vehicles were deemed more feasible in the short-term due to infrastructure and cost factors. Haase *et al* (2022) performed a potential sustainability assessment of alternative vehicle technologies and fuels with a life cycle-based MCDA framework using the TOPSIS method. This assessment used 13 indicators in the environmental dimension. The most economically

and socially sustainable option for 2020 and 2050 is the use of BEVs powered by wind, but FCEVs also improve substantially by 2050.

Pamučar *et al* (2021) proposed a new MCDM model, based on the full consistency method, and the neutrosophic fuzzy MARCOS method, for the selection of the most appropriate alternative fuel vehicles in New Jersey, USA. After analyzing the data according to the proposed method, purchase price, energy price, and social benefits have been found to be the three most important criteria.

The reviewed literature is largely concentrated in major freight markets, particularly in countries such as China, the United States, and selected European economies (Bai *et al* 2024, Liang *et al* 2024, Magnino *et al* 2024, Mu *et al* 2024, Mansour *et al* 2025, Syré *et al*, 2025, Xue *et al* 2025). However, most existing studies analyze these markets separately, and limited research provides a comparative techno-economic evaluation of HDT technologies across the three major freight markets within a single analytical framework. Furthermore, most of the previous research has focused on a single economic or operational indicator like TCO or levelized transportation cost and there is a lack of research on multiple economic and operational indicators. Important operational factors, including payload capacity, infrastructure availability, and energy cost conditions, are often examined individually rather than within an integrated decision framework. Consequently, the application of MCDM approaches to systematically compare diesel, battery electric, and hydrogen fuel cell truck technologies across different freight market contexts remains limited.

3. Materials and methods

Despite providing detailed cost-based assessments of the road transport transition, existing models remain limited by static energy price assumptions, weak links between total cost of ownership and technology adoption, and insufficient integration of environmental impacts with system-level cost evaluations. In addition, most studies focus primarily on battery-electric vehicles while overlooking alternative powertrains such as hydrogen-based systems. These limitations highlight the need for more comprehensive decision-support frameworks for heavy-duty transport decarbonization (Parviziomran and Bergqvist 2023).

To address this gap, the study proposes a multi-stage decision-analytic model to compare HDT technologies applicable in the United States, European Union and China considering the drastic techno-economic and infrastructural differences of the three regions.

Three different MCDM methods are employed for the assessment purpose. MCDM methods are widely used to solve decision-making problems that involve multiple conflicting criteria. Multi-attribute decision-making methods are a subset of MCDM that can be used to solve a decision-making problem having multiple attributes on a finite set of alternatives (Triantaphyllou *et al* 1998). In such problems, alternatives are compared, prioritized, and ranked based on their performance across these criteria, making MCDM approaches particularly suitable for complex techno-economic evaluations. In this study, the alternatives correspond to diesel, battery-electric, and fuel-cell truck technologies, while the attributes represent techno-economic and operational evaluation criteria.

First, the CILOS method determines objective weights for the evaluation criteria based on cross-criterion influence and relative performance loss. Then, the MARCOS and COCOSO methods are applied to the ranking of the diesel, battery electric, and fuel cell powertrains. Finally, the robustness of the results of the ranking is tested using the Evaluation based on EDAS method, which compares the alternatives to the regional average solution.

Figure 1 presents the integrated methodological workflow, illustrating how evaluation criteria and powertrain alternatives are defined using literature and IEA data, weighted through CILOS, ranked using MARCOS and COCOSO, and validated using EDAS to obtain a comparative assessment across major freight markets. The computation for the criteria weighting and ranking of alternatives was performed within the Microsoft Excel.

3.1. Criteria development and data foundations

This analysis uses the Global EV Outlook 2025 report provided by the IEA (2025) for techno-economic characteristics of ICEV, BEV and FCEV trucks that are comparable. 2024 baseline data were extracted from the Global EV Outlook 2025 for the three largest vehicle markets: US, EU and China, which are characterized by different cost structures (capital, energy price) and different states of infrastructure maturity.

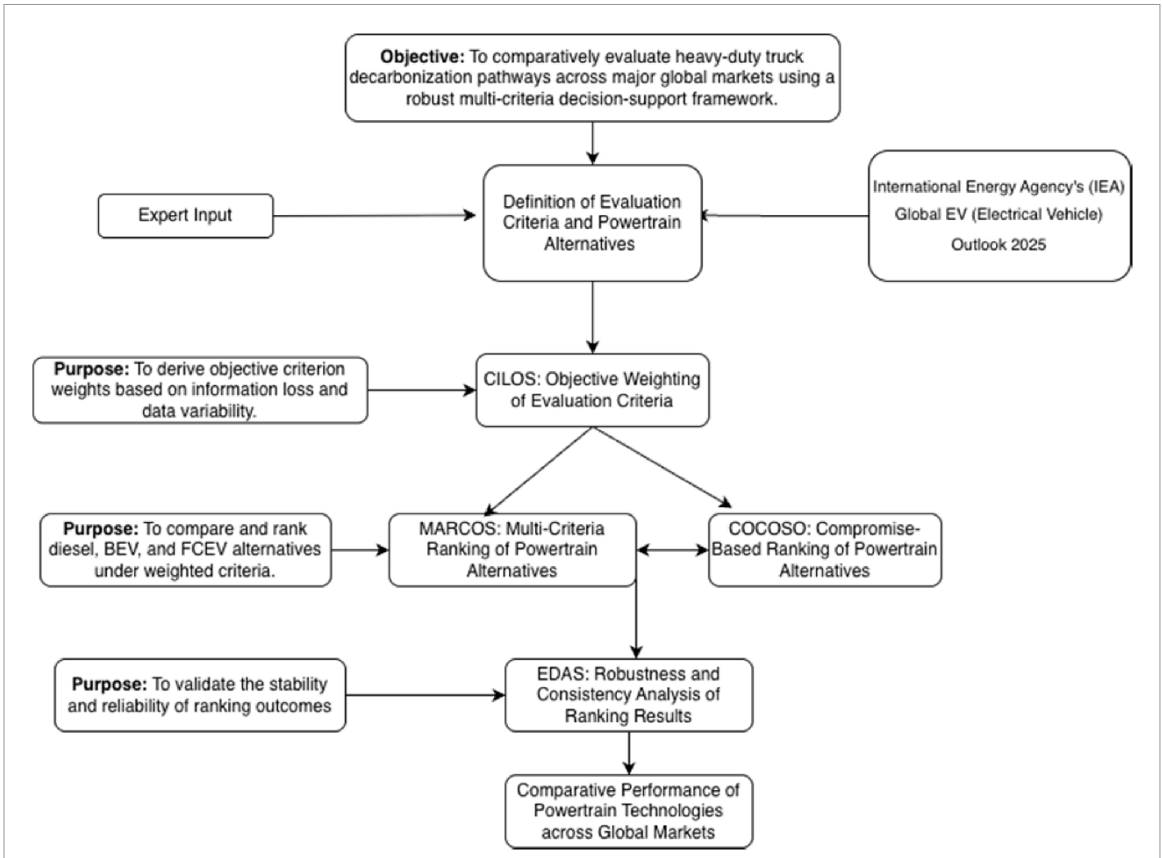


Figure 1. Overall methodological framework for the comparative evaluation of heavy-duty truck decarbonization pathways.

Furthermore, the selection of evaluation criteria was refined through expert consultation with academic researchers, ensuring that the criteria set is both data-driven and aligned with the study's analytical objectives.

In this study, HDTs refer to long-haul tractor–trailer combinations equivalent to U.S. Class 8 vehicles, typically used for long-distance freight transport with gross vehicle weights exceeding 33 tons. These vehicles represent the dominant segment in intercity freight logistics and are therefore used as the reference configuration for comparing diesel, BEV, and FCEV powertrains (IEA 2025).

Following data screening and harmonization, seven criteria were chosen for the multi-criteria analysis:

- C_1 Vehicle purchase cost (USD): Vehicle purchase prices (USD unit^{-1}) correspond to manufacturer-suggested retail prices reported for 2024. These represent upfront capital investment and therefore enter the model as cost-type criteria.
- C_2 Cost of maintenance (USD/km): Maintenance expenditures were taken directly from the IEA dataset as average 2024 values in USD km^{-1}. They include routine servicing, component wear, and powertrain-specific maintenance differences (e.g. reduced mechanical wear in BEVs).
- C_3 Insurance cost (USD): Insurance premiums were expressed as a fixed percentage of vehicle capital value (3% for diesel, 3.6% for BEV, and 4.5% for FCEV). These percentages reflect the perceived level of technical and operational risk for the new zero-emission truck technologies, which were multiplied by the purchase price to give their annualized insurance cost and used to compare the options (IEA 2025). Although insurance cost is calculated as a percentage of vehicle capital value, it represents a distinct operational cost component reflecting risk exposure, technology maturity, and insurance market conditions; therefore, it is treated as an independent criterion rather than merged with purchase cost in the MCDM analysis.
- C_4 Energy cost per km (USD/km): The operational energy cost per kilometer was derived as $C_{\text{energy}} = p_{\text{energy}} \times E_{\text{vehicle}}$, yielding, for example, 0.256 USD km^{-1} for BEV and 0.312 USD km^{-1} for FCEV in the United States.

- C_5 Payload capacity (t): Payload capacity reflects the effective freight mass each truck can carry. IEA heavy-duty specifications were used as the baseline. Minor differences between diesel, BEV, and FCEV arise from battery and hydrogen tank mass. Payload is treated as a benefit-type criterion.
- C_6 Exemptions (t): Regulatory mass allowances for zero-emission trucks were included as an additional benefit criterion. The EU grants 2 t exemption; the US and China grant 0.9 t and 0 t respectively. Incorporating these ensures the evaluation reflects effective freight capacity under regional legislation.
- C_7 Infrastructure cost/CAPEX (Capital expenditure and includes installation cost) & OPEX (Operating expenditure) (USD/km): Infrastructure costs capture the annualized investment and operation of refueling or recharging assets required for each powertrain. The derivation of this criterion—including the application of capital-recovery factors, utilization rates, land inclusion, and regional adjustments—is presented in detail in the following subsections.

Infrastructure costs were converted to a common per-kilometer metric (USD/km) by levelizing capital and operating expenditures over the system lifetime using a capital recovery factor and dividing the resulting annualized cost by annual vehicle-kilometers travelled (VKT). All values are presented in constant 2024 USD. The levelised infrastructure cost per kilometer, C_{infra}, is expressed as:

$$C_{\text{infra}} = \frac{(\text{CAPEX} \times \text{CRF}(i,n))\,\text{OPEX}_{\text{fix}} + \text{OPEX}_{\text{var}}}{\text{VKT}}$$

where CAPEX denotes the upfront investment cost (USD), OPEX_{fix} the annual fixed operating cost (USD yr^{-1}), OPEX_{var} the annual variable operating cost (USD yr^{-1}), i the discount rate, n the infrastructure lifetime, CRF the capital recovery factor, and VKT the annual VKT. All modeling assumptions and parameter values used in the infrastructure cost calculations are summarized in table 1.

In the initial phase of indicator selection, several parameters commonly used in comparative powertrain assessments were deliberately excluded from the final MCDM model due to their lack of discriminative power across alternatives. Labor cost, although differing between regions, remains identical across diesel, BEV, and FCEV trucks within each country, meaning it does not contribute to the differentiation of technological alternatives and therefore offers no utility within a weighting-based decision environment. Unladen vehicle weight has been omitted as the differences are small for heavy-duty long-haul powertrains and this factor is, in any case, implicitly considered via the energy per kilometer measure. More generally, unladen vehicle weight would not add any value to decision making over and above what is provided via energy per kilometer. Annual depreciation schedules, cost of financing and breakdown of maintenance labor were omitted as they were homogeneous for all technologies or were already represented by more general indicators (e.g. capital cost, maintenance cost). The remaining parameters were well distributed across the powertrain technologies and ensured a clear differentiation among them in the proposed MARCOS-COCOSO-EDAS framework, ensuring methodological robustness and the avoidance of indicator redundancy or dilution.

These are the economic and operational parameters for all three technologies that are assumed in this report, expressed in 2024 USD using the implicit deflator given in the IEA energy technology data set. The energy costs and energy efficiency values were adopted unchanged from the technical annexes, while maintenance costs were taken over as reported.

Several parameters from the IEA report, such as driver's wages, labor cost, and unladen weight, were excluded from the analysis for the following reasons:

(1) they do not vary across technologies within each region,

(2) they do not influence the comparative ranking of alternatives, and

(3) their inclusion would unduly favor cost-oriented criteria in the weighting of factors.

This approach minimizes bias and ensures that the relevant technology-sensitive discriminatory factors are included in the MCDM stage. The resulting standardized dataset provides a coherent quantitative foundation for cross-regional CILOS weighting and MARCOS–COCOSO–EDAS performance evaluation.

3.2. Application steps of CILOS method

The recently introduced CILOS method is employed to determine the comparative impact loss experienced by other evaluation criteria when a particular criterion is regarded as the most significant. This

Table 1. Key assumptions and input parameters for infrastructure cost modeling across powertrain technologies.

Category	Parameter	Value	Unit	Source
General	Discount rate (i)	8	%	IEA (2025)
General	Annual vehicle kilometers travelled (VKT)	168 000	km yr^{-1}	IEA (2025)
General	Daily driving distance	500	Km d^{-1}	IEA (2025)
General	Operating days	7	d $week^{-1}$	IEA (2025)
General	Operating weeks	48	weeks yr^{-1}	IEA (2025)
BEV—depot charger	Charger power	50	kW	IEA (2025)
BEV—depot charger	Chargers per vehicle	1	Unit/vehicle	IEA (2025)
BEV—depot charger	Infrastructure lifetime	15	Years	IEA (2025)
BEV—depot charger	CAPEX (US/EU/China)	23 000/22 000/19 000	USD	IEA (2025)
BEV—depot charger	Fixed OPEX share	5	% of CAPEX	IEA (2025)
BEV—fast charger	Charger power	350	kW	IEA (2025)
BEV—fast charger	Utilization factor (UF)	5	%	IEA (2025)
BEV—fast charger	Fast charging energy share (s_{350})	37.5	%	IEA (2025)
BEV—fast charger	Energy consumption	1.6	kWh/km	IEA (2025)
BEV—fast charger	Infrastructure lifetime	10	years	IEA (2025)
BEV—fast charger	Station CAPEX (US/EU/China)	289 500/246 500/185 500	USD	IEA (2025)
BEV—fast charger	Fixed OPEX share	5	% of CAPEX	IEA (2025)
BEV—fast charger	Land requirement	74	m^2	IEA (2025)
BEV—fast charger	Land value (US & EU/China)	1,642/242	USD/m^2	IEA (2025); adapted from; CEIC (2025)
BEV—fast charger	Land preparation markup	23	%	IEA (2025); adapted from Argonne (2023)
FCEV—hydrogen station	Station pressure	700	Bar	IEA (2025); adapted from European Commission (2021)
FCEV—hydrogen station	Station capacity	2500	Kg d^{-1}	IEA (2025); adapted from European Commission (2021)
FCEV—hydrogen station	Utilization factor	35	%	IEA (2025)
FCEV—Hydrogen station	Infrastructure lifetime	10	years	IEA (2025)
FCEV—hydrogen station	CAPEX (US & EU/China)	8.84/2.66	million USD	IEA (2025); adapted from European Commission (2021)
FCEV—hydrogen station	Fixed OPEX share	4	% of CAPEX	IEA (2025); adapted from European Commission (2021)
FCEV—hydrogen station	Variable electricity demand	1.4	kWh kg^{-1} H_2	IEA (2025); adapted from European Commission (2021)
FCEV—hydrogen station	Electricity price (US/EU/China)	0.16/0.24/0.08	USD/kWh	IEA (2025)
FCEV—hydrogen station	Hydrogen consumption	0.077	Kg km^{-1}	IEA (2025)
Diesel	Infrastructure share of fuel price	2	%	IEA (2025)

Note: UF = utilisation factor; s_{350} = share of total energy demand supplied by en-route fast charging; CAPEX includes installation and land preparation costs; all monetary values are expressed in constant 2024 USD.

method focuses on the loss of effectiveness among criteria, and its procedural steps are outlined as follows (Zavadskas and Podvezko 2016):

Step 1: construction of the initial decision matrix

The decision matrix is constructed in accordance with Equation (1),

$$A = \left[a_{ij}\right]_{m*n} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}, i = 1,2,\ldots,mj = 1,2,\ldots,n. \quad (1)$$

Step 2: conversion of cost-oriented criteria into benefit-oriented criteria

Since all criteria are required to be benefit-oriented in this method, any cost-oriented criteria must be converted into benefit-oriented ones using equation (2) (Podvezko *et al* 2020),

$$a_{ij} = \frac{\min_i a_{ij}}{a_{ij}}. \tag{2}$$

Step 3: normalization calculation

If any cost-oriented criteria existed in the initial decision matrix, they were previously converted into benefit-oriented criteria using equation (2). Each element of the resulting decision matrix is then normalized using equation (3), thus producing the normalized decision matrix,

$$x_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}}. \tag{3}$$

Step 4: construction of the s criterion square matrix

The maximum value of each criterion in the normalized decision matrix is determined using equation (4). For each criterion, the alternative corresponding to this maximum value is identified, and the rows of these alternatives are then used to construct the S square matrix,

$$s_j = \max_i x_{ij}, j \in \{1, 2, \ldots, n\} \quad . \tag{4}$$

Let k_j denote the index of the alternative that yields the maximum value for criterion j, defined as:

$$k_j = \arg\max_i x_{ij}.$$

The elements of the S matrix are then constructed as follows:

$$s_{ij} = x_{k_j j}, i, j \in \{1, 2, \ldots, n\}.$$

Thus, the S matrix is expressed as:

$S = [s_{ij}]_{n \times n}$

Step 5: construction of the relative P loss matrix

Using the data obtained in the fourth step of the method, each element of the relative loss matrix is calculated using equation (5), resulting in the formation of the P matrix. Here, p_{ij} represents the relative impact loss of the jth criterion,

$$p_{ij} = \frac{s_{jj} - s_{ij}}{s_{jj}}, p_{ii} = 0,\ i, j \in \{1, 2, \ldots, n\}. \tag{5}$$

Step 6: Construction of the F Matrix

The F matrix is constructed by applying the format of equation (6) to the elements of the relative P loss matrix,

$$F = \begin{bmatrix} -\sum_{j=1}^{n} p_{1j} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & -\sum_{j=1}^{n} p_{nj} \end{bmatrix}. \tag{6}$$

Step 7: solving the linear equation system

In the final step of the method, the linear equation presented in equation (7) is solved to obtain the W weight vector, which contains the normalized weight elements (w_1, w_2, …, w_n) corresponding to the criteria,

$$F.W^{\mathrm{T}} = 0. \tag{7}$$

3.3. Application steps of MARCOS

The MARCOS method is a MCDM approach that evaluates and ranks alternatives based on their performance across multiple criteria. The procedure is implemented through the following steps (Stević *et al* 2020):

Step 1: Multi-criteria models involve the definition of a set consisting of n criteria and m alternatives. The initial decision-making matrix is established based on the evaluations of the alternatives by experts according to the defined criteria.

Step 2: Expanding the input matrix with an ideal solution (AI) and its opposite (AAI).

$$E = \begin{matrix} \text{AAI} \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ \text{AI} \end{matrix} \begin{bmatrix} x_{aa1} & \cdots & x_{aan} \\ x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots \\ x_{m1} & \cdots & x_{mn} \\ x_{ai1} & \cdots & x_{ain} \end{bmatrix}. \tag{8}$$

For the beneficial criteria:

$$\begin{cases} \text{AAI} = \min\limits_{i} x_{ij} \\ \text{AI} = \max\limits_{i} x_{ij} \end{cases} .; \forall j = 1, 2, \ldots, n. \tag{9}$$

For the non-beneficial criteria:

$$\begin{cases} \text{AAI} = \max\limits_{i} x_{ij} \\ \text{AI} = \min\limits_{i} x_{ij} \end{cases} .; \forall j = 1, 2, \ldots, n \tag{10}$$

Step 3: The expanded matrix E is then normalized based on the formulas (11) and (12).

$$d_{ij} = \frac{x_{ij}}{x_{ai}}; \text{with beneficial criteria} \tag{11}$$

$$d_{ij} = \frac{x_{ai}}{x_{ij}}; \text{with non-beneficial criteria.} \tag{12}$$

Step 4: The weighted normalization matrix is calculated based on the weight distribution and the normalized matrix as follows:

$$W_{m\times n} = \left[w_{ij}\right]_{m\times n} = \left[d_{ij}\varpi_j\right]_{m\times n} \tag{13}$$

where ϖ_j is the weight of the jth criteria.

Step 5: Calculating the relation parameters S_i, S_{aai}, and S_{ai} by using the equation (14):

$$\begin{cases} S_i = \sum\limits_{i=1}^{n} v_{ij} \\ S_{\text{aai}} = \sum\limits_{i=1}^{n} x_{\text{aai}} \\ S_{\text{ai}} = \sum\limits_{i=1}^{n} x_{\text{ai}} \end{cases} . \tag{14}$$

Step 6: Calculating the parameters k_i^- and k_i^+ by utilizing the given formula below:

$$\begin{cases} k_i^- = S_i / S_{\text{aai}} \\ k_i^+ = S_i / S_{\text{ai}} \end{cases} . \tag{15}$$

Step 7: Calculating the utility function of alternatives $f(k_i)$ as:

$$f(k_i) = \left(k_i^+ + k_i^-\right) \times \left[1 + \frac{1 - f\left(k_i^+\right)}{f\left(k_i^+\right)} + \frac{1 - f\left(k_i^-\right)}{f\left(k_i^-\right)}\right]^{-1}. \tag{16}$$

Step 8: Ranking the alternatives based on the values $f(k_i)$. The alternative with the highest $f(k_i)$ is chosen as the best.

3.4. Application steps of CoCoSo

The CoCoSo method is a MCDM technique that combines the weighted sum and weighted product models to evaluate and rank alternatives under multiple criteria. The procedure is implemented through the following steps.

Step 1: The initial decision-making matrix is determined as shown below: (Yazdani *et al* 2018)

$$x_{ij} = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mn} \end{bmatrix}, i = 1,2,\dots,m\, j = 1,2,\dots,n. \tag{17}$$

Step 2: Conducting the data normalization based on the equations below:

$$d_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}; \text{with beneficial criteria} \tag{18}$$

$$d_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}; \text{with beneficial criteria.} \tag{19}$$

Step 3: Calculating the P_i and S_i values by the equations as follows:

$$P_i = \sum_{j=1}^{n} \left(d_{ij}\right)^{\varpi_j} \tag{20}$$

$$S_i = \sum_{j=1}^{n} \left(\varpi_j d_{ij}\right) \tag{21}$$

where ϖ_j is the weight of the jth criteria.

Step 4: Computing three appraisal score (AS) strategies to identify the relative weights of the remaining alternatives as:

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{22}$$

$$k_{ib} = \frac{P_i}{\min\limits_i P_i} + \frac{S_i}{\min\limits_i S_i}. \tag{23}$$

$$k_{ic} = \frac{(1-\tau) \times P_i + S_i}{(1-\tau) \times \max\limits_i P_{I_{+\tau*}} \max\limits_i S_I}; 0 \leqslant \tau \leqslant 1 \tag{24}$$

Step 5: The general parameter k_i is then computed by using the formula:

$$k_i = \frac{k_{ia} + k_{ib} + k_{ic}}{3} + \left(k_{ia} \times k_{ib} \times k_{ic}\right)^{\frac{1}{3}}. \tag{25}$$

Step 6: Ranking the alternatives based on the values k_i. The alternative with the highest k_i is chosen as the best.

3.5. EDAS method

The EDAS is a MCDM method that evaluates and ranks alternatives by measuring their distances from the average solution. Assuming n alternatives and m criteria, the computational steps of the EDAS method are presented below (Keshavarz-Ghorabaee *et al* 2015):

Step 1: Selecting the most important criteria that describe alternatives.

Step 2: The decision - making matrix $\left[X = X_{ij}\right]_{m\times n}$ is constructed. (26)

Step 3: Determine the average solution according to all criteria, shown as follows:

$$\mathrm{AV} = \left[\mathrm{AV}_j\right]_{1xn} \tag{27}$$

where,

$$\mathrm{AV}_j = \frac{\sum_{i=1}^{m} x_{ij}}{m}. \tag{28}$$

Step 4: Calculate the positive distance from average (PDA) and the negative distance from average (NDA) matrixes according to the type of criteria (benefit and cost), shown as follows:

$$\mathrm{PDA} = \left[\mathrm{PDA}_{ij}\right]_{mxn} \tag{29}$$

$$\mathrm{NDA} = \left[\mathrm{NDA}_{ij}\right]_{mxn} \tag{30}$$

if jth criterion is beneficial,

$$\mathrm{PDA}_{ij} = \frac{\max\left(0,\ \left(x_{ij} - \mathrm{AV}_j\right)\right)}{\mathrm{AV}_j} \tag{31}$$

$$\mathrm{NDA}_{ij} = \frac{\max\left(0,\ \left(\mathrm{AV}_j - x_{ij}\right)\right)}{\mathrm{AV}_j} \tag{32}$$

if jth criterion is cost,

$$\mathrm{PDA}_{ij} = \frac{\max\left(0,\ \left(\mathrm{AV}_j - x_{ij}\right)\right)}{\mathrm{AV}_j} \tag{33}$$

$$\mathrm{NDA}_{ij} = \frac{\max\left(0,\ \left(x_{ij} - \mathrm{AV}_j\right)\right)}{\mathrm{AV}_j} \tag{34}$$

where PDA_{ij} and NDA_{ij} denote the positive and negative distance of ith alternative from average solution in terms of jth criterion, respectively.

Step 5: Determine the weighted sum of PDA and NDA (SPi and SNi) for all alternatives, shown as follows:

$$\mathrm{SP}_i = \sum_{j=1}^{n} w_j \mathrm{PDA}_{ij} \tag{35}$$

$$\mathrm{SN}_i = \sum_{j=1}^{n} w_j \mathrm{NDA}_{ij} \tag{36}$$

where w_j is the weight of jth criterion.

Step 6: Normalize the values of SP and SN for all alternatives, shown as follows:

$$\mathrm{NSP}_i = \frac{\mathrm{SP}_i}{\max_i\left(\mathrm{SP}_i\right)} \tag{37}$$

$$\mathrm{NSN}_i = 1 - \frac{\mathrm{SN}_i}{\max_i\left(\mathrm{SN}_i\right)}. \tag{38}$$

Step 7: Calculate the AS for all alternatives, shown as follows:

$$\mathrm{AS}_i = \frac{1}{2}\left(\mathrm{NSP}_i + \mathrm{NSN}_i\right) \tag{39}$$

where $0 \leqslant \mathrm{AS}_i \leqslant 1$.

Table 2. CILOS-derived criterion weights across the U.S., E.U., and China.

Criterion	Type	United States	European Union	China
Purchase cost	Cost	0.090	0.0737	0.055
Maintenance cost	Cost	0.190	0.1746	0.177
Insurance cost	Cost	0.080	0.0673	0.066
Energy cost per km	Cost	0.150	0.1325	0.069
Payload capacity	**Benefit**	**0.400**	**0.4561**	**0.535**
Infrastructure cost (CAPEX + OPEX)	Cost	0.050	0.0488	0.041
Exemptions	Benefit	0.050	0.0470	0.058

4. Findings

4.1. Criterion weighting results (CILOS analysis)

CILOS analysis quantified the relative influence of seven techno-economic factors determining the feasibility of alternative HDV technologies across the United States, European Union, and China.The considered criteria include: purchase cost, maintenance cost, insurance cost, energy cost per kilometer, payload capacity, infrastructure cost and exemptions.

The resulting normalized weights (*Wj*) are summarized in table 2, reflecting regional variations in cost structure, operational priorities, and regulatory incentives.

These CILOS findings, and the evidence for a convergence towards payload capacity as the most important factor affecting HDV technology choice, suggest the operational importance of freight efficiency and vehicle productivity. Payload capacity is a critical operational factor in heavy-duty freight transport because energy storage technologies can significantly affect vehicle weight and cargo capacity. Previous studies indicate that battery weight may reduce payload capacity in battery-electric trucks, while hydrogen technologies may alleviate this limitation due to higher gravimetric energy density (Liang *et al* 2024, Syré et al 2025).

United States: Payload capacity (0.40), maintenance cost (0.19) are major weightages in operational considerations. Fleet operators consider very high reliability and uptime, and low total ownership and operational cost as major decision-making criteria. Energy cost (0.15) has moderate weightage and is the second major factor in case of stable fuel price.

European Union: Payload capacity remains the most influential criterion (0.456), followed by maintenance cost (0.1746) and energy cost per km (0.1325). Insurance (0.0673) and purchase cost (0.0737) have moderate importance, while infrastructure cost (0.0488) and exemptions (0.0470) receive relatively lower weights in the overall evaluation.

China: Payload capacity is the most influential criterion (0.535), followed by maintenance cost (0.177). Energy cost per km (0.069), insurance cost (0.066), and purchase cost (0.055) have moderate influence, while infrastructure cost (0.041) receives the lowest weight. Exemptions (0.058) contribute marginally to the overall evaluation.

In all three markets operational and economic characteristics of the vehicle (payload, maintenance and energy) account for greater than 70% of the total criteria weight, with operational and economic factors outweighing environmental and infrastructure elements in HDV transition pathways.

These regional weightings then feed into the subsequent MARCOS and COCOSO assessments, allowing multiple-criteria ranking of the different propulsion technology alternatives under various market and policy scenarios.

4.2. MARCOS results

The MARCOS method was applied to rank HDV powertrain alternatives—diesel, BEV, and FCEV—across the United States, the European Union, and China using the previously derived CILOS criterion weights. The analysis yields the relative utility measures (K_i^-, K_i^+) and the final utility function ($f(K_i)$), which form the basis for the ranking results presented in tables 3–5. A cross-regional comparison of rankings and dominant criteria is provided in table 6.

The MARCOS results for the United States rank diesel trucks as the most favorable alternative ($f(K_i) = 0.6883$), followed by BEVs (0.6414) and FCEVs (0.5945). This outcome reflects the advantages of diesel technologies in payload capacity, maintenance costs, and the maturity of existing refueling infrastructure. Although BEVs and FCEVs benefit from lower operating costs in some categories, their competitiveness is constrained by higher purchase costs and infrastructure limitations under current market conditions.

Table 3. MARCOS results for the United States.

Alternatives	S_i	K_i^-	K_i^+	$f(K_i)$	Rank
US–Diesel	0.8586	1.3495	0.8586	0.6883	**1**
US–BEV	0.8001	1.2575	0.8001	0.6414	2
US–FCEV	0.7416	1.1657	0.7416	0.5945	3

Table 4. MARCOS results for the European Union.

Alternatives	S_i	K_i^-	K_i^+	$f(K_i)$	Rank
EU–Diesel	0.859	1.308	0.859	0.682	**1**
EU–BEV	0.812	1.236	0.812	0.644	2
EU–FCEV	0.743	1.131	0.743	0.589	3

Table 5. MARCOS results for China.

Alternatives	S_i	K_i^-	K_i^+	$f(K_i)$	Rank
China–Diesel	0.827	1.237	0.827	0.652	2
China–BEV	0.828	1.238	0.828	0.653	**1**
China–FCEV	0.754	1.127	0.754	0.594	3

Table 6. Cross-regional comparison of MARCOS results.

Region	1st rank	2nd rank	3rd rank	Highest $f(K_i)$	Dominant criterion(s)
United States	Diesel	BEV	FCEV	0.6883	Payload capacity (0.40), Maintenance (0.19)
European Union	Diesel	BEV	FCEV	0.682	Payload capacity (0.456), Maintenance (0.1746)
China	BEV	Diesel	FCEV	0.653	Payload capacity (0.535), Exemptions (0.057)

The MARCOS results for the European Union rank diesel trucks as the most favorable alternative ($f(K_i) = 0.682$), followed by BEVs (0.644) and FCEVs (0.589). Here, higher $f(K_i)$ values indicate better overall performance and a more favorable alternative under the given criteria. Diesel maintains a competitive advantage due to higher payload capacity and the maturity of existing fueling infrastructure. BEVs benefit from lower maintenance and electricity costs under EU electrification policies, but higher capital and infrastructure requirements limit their competitiveness relative to diesel. FCEVs remain the least competitive option due to high investment costs and the limited development of hydrogen refueling infrastructure.

The MARCOS results for China rank BEVs as the most competitive alternative ($f(K_i) = 0.653$), narrowly outperforming diesel trucks (0.652), while FCEVs remain in third place (0.594). This outcome reflects strong policy incentives for electrification, lower purchase costs for BEV platforms, and the rapid expansion of charging infrastructure in China. Despite diesel maintaining advantages in payload capacity and established fuel networks, the minimal performance gap suggests that BEVs have reached near cost-competitiveness with diesel under current market and policy conditions.

Geographical differences in the powertrain technologies of HDVs can be observed. Diesel is the most dominant HDV alternative fuel in the USA and the European Union, while the China's dominant alternative is BEVs. This consistent low ranking of FCEVs across all three regions also confirms that context plays a meaningful role in the MARCOS ranking of technologies due to differences in cost structures, infrastructure, and policy regimes.

4.3. COCOSO results

The COCOSO method was applied to rank HDV powertrain alternatives—diesel, BEV, and.FCEV—across the United States, the European Union, and China using the same seven criteria and CILOS-derived weights. The method integrates additive and multiplicative aggregation schemes through three utility indices (K_{ia}, K_{ib}, K_{ic}), resulting in a final integrated performance score (K_i). The regional results are presented in tables 7–9, followed by a comparative assessment in table 10.

Table 7. COCOSO results for the United States.

Alternatives	S_i	K_{ia}	K_{ib}	K_{ic}	K_i	Ranking
US–Diesel	0.620	0.315	2.846	0.723	2.160	2
US–BEV	0.463	0.425	2.929	0.975	2.509	**1**
US–FCEV	0.367	0.261	2.000	0.599	1.632	3

Table 8. COCOSO results for the European Union.

Alternatives	S_i	K_{ia}	K_{ib}	K_{ic}	K_i	Ranking
EU–Diesel	0.648	0.366	3.986	0.809	2.777	2
EU–BEV	0.419	0.436	3.711	0.965	2.864	**1**
EU–FCEV	0.299	0.197	2.000	0.436	1.434	3

Table 9. COCOSO results for China.

Alternatives	S_i	K_{ia}	K_{ib}	K_{ic}	K_i	Ranking
CHINA–Diesel	0.691	0.376	3.309	1.000	2.638	**1**
CHINA–BEV	0.328	0.296	2.000	0.787	1.803	3
CHINA–FCEV	0.384	0.328	2.273	0.871	2.023	2

Table 10. Regional comparison of COCOSO results.

Region	1st rank	2nd rank	3rd Rank
United States	BEV (2.509)	Diesel (2.160)	FCEV (1.632)
European Union	BEV (2.864)	Diesel (2.777)	FCEV (1.434)
China	Diesel (2.638)	FCEV (2.023)	BEV (1.803)

The COCOSO results for the United States rank BEVs as the most competitive alternative ($K_i = 2.509$), followed by diesel (2.160) and FCEVs (1.632). This outcome differs slightly from the MARCOS results, reflecting the sensitivity of the COCOSO framework to criteria that jointly influence additive and multiplicative aggregation structures. In the U.S. context, BEVs benefit from lower operating costs, particularly in energy and maintenance components, which improve their overall performance despite infrastructure limitations. Conversely, diesel trucks retain advantages in payload capacity and infrastructure maturity, while FCEVs remain the least competitive option due to high capital requirements and the limited development of hydrogen supply infrastructure.

According to the COCOSO results, BEVs rank as the most competitive alternative in the European Union ($K_i = 2.864$), followed by diesel (2.777), while FCEVs remain in third place (1.434). The narrow gap between BEVs and diesel reflects the influence of strong charging infrastructure and supportive regulatory policies in the EU. While diesel trucks retain an advantage in payload capacity, BEVs strengthen their competitiveness through lower operating costs. FCEVs remain less competitive due to high investment costs and the limited development of hydrogen infrastructure.

The COCOSO results for China rank diesel trucks as the most competitive alternative ($K_i = 2.638$), followed by FCEVs (2.023) and BEVs (1.803). This pattern differs from the U.S. and EU results and reflects the stronger influence of cost-oriented criteria under Chinese market conditions. Diesel maintains advantages due to extensive fueling infrastructure and lower capital risk, while BEVs are constrained by higher energy and infrastructure costs. Although FCEVs benefit from policy support and longer operational range, their competitiveness remains limited by high purchase costs and the early-stage development of hydrogen infrastructure.

The technology competitiveness varies across the regions, with BEVs the most competitive in the US and the EU with supportive regulation, expanding charging infrastructure and lower operating costs. In China, diesel remains the dominant technology due to lower capital risk and a relatively developed refueling infrastructure. Outside of China, however, FCEVs remain less competitive due to the capital costs of developing hydrogen infrastructure and limited hydrogen refueling stations. The differences between COCOSO and MARCOS results stem from their distinct aggregation logics: while MARCOS emphasizes balanced performance across criteria, COCOSO gives greater weight to strong performance in specific cost components, which favors BEVs in policy-supported markets.

Table 11. EDAS results for the United States.

Alternatives	NSP	NSN	AS	Ranking
US–Diesel	1.00	0.20	0.60	**1**
US–BEV	0.45	0.61	0.53	2
US–FCEV	0.14	0.00	0.07	3

Table 12. EDAS results for the European Union.

Alternatives	NSP	NSN	AS	Ranking
EU–Diesel	1.00	0.30	0.65	**1**
EU–BEV	0.52	0.64	0.58	2
EU–FCEV	0.16	0.00	0.08	3

Table 13. EDAS results for China.

Alternatives	NSP	NSN	AS	Ranking
CHINA–Diesel	1.00	0.72	0.86	**1**
CHINA–FCEV	0.18	0.20	0.19	2
CHINA–BEV	0.31	0.00	0.15	3

Table 14. Cross-regional EDAS performance summary.

Region	Diesel (AS)	BEV (AS)	FCEV (AS)	Ranking Order
United States	0.60	0.53	0.07	Diesel > BEV > FCEV
European Union	0.65	0.58	0.08	Diesel > BEV > FCEV
China	0.86	0.15	0.19	Diesel > FCEV > BEV

4.4. Robustness validation via EDAS method

The EDAS method was employed to validate the robustness of the ranking results obtained from MARCOS and COCOSO by assessing the relative performance of HDV powertrain alternatives based on their positive and negative distances from the average solution. The normalized sums of positive distances (NSP), negative distances (NSN), and the AS form the basis of the rankings reported in tables 11–13. A cross-regional performance summary is presented in table 14.

The EDAS result shows diesel trucks remain the most cost-effective option in the US (AS = 0.60), mainly due to lower purchase price, insurance premiums, and infrastructure costs. Despite higher energy efficiency, lower competitiveness of BEVs in the US market, reflected by an (AS = 0.53), is likely due to infrastructure issues and initial costs.

The EDAS results for the EU show that diesel vehicles remain the least-cost option (AS = 0.65), albeit with a much smaller performance gap, largely due to more policy support for electrification and a greater share of renewable electricity. The main cost advantage for diesel vehicles is in vehicle purchase price, insurance and infrastructure availability. Accessibility of refueling infrastructure and high capital costs limit BEV competitiveness. Though FCEVs are the lowest competitive vehicle category because of investment costs into hydrogen refueling stations, their low penetration and readiness level may create an imbalance in comparison to the more ready BEVs.

In China, the EDAS results suggest that diesel trucks are still the best option, with an AS score of 0.86 due to greater differences in purchase cost, insurance, and infrastructure. Unlike the US and EU, FCEVs (AS = 0.19) slightly outperform BEVs (AS = 0.15) for HDTs in China. Nevertheless, the substantial score gap highlights that diesel technologies continue to maintain a strong short-term cost advantage in the Chinese HDT market, while alternative powertrains remain constrained by capital intensity and infrastructure limitations.

Cross-region results in table 14 reflect diesel's cost advantage with low vehicle and infrastructure costs. BEVs are more competitive in the US and EU, while FCEVs perform better than BEVs in China reflecting the regional transition to hydrogen-based transport policies.

However, the different rankings of COCOSO compared to the MARCOS-EDAS framework are not contradictory, just due to the different mathematical models behind them. MARCOS and EDAS result in a more conservative ranking, based on distances to ideal or average solutions (Keshavarz Ghorabaee *et al* 2021; Stević *et al* 2020). Conversely, COCOSO employs a hybrid aggregation mechanism that amplifies

cumulative advantages across criteria (Yazdani *et al* 2018). This explains why BEVs, which maintain balanced performance across multiple dimensions, achieve superior scores in COCOSO. Rather than methodological bias, this variation provides a multi-perspective sensitivity analysis, validating the findings under both utility-based and compromise-based decision logics.

5. Conclusion

This study evaluated the performance of diesel vehicles, BEVs, and FCEVs for heavy-duty freight transport in the USA, EU, and China using the triangulated MCDM method MARCOS, the COCOSO method, and the EDAS method. The results demonstrate a reasonable level of consistency across the methods, supporting the robustness of the multi-method evaluation approach.

Theoretically, this study contributes to the MCDM literature by developing a triangulated MCDM algorithm to assess transport sustainability via three decision logics including ratio-based MARCOS, compromise-based COCOSO, and deviation-from-average-based EDAS. In addition, the cross-regional analysis also contributes to the MCDM literature by assessing technology competitiveness using a mixture of regulatory frameworks, infrastructure readiness stages, and energy market structures to test the robustness and applicability of the triangulated MCDM framework.

Empirical studies have shown that diesel trucks remain the most cost-competitive short-haul option due to the existing fueling infrastructure and lower capital and insurance costs, although BEVs are becoming competitive in the more advanced markets of the European Union and the United States helped by regulation and charging infrastructure. In China, FCEVs are more competitive than BEVs due to local government support for hydrogen development.

Importantly, the different methods reflect contrasting perspectives: MARCOS and EDAS accordingly generate conservative stability-oriented rankings based on reference solutions, and COCOSO generates rankings from a cumulative perspective of performance superiority on multiple criteria. In this sense, the choice of model could be influenced by the decision-maker's planned performance orientation. For example, MARCOS-type stability measures may suit risk-averse decision-makers, whilst COCOSO's compromise principles may appeal to calculated planners.

From a policy perspective, the results suggest that technology-neutral but regionally differentiated transition strategies will be necessary for the decarbonization of freight transport. Investments in charging and hydrogen refueling infrastructure, together with coordinated transport and energy policies, will play a decisive role in accelerating the transition toward zero-emission HDVs.

The MCDM methodology applied in this paper is based on a set of assumptions and has a number of limitations. First of all, it is based on secondary data (IEA 2025), which may not correspond to the real market situation or regional differences. Next, some criteria like infrastructure availability, policy uncertainty, or technological learning are not modeled directly but are integrated by using cost-based criteria. Furthermore, differences in the order of the alternatives between different aggregation methods (e.g. MARCOS and COCOSO) of different MCDM methods should also be considered. This underlines the need for analysis of this sensitivity to the choice of decision-making method. The results are not meant to be taken as absolute statements, but rather as something to be compared against in a decision-making scenario.

6. Contributions and practical implications

While previous studies have separately considered vehicles or infrastructure, integrated modeling approaches that jointly consider vehicle design, infrastructure deployment interactions and energy provision are missing for long-haul trucking (Syré and Göhlich 2025). Even though, thus far, these studies have been useful to understand the decarbonization of road transport, they are limited by having excluded hydrogen and alternative fuels, the effects of electrification systems, and their context specificity. Furthermore, as demand-side policies and technology options are often addressed in isolation from each other and behavioral and operational barriers are not considered, realistic long-term decarbonization pathways for the HDV sector cannot be developed (Wan *et al* 2025). This study makes three main contributions to the literature and practice. First, it contributes to the methodological stream of the MCDM literature by proposing a methodological triangulation framework using MARCOS, COCOSO and EDAS methods to cross-validate the stability of the evaluation alternatives' rankings. This multi-model structure reduces single-method bias and improves the reliability of complex sustainability-oriented decision problems in transport systems. Furthermore, a comparison between three regions of

the world is provided to analyze de-carbonization pathways for HDTs while considering heterogeneous infrastructure maturity, energy prices, and regulatory frameworks. Third, this research contributes to the body of empirical research by operationalizing publicly available techno-economic data into a transparent and verifiable infrastructure cost normalization framework to enable comparison of diesel, BEV and FCEV powertrains on a per-kilometer basis.

From a practical perspective, the results offer actionable guidance for multiple stakeholder groups. For logistics operators and fleet investors, the findings support phased investment strategies that align vehicle procurement with regional infrastructure readiness and expected cost trajectories, thereby mitigating transition risks. For policymakers and infrastructure planners, the results highlight the importance of technology-neutral but regionally differentiated policy instruments, including coordinated grid investments, hydrogen corridor development, and carbon pricing mechanisms. For financial institutions and public funding agencies, the framework can support evidence-based prioritization of charging and refueling infrastructure investments, particularly where marginal decarbonization gains are highest.

7. Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used Grammarly to check grammar, improve language clarity, and enhance the overall readability of the manuscript. After using this tool, the authors reviewed and edited all content as needed and take full responsibility for the final version of the manuscript.

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Data availability statement

The data cannot be made publicly available upon publication because they are not available in a format that is sufficiently accessible or reusable by other researchers. The data that support the findings of this study are available upon reasonable request from the authors.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions

Aybike Esra Şahin 0000-0003-1829-648X
Conceptualization (equal), Formal analysis (equal), Methodology (equal), Project administration (equal), Writing – original draft (equal), Writing – review & editing (equal)

Şeyma Özekinci 0009-0006-6189-5436
Data curation (equal), Investigation (equal), Methodology (equal), Resources (equal), Writing – original draft (equal)

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