



# Comparing feasibility of low-carbon heavy-duty road freight vehicles

Clara Rajalehto<sup>\*</sup>, Petri Helo

School of Technology and Innovations, University of Vaasa, Wolffintie 32, 65200, Vaasa, Finland

## ARTICLE INFO

Handling Editor: Cecilia Maria Villas Bóas de Almeida

### Keywords:

Total cost of ownership  
Feasibility  
Monte Carlo  
Alternative fuels  
Low-carbon vehicles  
Liquid biomethane  
Electric vehicle

## ABSTRACT

The transportation sector remains heavily reliant on fossil fuels, rendering it one of the most significant energy consumers and a principal contributor to global pollution. In order to reduce emissions, the EU has established reduction targets and adopted new regulations that set emission standards for heavy-duty vehicles. A significant area of focus in recent literature has been the reduction of emissions through the utilisation of low-carbon vehicles. This case study aims to develop a Total Cost of Ownership model for low-carbon heavy-duty vehicles. This has been achieved by employing empirical data and Monte Carlo simulations to evaluate the viability of the available fuel options. The dataset comprised telemetry data collected from January to October 2023 from a Finnish food logistics company utilising low-carbon fuel options. The findings indicate that, within the context of the studied vehicles, liquid biomethane and electric trucks are currently cost-competitive alternatives. In 82 % of cases, electric vehicle trucks exhibited a lower total cost of ownership than diesel or liquid biomethane trucks. Electric vehicles were best suited for shorter hauls, typically under 390 km, due to their limited range and thus higher cost per kilometre. Contribution of this paper is empirical demonstration showing that liquid biomethane vehicles offer the greatest overall potential for cost and emissions cost savings compared to diesel and is the most technically feasible option, but it also has the most cost uncertainty.

## 1. Introduction

The European Union (EU)<sup>1</sup> aims to reduce greenhouse gas (GHG) emissions at least by 55 % by 2030 from 1990 levels and ultimately intends to be carbon neutral by 2050 (European Commission, 2023). The EU has successfully reduced GHG emission almost in all economic sectors, but there is one notable exception (European Commission, 2024). To this day, the transportation sector remains highly dependent on fossil fuels, posing a significant challenge to achieving the EU's climate objectives. A key challenge in the transition to carbon-neutral transportation is that no single alternative fuel or technology currently has the capacity to fully replace fossil fuels across all applications. For instance, concerns have been raised about the scarcity of critical metals, such as lithium and cobalt, which are essential for battery production (Bongartz et al., 2021). Limited availability and geopolitical dependencies could constrain the large-scale adoption of battery-electric heavy-duty vehicles. Similarly, while biofuels offer a viable low-carbon alternative, their production capacity is inherently limited by feedstock availability and land use competition (Pääkkönen et al.,

2019). These constraints suggest that a diversified approach—rather than reliance on one dominant technology—will be necessary to achieve meaningful decarbonization.

However, for companies considering investments in alternative fuel technologies, this raises a strategic question: should firms diversify their investments across multiple emerging solutions, or should they first focus on a single technology before expanding? While long-term decarbonization efforts will likely involve a combination of solutions, initial investments may be more targeted due to resource constraints and technological uncertainties. Alternative fuels—fuels derived from renewable sources (Alonso-Villar et al., 2022) – have gained attention as a solution to decarbonise the transport sector (Alonso-Villar et al., 2022; Forrest et al., 2020; Noll et al., 2022). This attention, however, has not yet translated into widespread adoption – in the first quarter of 2024, 95.1 % of newly registered commercial vehicles in the EU were still powered by diesel (ACEA, 2024), highlighting the persistent gap between potential solutions and practical implementation.

Bae et al. (2024) suggest that the main hindrance of adopting other options than diesel in low-carbon heavy duty road freight vehicles seems

This article is part of a special issue entitled: SCM Innovation Practices published in Journal of Cleaner Production.

<sup>\*</sup> Corresponding author.

E-mail addresses: [clara.rajalehto@uwasa.fi](mailto:clara.rajalehto@uwasa.fi) (C. Rajalehto), [petri.helo@uwasa.fi](mailto:petri.helo@uwasa.fi) (P. Helo).

<sup>1</sup> See Appendix D for abbreviations.

<https://doi.org/10.1016/j.jclepro.2025.145524>

Received 2 September 2024; Received in revised form 10 April 2025; Accepted 11 April 2025

Available online 19 April 2025

0959-6526/© 2025 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

to be the technical demands of heavy-duty transport such as the range and weight. In recent literature however, alternative fuel vehicles (AFV) especially liquid biomethane (LBG) (Björner Brauer and Khan, 2021; Dahlgren, 2022) and electric vehicles (EV) have emerged as feasible solutions to decarbonise road freight transport sector (Alarcón et al., 2023; Noll et al., 2022). However, the feasibility in real world conditions and usage of actual empirical data in commercial heavy duty road freight sector remains under researched presenting a research gap. To support this transition, newer research utilising real world empirical data is needed. Therefore, this paper examines the feasibility of EV and LBG vehicles compared to diesel vehicles in road freight transportation sector.

This study addresses these three key challenges in the transition to low-carbon heavy-duty freight: (1) the gap between emission reduction targets and industry adoption, with diesel still dominating new vehicle registrations; (2) the lack of empirical data on the real-world economic and operational feasibility of AFVs; and (3) the economic uncertainties surrounding LBG, particularly regarding long-term costs. Using real-world telemetry data from a Finnish logistics company and Monte Carlo simulations, this case study evaluates the TCO and operational feasibility of LBG and EV alternatives compared to diesel vehicles in commercial heavy-duty transport.

## 2. Literature review

There are several AFV technologies available for road freight transport such as biodiesel, compressed natural gas (CNG), liquid natural gas (LNG) and hydrogen fuel cell (FCEV) (Krause et al., 2024). According to the reviewed literature each of these technologies still have their downsides or their commercial availability is somewhat limited, which is why they are excluded from this study. Instead, we focus on technologies that are currently commercially viable to identify practical solutions for companies considering investments in the near future. The main issue of biodiesel and renewable diesels is the limited availability (Padder et al., 2024). Moreover, even though compressed and liquefied natural gas (i.e. methane) are thought as alternative fuels due to their ability to burn more purely they are still technically fossil based (Dahlgren, 2022; Gustafsson and Svensson, 2021). Hydrogen fuel cell technology is thought as one of the most promising technologies for freight transport, but its maturity is still in its early stages (Noll et al., 2022).

EVs and LBG vehicles have emerged as the leading commercially available solutions for sustainable freight transport. While EVs have historically faced range limitations, recent literature suggests they have reached sufficient maturity for practical adoption in several contexts. Alonso-Villar et al. (2022) demonstrated EV viability in delivery and regional haul operations, while Forrest et al. (2020) extended this feasibility to medium and heavy-duty applications. In the European context, Noll et al. (2022) found that EVs could be viable across all segments, provided there is adequate infrastructure and policy support. The research on LBG as a fuel option remains limited, particularly regarding its economic viability. Gustafsson and Svensson (2021) highlighted LBG's substantial environmental advantages over fossil fuels but noted that its production costs still exceed those of conventional alternatives. Nevertheless, LBG vehicles benefit from existing commercial availability and an established fuelling infrastructure network (Dahlgren, 2022).

According to Arora et al. (2021) the history of EV's dates back to 1800s and since then there has been several attempts to design EV that could become the primary mode of transportation. The first generation of EVs faced challenges due to the weight of the batteries and the underperformance of the electric motors. As a result, people lost interest in EVs, especially when electric self-starters for gasoline cars came out and oil prices dropped (Rajashekara, 1994). However, this began to change in the early 1980s when environmental concerns and greenhouse gas emissions became more prominent issues. To this day EVs suffer

from drawbacks compared to diesel counterparts, such as higher purchase prices and limited range capabilities. In the literature EVs usually exhibited the lower emissions than its counterparts (Alonso-Villar et al., 2022). EVs are thought not to have any direct emissions meaning that its tailpipe emissions are zero (International Organization for Standardization, 2023). EVs emissions come from the production of vehicles and the used electricity, and therefore the overall emission reduction is determined by how the used electricity was produced (Alonso-Villar et al., 2022; Noll et al., 2022).

Similarly, the emission reduction potential of LBG varies based on the feedstock and production methods of the raw biogas (Björner Brauer and Khan, 2021; Gustafsson and Svensson, 2021). Raw biogas, primarily composed of methane and CO<sub>2</sub> with trace gases, can be produced from various organic materials (Dahlgren, 2022; Padder et al., 2024), including materials such as agricultural waste, manure and biowaste (Padder et al., 2024; Pellegrini et al., 2018). LBG is produced from biogas which can be also processed to produce other fuels such as compressed biomethane (CBG), hydrogen, methanol, dimethyl ether and Fischer-Tropsch fuels (e.g. synthetic diesel) (Dahlgren, 2022). LBG is produced from biogas by upgrading it to biomethane and then liquified by cooling to cryogenic temperature (~-162 Celsius) (Dahlgren, 2022; Pellegrini et al., 2018). LBG can be used as a direct substitute to natural gas (LNG). Liquid form takes less space than gaseous form meaning that it is more space efficient and energy dense, making it better solution for heavy duty vehicles than CBG or CNG (Pellegrini et al., 2018).

First applications of natural gas as a fuel track back to 1930s. In 1980s and 1990s the interest grew due to the increased interest in pollution and energy independence (Dahlgren, 2022). However, biomethane was seldom thought as a transportation fuel at that time. Coming to the early 2000s when the global warming became a hot topic biomethane started to gain interest as a more sustainable fuel option. Today LBG represents a technically viable alternative to fossil fuels for heavy freight trucks due to its similar operational characteristics to diesel and potential for GHG emission reductions (Pääkkönen et al., 2019), although it has gotten less attention in previous literature compared to other technologies (Gustafsson and Svensson, 2021).

Another aspect when assessing which technology to adopt is the economic feasibility. A common tool for assessing the economic feasibility is the TCO analysis, which compares the estimates of the costs over the ownership period (Noll et al., 2022). Companies often use TCO, since it gives a good indication of the overall costs over owning period by taking into account the purchase price cost, operating costs and other possible costs (Noll et al., 2022). TCO analysis methods have evolved to address the specific characteristics of AFVs, particularly through the incorporation of probabilistic approaches and sustainability considerations (Ji and Gan, 2022; Wang et al., 2024).

The taxonomy and framework for TCO was originally defined for logistics context in the 1990s (Ellram, 1993, 1995). One of the first applications of TCO to EVs was done by Delucchi and Lipman, 2001 and since then the related body of literature has been growing steadily (Ji and Gan, 2022; Roosen et al., 2015). One of the more recent developments have been the gradual emergence of probabilistic approaches to TCO (e.g. Monte Carlo simulation). For example, Jones et al. (2020) utilised what-if analysis to compare hydrogen fuel cell and EVs. Wu et al. (2015) utilised a Monte Carlo simulation to compare TCOs of non-commercial vehicles.

There has also been an emergence of further classification of TCO to also consider sustainability perspectives including environmental, social, and economic dimensions. For example, Ji and Gan (2022) considered socioeconomic attributes in EV purchasing decisions and found a positive correlation between socioeconomic attributes and EV purchasing intent. Whereas Alonso-Villar et al. (2022) consider environmental feasibility in their study, identifying cleaner road freight vehicle options considering regional availability of alternative fuels and energy security in Iceland.

Even though recent literature suggests that AFVs are more expensive than diesel vehicles (Alarcón et al., 2023; Wang et al., 2024), there is also a growing body of literature suggesting that EVs are soon to be cost competitive alternatives (Gunawan and Monaghan, 2022; Jahangir Samet et al., 2024; Noll et al., 2022). Contextually it is good to note that most of the previous literature related to EVs focus on the non-commercial vehicles, meaning that the driving profiles and usage cases differ significantly from the commercial road freight vehicles (e.g. Bjerkan et al., 2016; Bubeck et al., 2016; Danielis et al., 2018; Hagman et al., 2016; Lévy et al., 2017; Palmer et al., 2018). However, recently there has been increasing focus on AFVs in the freight sector.

Recent studies have shown varying results regarding the economic viability of AFVs in commercial freight transport. Wang et al. (2024) conducted a comparative analysis of diesel, battery electric vehicles (EV), and fuel cell electric vehicles (FCEV) in medium- and heavy-duty commercial freight operations in the UK. Their findings indicated that EVs had 11 %–33 % higher TCO than diesel vehicles, highlighting the cost gap between the solutions. However, Jahangir Samet et al. (2024) reached a more optimistic conclusion, demonstrating that EVs could be economically cost competitive solutions in the medium and heavy-duty truck segment.

In another significant study, Zhang et al. (2024) compared multiple fuel types in the heavy-duty segment, including diesel, liquefied natural gas (LNG), biodiesel, FCEV, and methanol. Their research concluded that LNG vehicles demonstrated superior economic performance compared to diesel alternatives. While these studies provide valuable insights, they notably exclude liquid biomethane (LBG) from their analyses. Additionally, only a limited number of studies, including Lévy et al. (2017), Mojtaba Lajevardi et al. (2019), and Zhang et al. (2024), have incorporated emissions costs into their analyses, primarily focusing on the relationship between avoided emissions and TCO.

Despite this growing body of research, empirical evidence remains limited (Appendix C), particularly regarding the performance and viability of LBG solutions in commercial freight operations. This gap in the literature highlights the need for studies incorporating real-world operational data for LBG and BEV vehicles.

### 3. Methodology

The data presented in this study were collected from heavy-duty road vehicles used for long haul in Finland between January and October 2023. The vehicles transport perishable goods, which have specific features (Aazami and Saidi-Mehrabad, 2021). However, we believe that this environment can be generalized into other contexts too. While the data collection period is relatively short, it is justified by the nature of this pilot project where the participating logistics company had recently invested in new AFVs. The electric and LBG vehicles were acquired and deployed in late 2022, so the data represents their complete available operational history. While a longer time series would be valuable for traditional diesel vehicles, the nascent state of EVs and LBG heavy-duty vehicles in commercial operations means that extended historical data is not yet available. This limitation is common in early-stage evaluations of emerging transport technologies and is acknowledged in our analysis.

The dataset comprised vehicle-specific driving data from EV, LBG, and diesel-powered vehicles operating on comparable routes. All vehicles in the study are manufactured by the same company and have identical cargo capacity of 40 FIN-pallets (37 tons). Trucks selected for comparison represent the same brand for renewable fuel and diesel in order to minimize other differences in vehicles and to help concentrate on differences on fuel emissions. This study has access to telemetry and finance data. The case study has not been funded by any vehicle manufacturer. Difference brands and models of trucks may have varying results, but this study focused only on the comparison of fuel types on comparable truck body configurations. The collected parameters included vehicle dynamics (speed and acceleration), energy consumption across varying routes and conditions, and GPS tracking data. The

operational environment featured predominantly asphalted roads (98 %), minimal traffic congestion, and variable topography with average route segments of 4 km ascent and 4 km descent, though predominantly flat terrain (80 % at 0 % gradient). The present analysis consists of three main elements. First, we will create the TCO framework and identify the variables that have the most uncertainty. Second, we will use Monte Carlo simulation to model this uncertainty to see their impact on TCO. Lastly, we will calculate the emission profiles of each vehicle' using ISO14083 as our basis and quantify GHG emissions impact on TCO.

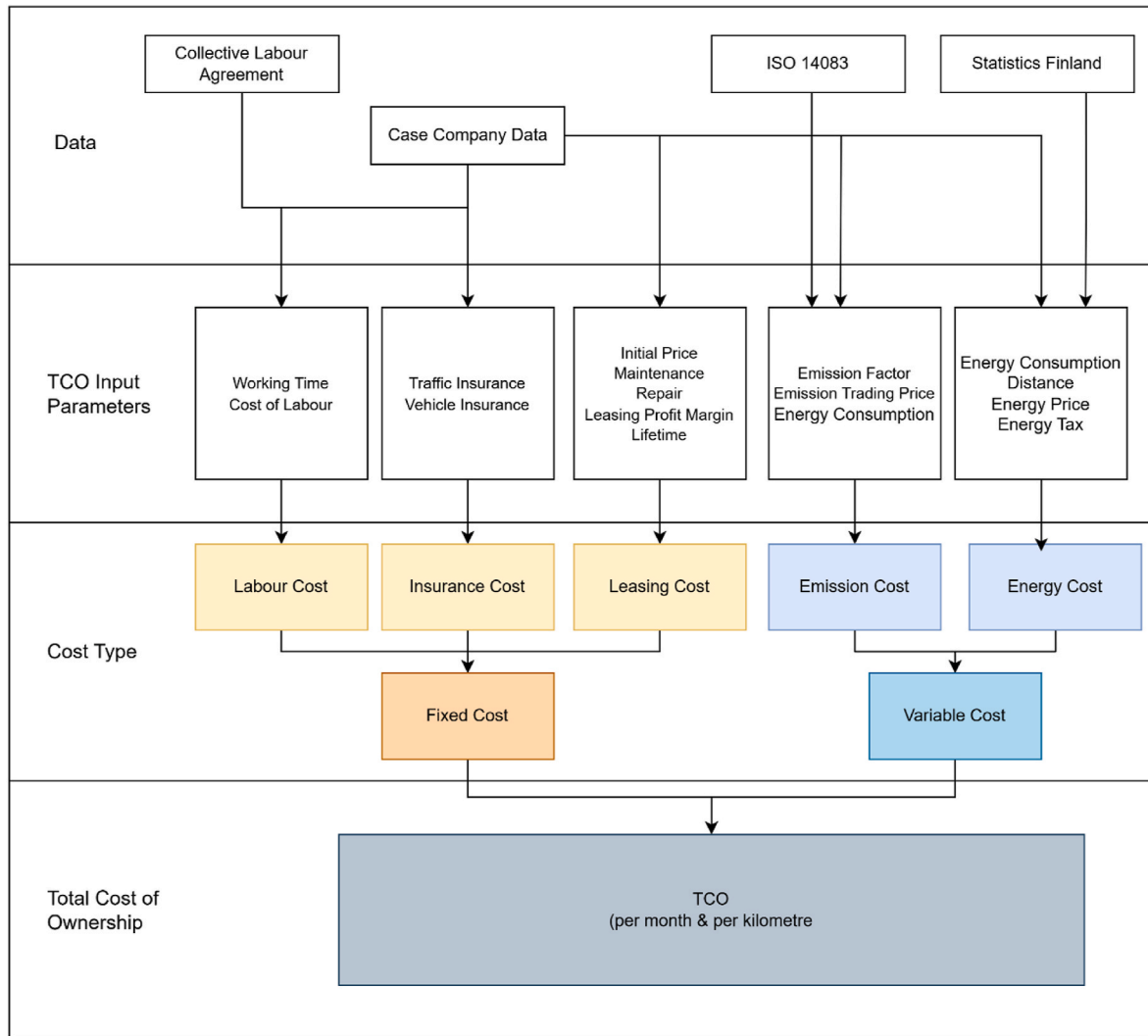
To evaluate the comparative economic performance of alternative vehicle technologies, we conducted a Total Cost of Ownership (TCO) analysis across a spectrum of daily driving distances. Our initial assessment deliberately set aside electric vehicle range limitations to isolate the relationship between TCO and variable driving distance under a fixed cost structure, assuming optimal operating conditions. This methodological approach enabled us to precisely quantify the distance-cost relationship without introducing confounding variables related to charging infrastructure requirements, range constraints, or performance limitations (*ceteris paribus*). In subsequent analyses, we utilised simulations that systematically incorporated these previously excluded variables to provide a more nuanced and operationally realistic assessment.

In order to ascertain the economic performance of each fuel type, the TCO analysis model, as proposed by Wu et al. (2015), was employed. This model was adjusted to fit the case specific circumstances such as contractual agreements involving a leasing of the vehicles. In this model, the costs have been divided into two main categories: fixed and variable costs. This study applies categorisation based on the cost model proposed by Izadi et al. (2019). The objective of this categorisation was to identify those elements that introduce uncertainty into the calculations i.e. variable costs. Fig. 1 presents applied TCO framework. Fixed costs included parameters that remained constant, such as leasing cost, insurance, and labour costs. In this instance, a five-year lease period was assumed. Similarly, variable costs were costs that exhibited regular fluctuations, such as energy costs. Consequently, these parameters were deemed to possess a stochastic nature. Equation (1) summarizes the calculation, where  $n$  is the leasing period,  $C_f$  is the fixed cost and  $C_v$  is the variable cost.

$$TCO = \sum_{t=1}^n C_f + C_v \quad (1)$$

If a parameter is stochastic in nature, it implies the presence of uncertainty. To illustrate, the price of fuel underwent frequent fluctuations, thereby introducing a considerable degree of uncertainty with respect to the cost of fuel. This uncertainty was modelled using probabilistic Monte Carlo simulation. Monte Carlo was chosen because of its flexibility in handling the diverse probability distributions present in our cost parameters and its established robustness in TCO analysis contexts. The stochastic nature of TCO parameters was evaluated based on the variability of the collected data, their relative impact on TCO sensitivity, and their inherent uncertainty. In the case of parameters exhibiting stable or constant cost data and minimal impact on the TCO, modelling was not deemed necessary. Subsequently, a Monte Carlo method was employed, entailing repeated simulations utilising probabilistic inputs with defined stochastic distributions. In the present study, 1000 simulations were conducted for each vehicle technology.

In literature maintenance and repair costs are usually regarded as variable costs (Katreddi et al., 2023). However, in this instance, due to the nature of the leasing arrangements, these costs are classified as fixed costs. This study is based on case where company leases the trucks. Due to the leasing arrangements, all maintenance, repair, tyre, initial price, depreciation and profit margin of the leasing company are incorporated into the fixed leasing contract, thereby rendering these costs fixed in nature. Because of the cost categorisation and leasing arrangements only variable costs in this case are energy costs. This simplifies the TCO model



**Fig. 1.** TCO framework for evaluation. Categorisation of input parameters into variable and fixed costs. These costs used in the Total Cost of Ownership on a per month and per kilometer basis.

and reduces the overall uncertainty inherent in the model. Thereby, although fixed costs can also be uncertain, this study focuses on these isolated parameters related to energy costs.

In addition, infrastructural costs are not considered in this study due to the good public fuelling and charging infrastructure in the routes in question. A maximum daily distance was established for each vehicle, thereby ensuring that refuelling or recharging is not necessary. It was assumed that the vehicle and battery lifespan would exceed or match the five-year leasing contract. For this reason, the end-of-life costs of vehicle or battery is not considered due to the leasing arrangement. For model simplicity, we did not account for battery capacity degradation in EVs, and consequently, no additional battery replacement costs were incorporated. Wang et al. (2024) found that battery capacity degradation has only minimal effect on the TCO, which aligns with our assumptions. Since in this study we only compare one specific EV model, we have not considered the effect of different battery chemistries. We have not introduced temperature-based degradation of batteries separately into the model, as our operational data already encompasses seasonal temperature variations through the inclusion of winter months in Nordic conditions.

To estimate the battery capacity requirements for long-distance operations, we assumed a linear relationship between battery capacity and range. Based on our data from Finnish operating conditions, we calculated the theoretical battery capacity needed for EVs to service routes

without mid-journey recharging. For EVs, we established a practical limitation of 393 km per charge cycle, with a 2.5-h charging period required to restore full battery capacity. Our calculations determined that an EV can theoretically complete two full charge cycles in one day, assuming an average speed of 60 km/h and average charging power of 216 kW. This operational framework allows EVs to achieve a maximum daily range of 786 km through two complete charge cycles.

Table 1 presents the technical specifications of the vehicles analysed in this study. All vehicles are configured with a maximum gross

**Table 1** Summary of the vehicle specifications considered in the scope of this study (case company data).

	Diesel	LBG	EV
Vehicle type	Volvo FH6x4	Volvo FH6x4	Volvo FH Electric
Average consumption (C <sub>a</sub> )	42 l/100 km	32 kg/100 km	110 kWh/100 km
Purchase price	162 000 €	204 000 €	300 000 €
Average maximum range	1463 km	703 km	393 km
Emission factor (ε)	2,64 kgCO <sub>2</sub> e/l	0,39 kgCO <sub>2</sub> e/kg	0,21 kgCO <sub>2</sub> e/kWh
Insurance	4955 €/a	4782 €/a	5128 €/a
Labor cost	27,70 €/h	27,70 €/h	27,70 €/h
Labor time	202 h/month	202 h/month	202 h/month

combination weight of 64 tons and comparable cargo carrying capacities. The carrying capacities is determined by the number of pallets, in this case the carrying capacity is 40 pallets. In this study the case company uses FIN-pallets that are 1200 mm × 1000 mm and its computational weight is 925 kg per pallet. In total each vehicle has a carrying capacity of 37 tons. The alternative fuel storage systems - whether LBG tanks or EV batteries - are strategically positioned in locations traditionally used for diesel tanks, ensuring no reduction in available cargo space. This design consideration is particularly relevant for our case study, as the transported goods (food products) are volume-limited rather than weight-limited. Consequently, the additional weight of battery systems in EVs does not meaningfully impact the operational cargo capacity, as the limiting factor is cargo volume rather than weight restrictions.

The dataset comprised vehicle-specific driving data from EV, LBG, and diesel-powered vehicles operating on comparable routes. In this case study, all operated routes are within the range capabilities of each vehicle, however diesel and LBG vehicles have the capability of driving more routes due to better range capabilities. The limited range capability of EVs in considered in the simulations (Table 2).

To assess the TCO, comprehensive cost parameters were collected. Environmental impact analysis incorporated regional emission factors to account for specific energy sources, energy mix, and production processes relevant to the study region. The average fuel consumption values were determined under specific operational conditions including average payload, geographic region, road types, traffic conditions, road gradient profiles, seasonal variations, and vehicle specifications, which are detailed in the methodology section.

The calculation of energy costs is dependent upon the collation of data pertaining to consumption, travel distances and energy prices, inclusive of applicable taxes. Each of these components contributes to the overall uncertainty of the energy cost. Fluctuations in consumption may be attributed to a number of factors, including driving style, route topography, and temperature conditions. Similarly, travel distances and energy prices are subject to fluctuations for a number of reasons. The telemetry data were used to establish distributions for consumption and travel distance. The price data for electricity, LBG, and diesel were sourced from local distributors utilised by the case company. In the case of diesel and LBG, a lognormal distribution was assumed, in accordance with the findings of Ally and Pryor (2016). For electricity, a normal distribution was determined based on observations by Zhou et al. (2009), who found that electricity prices typically follow a normal distribution under a relaxed supply-demand relationship. However, in situations of tight supply and demand, prices deviate from the normal distribution, showing a right-skewness. In real electricity markets,

**Table 2**  
Simulation input parameters of stochastic variables per vehicle type from case company data.

	Diesel	LBG	EV
Average consumption (AC)			
Lower Bound	25,5 l/100 km	27,2 kg/100 km	93,5 kWh/100 km
Mode	41,0 l/100 km	32,0 kg/100 km	110,0 kWh/100 km
Upper Bound	47,7 l/100 km	36,8 kg/100 km	126,5 kWh/100 km
Daily Distance (D)			
Lower Bound	116 km	116 km	116 km
Mode	537 km	537 km	201 km
Upper Bound	722 km	722 km	393 km
Fuel price			
Mean	1,96 €/l	1,72 €/kg	0,07 €/kWh
Standard Deviation	0,36 €/l	0,69 €/kg	0,06 €/kWh
ETS price ( $P_{GHG}$ )			
Shape	5,37	5,37	5,37
Scale	0,08	0,08	0,08

undersupply conditions lead to a distinct narrow-peak characteristic. A summary of the simulation input parameters is provided in Table 2.

Emission factors for fuels should be selected carefully from reputable sources. The standard SFS-EN ISO 14083:2023 offers an extensive list of factors for European fuels. It is particularly important to choose accurate emission factors for electricity, as emissions from electricity generation vary by country and can significantly affect the results. Finland's electricity grid relies predominantly on low-carbon sources—hydroelectric, wind, and nuclear power—resulting in lower greenhouse gas (GHG) emissions compared to the EU average specified in ISO14083:2023. The emissions for the simulated cases are calculated based on the vehicles' operational performance. The results for the transportation tasks are aggregated to provide values that represent overall performance. The total amount of greenhouse gases  $E_{GHG}$  is determined using the following Equation (2), where AC is average consumption, D is distance and  $\epsilon$  ( $\frac{kgCO_2e}{kg \text{ or kWh or l}}$ ) is the emission factor.

$$E_{GHG} = AC * D * \epsilon \quad (2)$$

Equation (3) outlines the calculation of total operational emissions from vehicle use, where  $G_{VO,TC}$  is the operational greenhouse gas emissions of the transport chain and  $G_{VO,TCi}$  is the operational greenhouse gas emissions allocated to each transport chain element in the chain.

$$G_{VO,TC} = \sum_i G_{VO,TCi} \quad (3)$$

The emissions costs are incorporated into the TCO calculations to evaluate the environmental economic impact of each vehicle technology. For EVs, emissions costs were already reflected in electricity prices through distribution systems, while comparable mechanisms are not yet fully implemented for diesel and LBG fuels. To ensure comparability, we calculated emissions costs per kilometre for each energy source, including conventional grid electricity for EVs, solar-powered electricity for EVs, LBG, and diesel.

The estimated emission cost is based on a combination of factors, including the quantity of fuel consumed, the distance travelled, the price of emissions within the European Emission Trading System (ETS), and data pertaining to the emission factor. The initial step involved fitting the most appropriate price distribution, derived from the price of emissions allowances (EUA) within the energy sector, with similar time frame as collected telemetry data from January and October 2023. This was done using R by testing different distributions and applying Akaike Information Criterion (AIC). The Weibull distribution, which best represented the observed price fluctuations, was then incorporated to the simulations of the TCO model in order to ascertain the emission cost for each vehicle. The calculation of emission cost ( $C_{GHG}$ ) is presented in Equation (4), where  $E_{GHG}$  is the total emissions and  $P_{GHG}$  is the price of emissions within the (ETS).

$$C_{GHG} = E_{GHG} * P_{GHG} \quad (4)$$

In this study a Spearman rank correlation analysis was employed to identify the sensitivity patterns in TCO across different vehicle technologies. This non-parametric measure allowed the quantification the strength and direction of association between TCO and variables including daily travel distance, fuel price, and average consumption. The correlation coefficient ( $\rho$ ) provided a standardized measure of association strength, with values closer to 1 or -1 indicating stronger relationships. We calculated the correlation coefficients with following formula:

$$\rho_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (5)$$

Where  $d_i = R(X_i) - R(Y_i)$  is the difference between the ranks of corresponding values and  $n$  is the number of observations (simulated data points).

#### 4. Results

Fig. 2 depicts the TCO per daily driven kilometre for each vehicle, assuming a fixed average cost level and excluding any potential cost uncertainties changing only the driven kilometres. This analysis isolates the impact of distance on cost under ideal conditions, excluding considerations of range limitations, charging infrastructure, and other possible performance constraints.

For routes under 100 km per day, diesel vehicles represent the most cost-effective option, while EVs are the most expensive. Diesel's advantage stems from lower fixed costs, making it economical for shorter commutes. However, as daily driving distance increases, diesel's higher variable fuel costs gradually erode this advantage. LBG performs nearly as well as diesel in the sub-100 km range.

LBG emerges as a competitive option, particularly when the daily driving distance exceeds 120 km. This is primarily attributable to its comparatively lower variable costs in comparison to diesel, which enables it to become the most cost-effective solution for distances in excess of this threshold. Following a distance of 210 km, LBG remains the most cost-effective option. However, diesel surpasses EVs in costs, rendering it the costliest solution. These findings also indicate that LBG is not the costliest solution in any given scenario.

It is noteworthy that LBG retains this cost advantage until the driving distance reaches approximately 270 km, at which point EVs become the most economical option – a distance still within the operational range capabilities of EVs. Despite higher initial costs, EVs offer the lowest variable costs over longer distances, primarily due to lower electricity costs compared to fossil fuels. This enables EVs to achieve greater cost-efficiency than diesel and LBG vehicles beyond 270 km per day, demonstrating their potential for substantial savings with higher mileage usage.

Subsequently, an analysis of the simulation results will be conducted, taking into account the cost uncertainties. Fig. 3 presents the total lifetime cost structures for all drive technologies considered in this study, across a range of scenarios. The results indicate that, in the most unfavourable scenario, LBG may prove to be the most expensive option. A comparison of the worst-case scenarios for LBG and diesel indicates

that LBG is 37 % more expensive. Nevertheless, in the optimal scenario, LBG is also predicted to be the most cost-effective option. This suggests that LBG exhibits the greatest cost volatility. Conversely, when considering expected scenarios, EVs are projected to be the most cost-effective solution, with estimated expenses approximately 17 % lower than those of diesel and 11 % lower than those of LBG. The costs associated with EVs are largely fixed, with minimal overall uncertainty. In order to gain a deeper understanding of the short-term costs, a division has been made between the overall TCO and the monthly TCO.

Fig. 4 illustrates the monthly TCO distributions for each vehicle category, with supplementary statistical data provided in Table 3. The standard deviation varies considerably across vehicle types, indicating different levels of cost predictability. Vehicles with higher standard deviations exhibit greater cost fluctuations and uncertainty in monthly expenses, while lower standard deviations indicate more consistent and predictable costs.

The expected values are at the peaks of the histograms, illustrated in Fig. 4, facilitate a rapid assessment of the mean monthly TCO across the diverse range of vehicles. It can be observed that vehicles with expected values that are significantly lower than the others are, on average, more cost-effective over the course of a month. Nevertheless, the relationship between expected values and standard deviation is of critical importance. A vehicle with a lower expected cost but a high standard deviation may ultimately prove to be less favourable due to the inherent unpredictability of costs.

The simulation results, which take into account both uncertainties and technical capabilities (see Table 2), are presented in Fig. 5 as a cumulative distribution function (CDF) for the monthly TCO per kilometre. The data clearly indicates that, in the majority of cases, LBG vehicles represent the most cost-effective solution. This result serves to illustrate the potential economic advantages of LBG vehicles, which are driven by factors such as fuel prices and range capabilities. Nevertheless, in scenarios where costs are highest, diesel vehicles emerge as a competitive alternative to LBG. In contrast, EVs consistently demonstrate the highest cost per kilometre (€/km) in comparison to both diesel and LBG vehicles across the majority of simulated scenarios.

The elevated cost of EVs can be attributed to a confluence of factors,

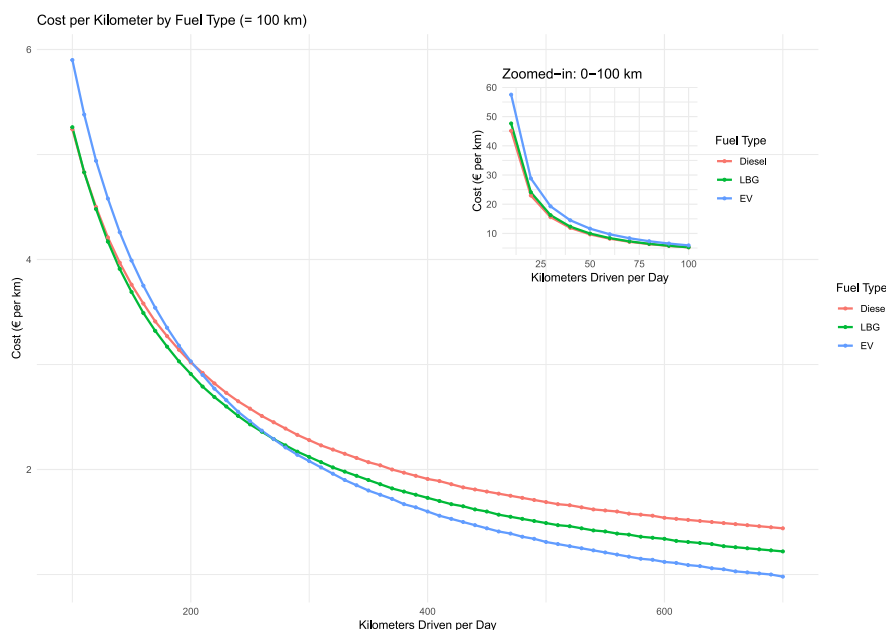
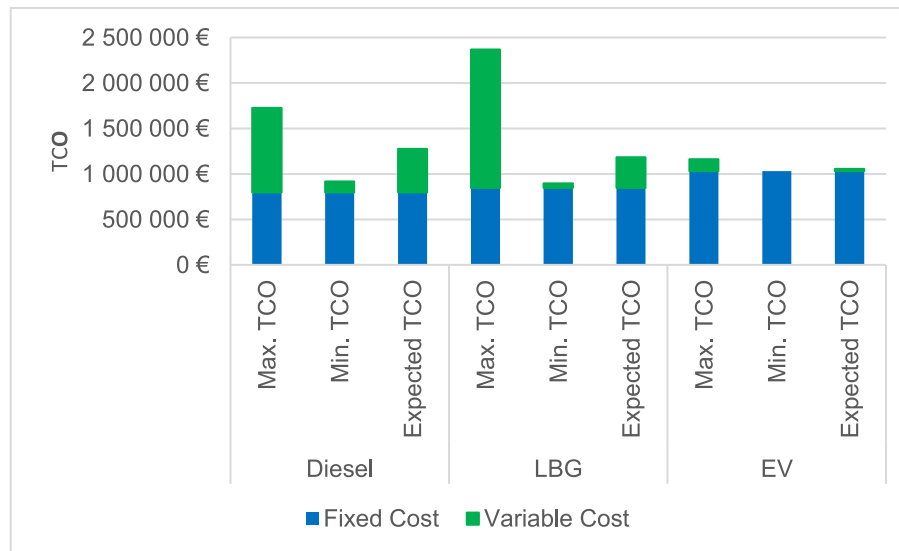


Fig. 2. TCO (€) as a function of driven kilometers, assuming fixed average costs and no stochastic variations (*ceteris paribus*).

Comparison of the Total Cost of Ownership (TCO) per kilometer for three types of vehicle fuels: Diesel, LBG, and EV. The vertical axis represents the TCO in euros, ranging from €0 to €6.00, while the horizontal axis shows the distance driven in kilometers, from 0 to 700 km. All three lines start at a higher cost per kilometres and decrease as the distance increases. The graph illustrates cost differences between vehicle types over increasing travel distances.



**Fig. 3.** TCO cost structure scenario comparison.

A bar chart comparing the Total Cost of Ownership (TCO) for three different categories: Diesel, LBG, and EV. Each category is represented by three sets of bars indicating the Maximum TCO, Minimum TCO, and Expected TCO. The bars are color-coded, with green representing Variable Costs and blue representing Fixed Costs. The vertical axis shows monetary values in euros, ranging from €0 to €2 500 000.

including a reduced range and a higher fixed cost. These elements have a considerable impact on the cost structure of EVs, rendering them less competitive in terms of cost per kilometre. However, under optimal conditions—such as low electricity prices and efficient operational patterns—EVs can achieve lower per-kilometre operating costs than diesel and LBG vehicles operating at their highest expense levels. The equilibrium between these two fuel options, diesel and LBG, indicates a responsiveness to contextual variables such as fuel costs and operational efficiency. This highlights the necessity of considering a multitude of factors when assessing the cost-effectiveness of different vehicle types, particularly in contexts characterised by diverse economic and operational circumstances.

A visual representation of the CDF of the monthly TCO for each vehicle category is provided in Fig. 6. The curve for EV trucks displays a notably steeper decline compared to those for diesel and LBG vehicles, indicating that EV trucks generally achieve superior TCO in most simulated scenarios. Further analysis indicates that, on average, EVs are 17.4 % more cost-effective than diesel vehicles and 8.6 % more economical than LBG vehicles. In approximately 82 % of all cases, the costs associated with EV trucks are observed to be lower than those of diesel or LBG vehicles.

The data suggests that the reduced TCO of EVs can be primarily attributed to their enhanced energy efficiency and reduced energy prices, which offset the higher initial investment costs typically associated with EVs. Furthermore, the pronounced slope of the curve for EVs can be attributed to two factors: their shorter driving range and the relatively stable electricity prices, which are less volatile than the fluctuating costs of diesel and LBG. The restricted range of EVs results in a more concentrated distribution of costs, while the consistent pricing of electricity contributes to a more predictable TCO for these vehicles.

The cost of emissions is incorporated into the TCO per month, as illustrated in Fig. 7. The results demonstrate that the emergence of EVs as a more cost-effective solution, when compared to diesel, is even more pronounced when emissions costs are taken into account. Similarly, LBG demonstrates cost competitiveness due to its low emission factor in comparison to diesel. The discrepancy in cost between EVs and LBG diminishes when emissions costs are taken into account. When emissions are taken into account, both the EV and LBG demonstrate superior performance in comparison to diesel. It is noteworthy that the emissions costs are already incorporated into the energy prices through the

distribution of electricity, whereas similar systems are not yet in place for diesel and LBG.

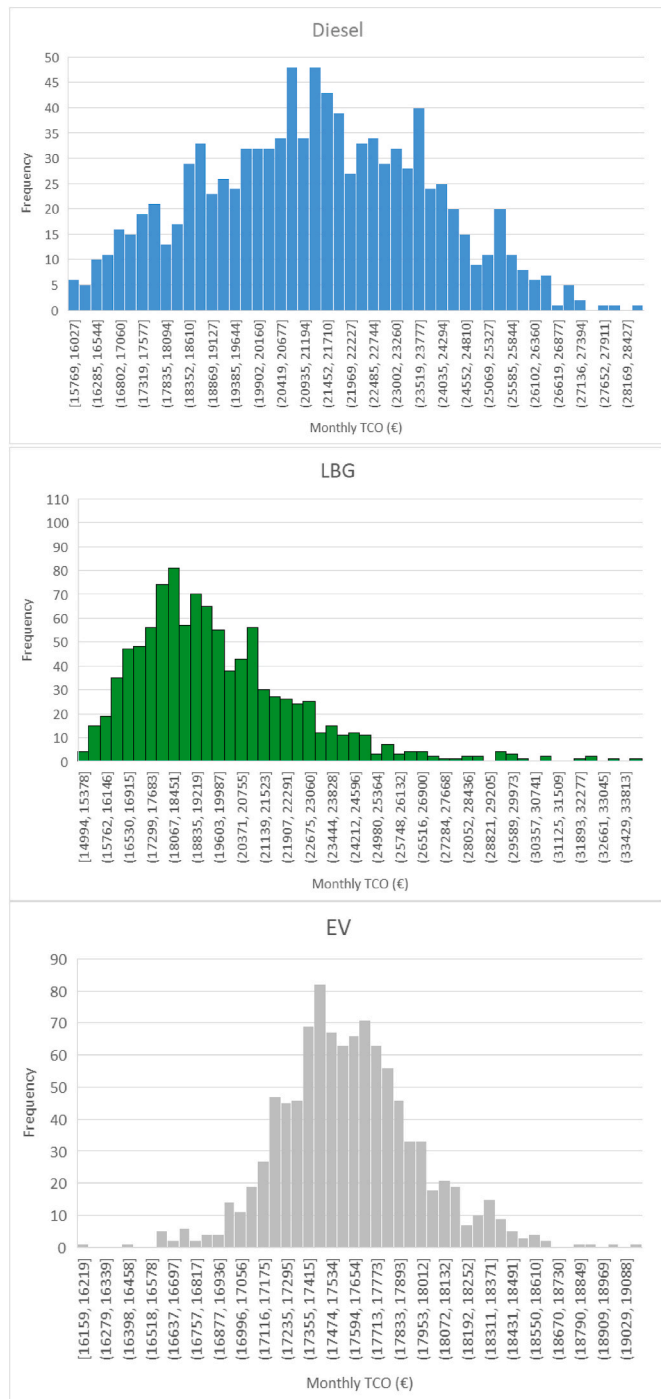
The accumulation of emission costs per kilometre across different energy sources is shown in Fig. 8. The data reveals that EVs powered by conventional grid electricity, which typically comes from a mix of sources, generate higher emission costs than LBG vehicles. LBG's lower emission costs stem from its renewable nature and lower GHG emissions throughout its lifecycle. Solar-powered EVs demonstrate the lowest emission costs among all options examined. This comparison highlights that EVs are not inherently the lowest-emission choice - their climate impact depends heavily on the source of electricity used for charging. Diesel vehicles show the highest emission costs, resulting in a substantially larger carbon footprint compared to other energy sources.

Fig. 9 illustrates the potential consumption averages and the number of refuelling or charging cycles. While these charging requirements do not directly affect the TCO calculations—beyond the inclusion of winter-month data in the analysis—they provide critical insights for fleet managers evaluating EV deployment.

The operational viability of EVs is predominantly constrained by battery capacity, which exerts a considerable influence on their range capabilities. An increase in energy consumption has the potential to negatively impact overall operational performance, particularly in the context of EVs. This increased energy demand not only results in more frequent charging but also extends the charging duration, thereby affecting the total travel time. The effects of refuelling and charging are demonstrated in Fig. 10.

These results indicate that, given the specifications of EVs in this case, the most favourable TCO is achieved on routes ranging from 200 to 390 km. Within this distance range, EVs can complete their routes without requiring a recharge, making them financially competitive with diesel and LBG vehicles. Diesel and LBG vehicles demonstrate lower TCO over longer distances, where the EVs' need for recharging increases.

Assuming a linear relationship between battery capacity and range, our results suggest that an EV would need a 1625-kWh battery to service routes up to 721 km in Finnish conditions without need to recharge in between. This far exceeds current practical battery capacities, which typically range from 1 kWh to 700 kWh (Alonso-Villar et al., 2022). This limitation highlights how geographic constraints and route requirements can challenge EV adoption, particularly in regions requiring longer-distance transport operations.



**Fig. 4.** Monthly TCO distributions per vehicle. Three histograms, each representing the Total Cost of Ownership (TCO) distributions for different vehicle types: Diesel, LBG, and EV.

The Spearman rank correlation analysis (Fig. 11) reveals distinct sensitivity patterns in the TCO across different vehicle technologies (Fig. 11). For EVs, daily travel distance emerges as the most significant factor with a strong positive correlation ( $\rho = 0.94$ ), while fuel price ( $\rho = 0.29$ ) and average consumption ( $\rho = 0.10$ ) show relatively weak correlations. This suggests that route distance, rather than energy costs or consumption, primarily drives EV operating economics.

LBG vehicles display a similar but less pronounced pattern, with daily travel distance maintaining the strongest correlation ( $\rho = 0.79$ ). However, LBG vehicles show greater sensitivity to fuel price ( $\rho = 0.53$ ) compared to EVs, while average consumption ( $\rho = 0.13$ ) remains weakly

**Table 3**

Comparative monthly TCO statistics from simulations for Diesel, LBG, and EVs.

	Diesel	LBG	EV
Mean	2.13E4	1.97E4	1.76E4
Median	2.13E4	1.92E4	1.76E4
Variance	6.46E6	7.90E6	1.27E5
Standard Deviation	2.54E3	2.81E3	3.57E2
Coefficient of Variation	0,12	0,14	0,02
Min	1.53E4	1.50E4	1.63E4
Max	2.88E4	3.95E4	1.94E4
Range	1.35E4	2.45E4	3.05E3
Standard Error	80	89	11

correlated with TCO.

Diesel vehicles present a distinctly different sensitivity profile. Fuel price demonstrates the strongest correlation ( $\rho = 0.85$ ), indicating that diesel TCO is highly susceptible to fuel market fluctuations. Daily travel distance shows a notably weaker correlation ( $\rho = 0.28$ ) compared to AFVs, while average consumption maintains a moderate correlation ( $\rho = 0.35$ ).

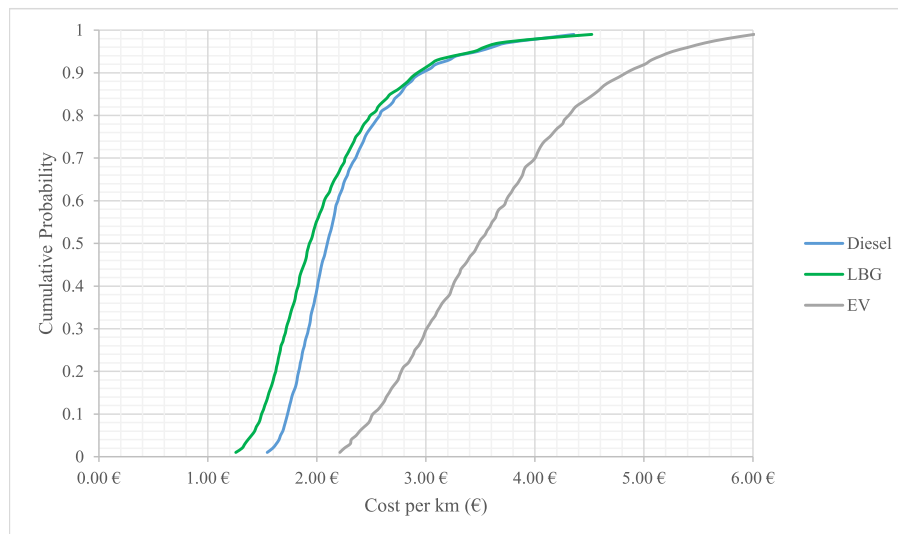
### 5. Discussion

In this study we have modelled the feasibility of different AFV options using actual empirical data to see how they compare. According to our literature review, only few studies have utilised primary empirical data on the heavy-duty transport sector. For example, Wang et al. (2024) have utilised primary data regarding fuel use and distance of medium and heavy duty vehicles. However, they do not specify whether this data is regarding all of the compared AFVs or only diesel and then modelled accordingly to other alternatives. They found that BEVs have 9%–34% higher TCO than diesel counterparts.

Another example of usage of primary data is the study by Gunawan and Monaghan (2022) where they focus on the potential of wind energy and its usage in heavy duty transport. Their focus is on the energy production scenarios, which differs from our study, but they also consider carbon abatement cost where they combine reduced emissions and TCO. We expand this thinking and use current ETS prices to estimate the effect on TCOs. Mojtaba Lajevardi et al. (2019) also use similar method in estimating abatement cost. They have also used primary data, though like Wang et al. (2024) they did not specify the vehicle drivetrain technology in their primary data collection.

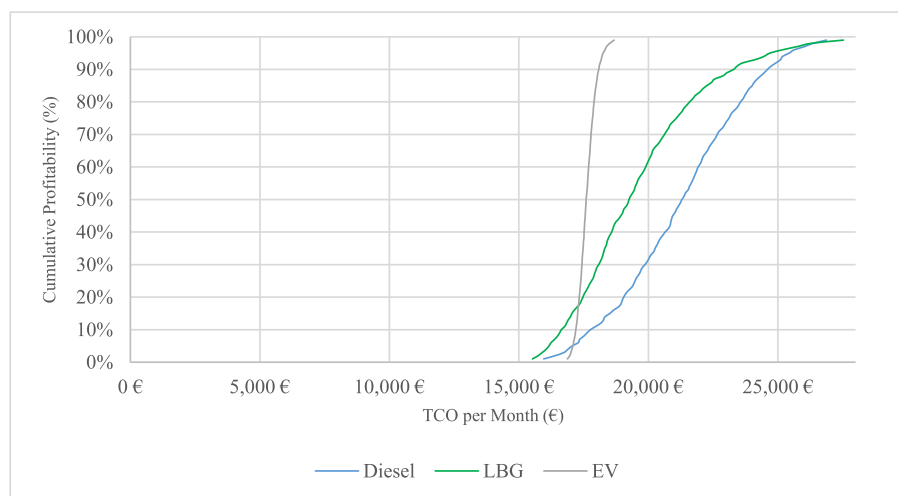
The study's approach is particularly relevant in the current business environment where many companies have established emission reduction targets, often framed as "halving" or "net-zero" goals. These organizations attempt to achieve these targets through various measures, including transitioning their transportation fleets to more environmentally friendly alternatives. However, since these transitions may not be immediately achievable or may require extended implementation periods, companies often purchase emission compensation. Notably, the market price for emission compensation closely aligns with the emissions trading price used in the energy production sector, making it a reliable benchmark for our analysis. By quantifying greenhouse gas emissions in terms of costs and investments, the present model enables the integration of environmental parameters into practical decision-making frameworks for commercial freight transport.

In this study, we deliberately excluded direct consideration of government subsidies and support mechanisms to ensure methodological consistency and comparative fairness across alternative fuel options. While acknowledging that government support for biomethane production likely influenced LBG prices during our data collection period, we treated these effects as embedded within the market prices rather than as separate variables. This approach is justified given the temporary nature and frequent changes in support systems across different jurisdictions. Similarly, diesel prices reflect varying biofuel blending mandates that fluctuate annually—sometimes even within a single



**Fig. 5.** Cumulative distribution function of monthly TCO per kilometre.

A graph with three lines representing different vehicle types: Diesel, LBG, and EV. The x-axis is labelled “€/km” and ranges from 0 to 6, while the y-axis shows percentages from 0% to 100%. Each line illustrates the cumulative percentage of the total cost of ownership (TCO) per kilometer for each vehicle type, allowing for a comparative analysis of their cost efficiency per kilometer.



**Fig. 6.** Cumulative distribution function of TCO per month.

A graph with three curves representing different vehicle types: Diesel, LBG, and EV. The x-axis is labelled “€/month” and ranges from 0 to 25,000, while the y-axis shows percentages from 0% to 100%. Each curve illustrates the cumulative percentage of the Total Cost of Ownership (TCO) per month for each vehicle type, allowing for a comparative analysis of their monthly costs.

year—and differ significantly between countries. By analysing market prices as they stand, our model captures the real-world economic conditions that fleet operators face when making vehicle acquisition decisions, regardless of the underlying policy mechanisms that shape those prices.

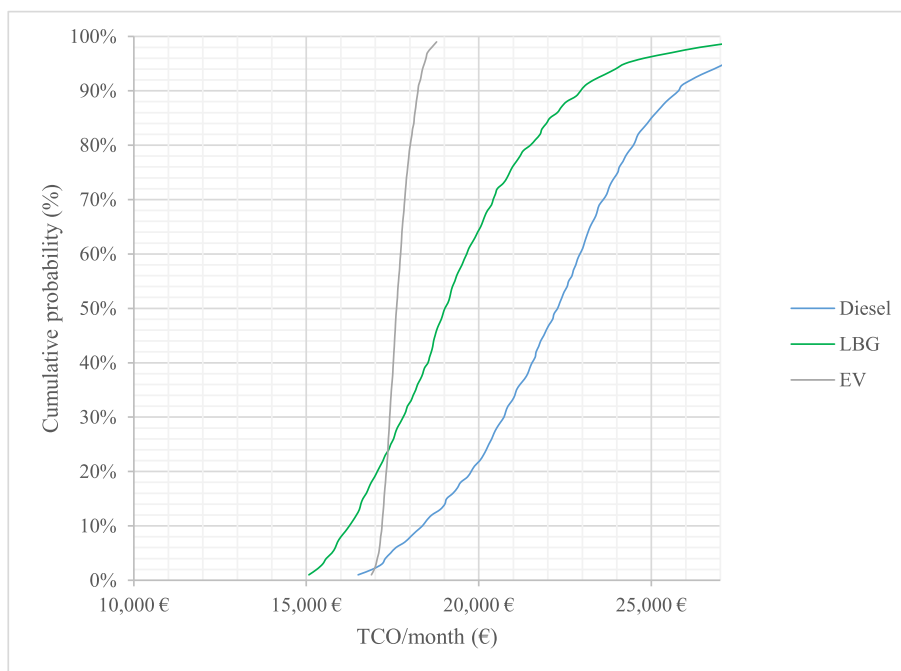
The primary contribution of this paper lies in demonstrating the economic feasibility of AFVs in commercial freight transport using empirical data. Studies have shown varying economic outcomes, from EVs having 11–33 % higher TCO than diesel (Wang et al., 2024) to EVs demonstrating economic competitiveness in specific scenarios (Jahangir Samet et al., 2024; Alonso-Villar et al., 2022).

This study addresses several gaps in the existing literature. First, while most recent research has concentrated on EVs and FCEVs, the scope is expanded by incorporating LBG as a viable alternative. This builds upon Gustafsson and Svensson’s (2021) findings that LBG could reduce GHG emissions by up to 75 % compared to diesel. Second, we

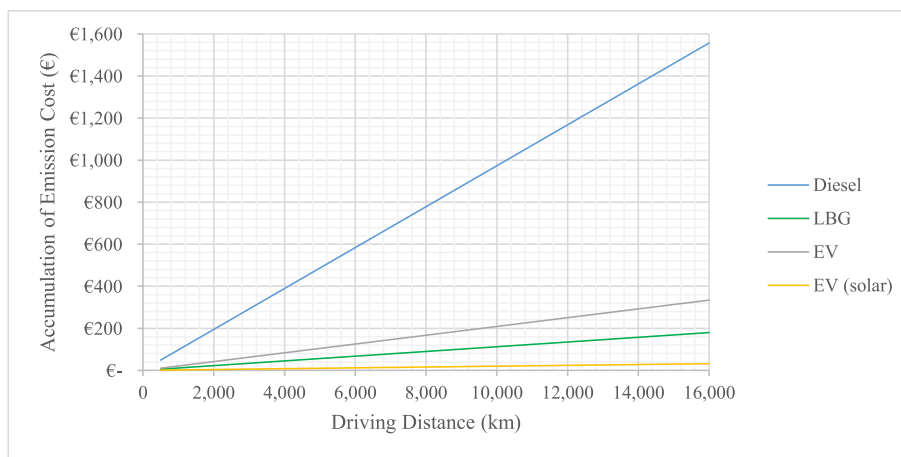
enhance the practical relevance of our findings through the use of real-world telemetry data rather than relying solely on secondary sources.

There is limited discussion on the impact of temperature on EV operational capabilities, particularly regarding battery performance. While battery degradation has been found to have minimal effects on TCO, temperature and weather conditions remain largely unaddressed (Wang et al., 2024). However, research indicates that cold climates, especially around  $-15^{\circ}\text{C}$ , pose challenges for long-haul EV operations, highlighting the importance of opportunity charging during loading, unloading, and rest periods to ensure feasibility (Jahangir Samet et al., 2024).

Our findings are consistent with international research. For instance, Alonso-Villar et al. (2022) demonstrated that EVs can achieve economic competitiveness with diesel in regional hauls in Iceland, while Jahangir Samet et al. (2024) confirmed similar results on a global scale,



**Fig. 7.** Cumulative distribution function of TCO including respective emissions cost of each vehicle. A graph with three lines representing different vehicle types: Diesel, LBG, and EV. The x-axis is labelled “€/month” and ranges from 10 000 to 25 000, while the y-axis shows percentages from 0% to 100%. Each line illustrates the cumulative percentage of the Total Cost of Ownership (TCO) per month, including emissions costs, for each vehicle type.



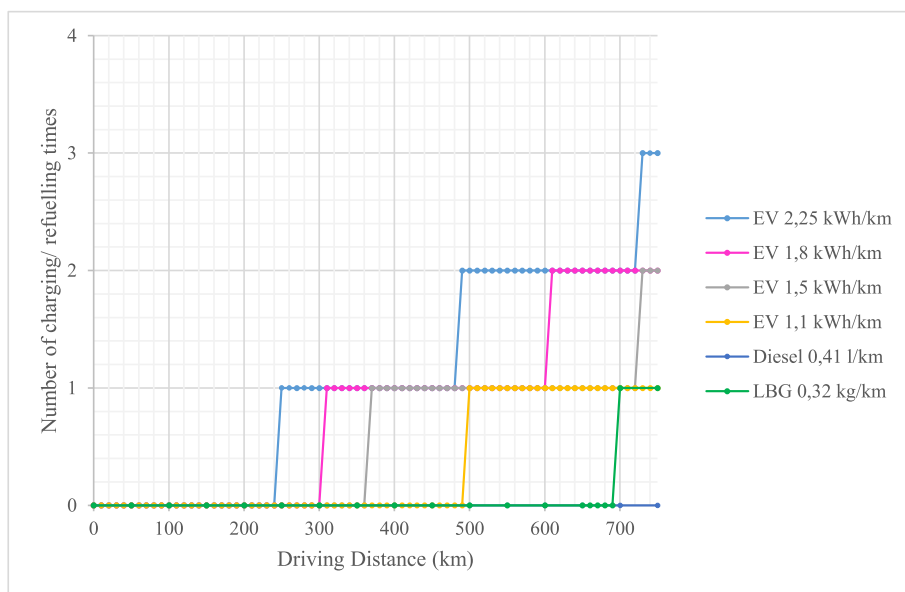
**Fig. 8.** Emission costs (€) of different vehicle types as a function of distance travelled (0–16 000 km). A graph comparing emission costs of different vehicle types over distances ranging from 0 to 16,000 kilometers. The vertical axis represents the emission cost in euros, while the horizontal axis shows the distance in kilometers. The graph illustrates how emission-related expenses vary across vehicle types, highlighting cost differences over increasing travel distances.

supporting the broader applicability of our conclusions. The alignment across different geographic contexts enhances the robustness of our findings.

Our findings show that LBG exhibits significant price volatility. This volatility can be attributed to several factors, with political decision-making playing a crucial role. Government policies and regulations, such as subsidies, carbon pricing mechanisms, and renewable energy mandates, directly impact the cost structure and market demand for LBG. For instance, the EU’s REPowerEU initiative and the Fit for 55 package aim to boost biomethane production but also introduce regulatory uncertainties that affect pricing stability (Chiaramonti and Testa, 2024). Beyond regulatory frameworks, geopolitical events and energy security concerns also contribute to volatility in this case. The recent

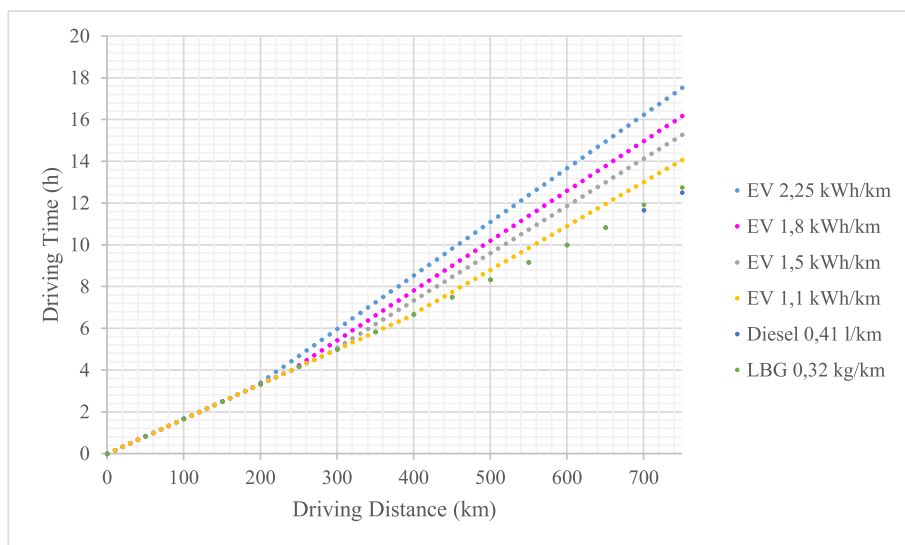
European energy crisis and supply chain disruptions have increased competition between biomethane and fossil natural gas, further affecting LBG pricing. Furthermore, the European biomethane market is still in its early stages (Chiaramonti and Testa, 2024). Also, different feedstock sources can result in different production costs, depending on substrate availability and processing requirements.

Despite the initial expense, in this case study EVs offer the lowest variable costs over longer distances, primarily due to the reduced cost of electricity in comparison to fossil fuels. Consequently, EVs become progressively cost-effective as the distance driven on a daily basis increase, attaining a greater cost-efficiency than diesel and LBG vehicles after 270 km per day. This trend illustrates the potential for EVs to offer substantial cost savings for users with higher mileages, despite the initial



**Fig. 9.** Refuelling or charging frequency as a function of distance travelled (0–700 km), illustrating the impact of different energy consumption rates on the number of refuelling or charging events required.

A graph illustrating how different energy consumption rates impact the frequency of refuelling or charging over distances ranging from 0 to 700 kilometers. The vertical axis shows the number of times refuelling or charging is needed, while the horizontal axis represents the distance in kilometers.



**Fig. 10.** Total time spent traveling as a function of distance (0–700 km), illustrating the impact of refuelling or charging on overall travel time.

A graph illustrating the impact of refuelling or charging on the total time spent traveling over distances ranging from 0 to 700 kilometers. The vertical axis represents time in hours, while the horizontal axis shows the distance in kilometers.

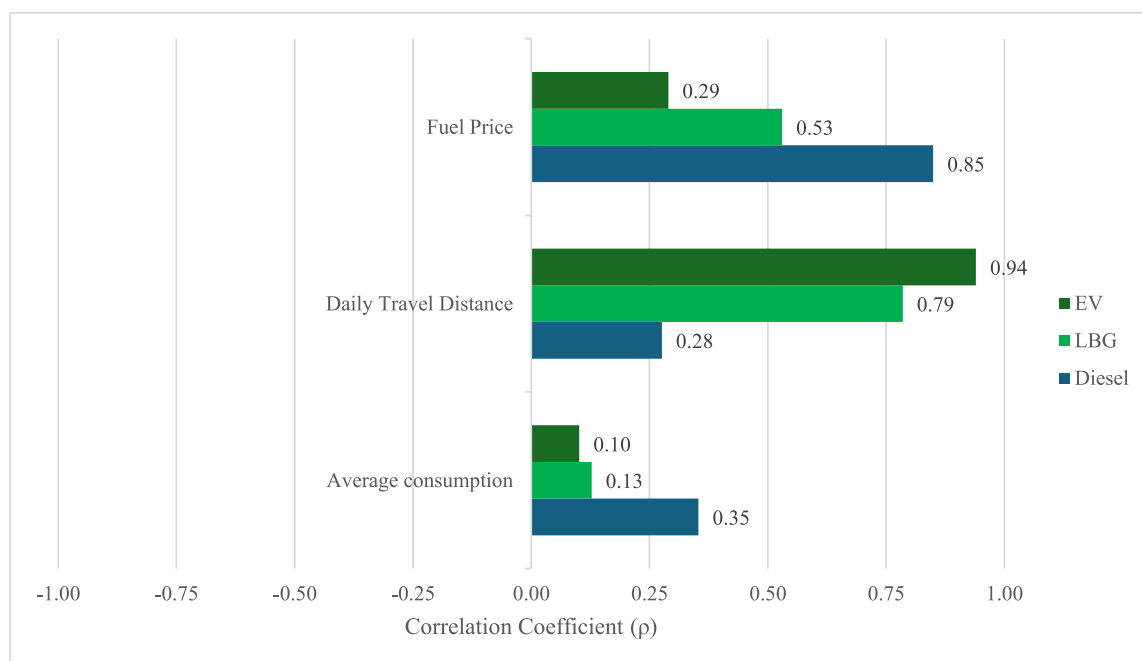
higher purchase price. Nevertheless, it is important to acknowledge that EVs have restricted range capabilities, despite their approximately fourfold energy efficiency compared to diesel. While charging requirements (approximately 2.5 h per full charge) might initially appear to limit operational flexibility, strategic planning can align charging periods with mandatory loading times, potentially eliminating any practical time penalties compared to diesel and LBG alternatives. This synchronisation of charging and loading activities allows EVs to achieve a maximum daily range of 786 km through two complete charge cycles, though careful route planning remains essential for longer hauls.

A key contribution of our study is the examination of leasing arrangements, an aspect largely overlooked in existing TCO analyses despite its increasing relevance in the transportation industry. Leasing offers a potential risk-mitigation strategy for adopting new technologies

by incorporating maintenance, residual values, and other cost variables, thereby reducing financial uncertainty for operators.

The adoption of ISO 14083:2023 for emissions calculations is becoming increasingly important due to regulatory developments such as the Corporate Sustainability Reporting Directive and the expansion of the Emissions Trading System (ETS) to road transport (Directive, 2023; European Commission, 2023). While most studies use Well-to-Wheel or Life Cycle Assessment methods, compliance with ISO 14083 is now essential.

Carbon pricing plays a critical role in decarbonizing road transport, but its long-term trajectory remains uncertain. Although transport is not currently included in emissions trading schemes, many companies are voluntarily implementing carbon compensation measures, effectively creating an opportunity cost that can be incorporated into TCO analyses.



**Fig. 11.** Spearman rank correlation analysis of variables with stochasticity (sensitivity analysis).

A correlation graph illustrating the Spearman rank correlation analysis of variables with stochasticity (fuel price, distance, and average consumption) Horizontal axis represents the spearman's rho.

If the EU maintains its current emission reduction targets, the emission cap may need to be tightened, potentially driving ETS prices significantly higher. Such developments could worsen the profitability of diesel while improving the competitiveness of alternative fuels such as LBG and EVs. [Haywood and Jakob \(2023\)](#) provide context for these concerns, arguing that achieving significant GHG reductions would require a carbon price exceeding 500€ per ton of CO<sub>2</sub>, whereas a lower price of €45 per ton would lead to only modest fuel price increases and limited emissions reductions. Conversely, policy shifts or economic factors could also result in lower carbon prices, affecting the cost dynamics of different technologies and the value proposition of voluntary compensation efforts.

## 6. Conclusions

The objective of this case study was to evaluate the financial viability of EVs and LBG vehicles in comparison to traditional diesel HDVs. A targeted analysis was conducted to assess the TCO and TCO per kilometre across different operational scenarios within this case specific context.

The findings indicate that for distances of less than 100 km, diesel represents the most cost-effective option, given its lowest fixed cost structure. For distances between 100 and 270 km, LBG demonstrates the lowest TCO. For distances between 270 and 390 km, EVs offer the lowest TCO. The energy efficiency of an EV is approximately four times that of a diesel truck, contributing to lower operating costs over the vehicle's lifetime. However, beyond an EV's single-charge range, the required recharging times make them impractical. Consequently, the LBG truck emerges as the most viable solution for longer routes in this case.

The low variable costs associated with EVs result in lower overall costs than those incurred by diesel and LBG vehicles in 82 % of the simulated cases. However, when analysing TCO per kilometres (TCO/km), the results differ due to the range capabilities of vehicles. The point of cost parity for LBGs is at 110 daily kilometres, while for EVs it is at 210 daily kilometres. Given the range capabilities of EVs, they have the highest cost per kilometre in the majority of scenarios. This indicates

that the technical feasibility of EVs has not yet reached a sufficient level of range capability for HDVs. These findings emphasise the necessity of considering the long-term financial benefits of EVs. It is anticipated that the economic benefits of EVs will increase further as technology advances and EV infrastructure expands, thereby further establishing EVs as a competitive alternative to conventional diesel and LBG vehicles.

EVs powered by renewable energy sources demonstrate the lowest emission costs among the studied alternatives. However, when charged with conventional grid electricity, which often relies heavily on fossil fuels, EVs generate higher emission costs than LBG vehicles. LBG shows consistently low emission costs. The emission cost analysis indicates that the climate impact of EVs depends critically on the carbon intensity of the electricity used for charging, while LBG maintains relatively stable emission costs regardless of operating conditions.

We further differentiate our research through following key contributions: introducing a leasing-based TCO calculation and incorporating potential emissions costs through the ETS. Our findings challenge the prevailing assumption that AFVs require policy support to achieve economic viability. While previous studies, suggested the need for incentives, our empirical evidence demonstrates that EVs and LBG vehicles can be competitive in specific operational scenarios without policy interventions. This insight is particularly valuable for transportation companies evaluating sustainable fleet options in the current regulatory environment.

### 6.1. Managerial implications

As renewable energy infrastructure and biomethane production expand, both EVs and LBG vehicles present promising pathways toward sustainable transportation solutions. However, currently overall better feasibility can be attributed to LBG. While EVs excel in short-range applications, LBG stands out as a more viable option for long-haul transport. Given the cost volatility of LBG, firms should assess their risk tolerance before investing. While LBG provides the lowest emissions and cost benefits under favourable conditions, its price fluctuations pose a challenge. Companies looking for long-term cost stability might consider

EVs, particularly for regional transport routes. Fleet managers should integrate strategic charging plans, utilising downtime during loading and unloading to mitigate range constraints. Contrary to the assumption that AFVs require policy support, findings suggest EVs and LBG can be cost-competitive in specific scenarios without incentives. This insight is valuable for transport companies considering sustainable fleet investments in the current regulatory landscape. Nonetheless, ongoing advancements in battery technology and renewable energy integration could shift this balance in the future, making both options crucial in the transition to greener transportation.

## 6.2. Limitations and future research

While our model offers insights for this case study, several limitations affect generalisability. This study utilised consistent truck models across all propulsion technologies to ensure comparability under controlled conditions. Our findings are specific to food transport operations using these vehicles within the described parameters. However, it is important to note that the core technologies examined in this study—diesel, electricity, biomethane—operate on similar fundamental principles across manufacturers. Therefore, while specific implementation details may vary, our findings regarding the relative advantages and limitations of each technology can reasonably be generalized to similar heavy-duty vehicles from other manufacturers. This sampling limitation should be considered when interpreting the comparative performance and cost assessments presented in this study. Notably, EVs incorporate diverse battery chemistries and configurations with varying cost profiles, performance characteristics, and degradation patterns. Our analysis focused specifically on the battery technology deployed in the selected model, and results might differ with alternative battery compositions. The TCO calculations represent current technological maturity levels, though our methodology provides a transferable framework applicable to different vehicle manufacturers, operational contexts, and geographic regions. As technology rapidly evolves—particularly in the electric vehicle sector—future comparative assessments may yield different outcomes. For broader applicability, further research incorporating multiple vehicle manufacturers, diverse battery technologies, and longitudinal data would strengthen these findings. This study should be interpreted as a targeted case analysis rather than a comprehensive evaluation of all low-carbon heavy-duty transport alternatives currently available.

It is important to note that the cost estimates and emission factors provided are based on the current prices in EU and in Finland. The future trajectory of costs remains uncertain, especially for emerging technologies such as batteries, which might affect the initial purchase costs of the vehicles. Additionally, the growing popularity of vehicles powered by alternative fuels could impact the initial purchase costs. The complexity of input parameters and the variability in factors such as fuel prices and vehicle efficiency can affect the reliability of the TCO model. These uncertainties introduce risk and can lead to fluctuations in the predicted TCO values. Our model uses assumptions and probability distributions, which could introduce bias into the calculations. Given the unique contextual factors, the applicability of the findings may be limited across different industries and regions.

This study's TCO model is based on a leasing arrangement rather than vehicle ownership, which impacts lifetime capital costs and end-of-life considerations. A comprehensive comparative analysis between vehicle ownership and leasing arrangements would provide valuable insights into the long-term financial implications of different ownership models. This is particularly relevant for AFVs, where end-of-life residual values and maintenance costs may differ significantly from conventional vehicles.

Technical development remains crucial, particularly in advancing battery technologies for improved range and charging efficiency. This study did not consider different battery chemistries and form factors; however, future research could elaborate on their distinct cost,

performance, and degradation characteristics. We also believe that long-term implications of battery degradation under various climatic conditions should be studied.

While our empirical data supports the economic advantage of EV trucks, the true cost-effectiveness of EVs must be evaluated within the broader context of energy system transformation and sustainable development goals. Future research directions should focus on quantifying these systemic costs and benefits to provide a more comprehensive understanding of the total economic impact of EV adoption in heavy-duty transport. The interplay between immediate operational cost advantages and longer-term systemic considerations will ultimately determine the success of EV adoption in transforming the heavy-duty transport sector. Additionally, exploring the impact of varying carbon price scenarios on the TCO will be crucial in understanding how evolving policy frameworks influence market competitiveness and investment decisions.

## CRedit authorship contribution statement

**Clara Rajalehto:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Petri Helo:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization.

## Declaration of competing 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.

## Acknowledgements

The authors extend their gratitude to the case company for generously providing the data necessary for conducting this research. This paper's earlier version was presented in NOFOMA 2024 conference in Stockholm. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jclepro.2025.145524>.

## Data availability

The data that has been used is confidential.

## References

- Aazami, A., Saidi-Mehrabad, M., 2021. A production and distribution planning of perishable products with a fixed lifetime under vertical competition in the seller-buyer systems: a real-world application. *J. Manuf. Syst.* 58, 223–247. <https://doi.org/10.1016/j.jmsy.2020.12.001>.
- ACEA, 2024. New commercial vehicle registrations: vans +12.6%, trucks -4%, buses +23.3% in Q1 2024. ACEA - European Automobile Manufacturers' Association. URL: <https://www.acea.auto/cv-registrations/new-commercial-vehicle-registrations-vans-12-6-trucks-4-buses-23-3-in-q1-2024/>.
- Alarcón, F.E., Cawley, A.M., Sauma, E., 2023. Electric mobility toward sustainable cities and road-freight logistics: a systematic review and future research directions. *J. Clean. Prod.* 430, 138959. <https://doi.org/10.1016/j.jclepro.2023.138959>.
- Ally, J., Pryor, T., 2016. Life cycle costing of diesel, natural gas, hybrid and hydrogen fuel cell bus systems: an Australian case study. *Energy Policy* 94, 285–294. <https://doi.org/10.1016/j.enpol.2016.03.039>.
- Alonso-Villar, A., Davíðsdóttir, B., Stefánsson, H., Ásgeirsson, E.I., Kristjánsson, R., 2022. Technical, economic, and environmental feasibility of alternative fuel heavy-duty vehicles in Iceland. *J. Clean. Prod.* 369, 133249. <https://doi.org/10.1016/j.jclepro.2022.133249>.
- Arora, S., Abkenar, A.T., Jayasinghe, S.G., Tammi, K., 2021. Chapter 2 - drivetrain configurations for heavy-duty electric vehicles. In: Arora, S., Abkenar, A.T.,

- Jayasinghe, S.G., Tammi, K. (Eds.), *Heavy-Duty Electric Vehicles*. Butterworth-Heinemann, pp. 37–48. <https://doi.org/10.1016/B978-0-12-818126-3.00003-8>.
- Bae, Y., Rindt, C.R., Mitra, S.K., Ritchie, S.G., 2024. Fleet operator perspectives on alternative fuels for heavy-duty vehicles. *Transp. Policy* 149, 36–48. <https://doi.org/10.1016/j.tranpol.2024.01.023>.
- Bjerkan, K.Y., Norbeck, T.E., Nordtømme, M.E., 2016. Incentives for promoting battery electric vehicle (BEV) adoption in Norway. *Transport. Res. Transport Environ.* 43, 169–180. <https://doi.org/10.1016/j.trd.2015.12.002>.
- Björner Brauer, H., Khan, J., 2021. Diffusion of biogas for freight transport in Sweden: a user perspective. *J. Clean. Prod.* 312, 127738. <https://doi.org/10.1016/j.jclepro.2021.127738>.
- Bongartz, L., Shammugam, S., Gervais, E., Schlegel, T., 2021. Multidimensional criticality assessment of metal requirements for lithium-ion batteries in electric vehicles and stationary storage applications in Germany by 2050. *J. Clean. Prod.* 292, 126056. <https://doi.org/10.1016/j.jclepro.2021.126056>.
- Bubeck, S., Tomaschek, J., Fahl, U., 2016. Perspectives of electric mobility: total cost of ownership of electric vehicles in Germany. *Transp. Policy* 50, 63–77. <https://doi.org/10.1016/j.tranpol.2016.05.012>.
- Chiaramonti, D., Testa, L., 2024. Deploying EU biomethane potential for transports: centralized/decentralized biogasrefinery schemes to SAF and maritime fuels. *Appl. Energy* 366, 123306. <https://doi.org/10.1016/j.apenergy.2024.123306>.
- Dahlgren, S., 2022. Biogas-based fuels as renewable energy in the transport sector: an overview of the potential of using CBG, LBG and other vehicle fuels produced from biogas. *Biofuels* 13, 587–599. <https://doi.org/10.1080/17597269.2020.1821571>.
- Danielis, R., Giansoldati, M., Rotaris, L., 2018. A probabilistic total cost of ownership model to evaluate the current and future prospects of electric cars uptake in Italy. *Energy Policy* 119, 268–281. <https://doi.org/10.1016/j.enpol.2018.04.024>.
- Delucchi, M.A., Lipman, T.E., 2001. An analysis of the retail and lifecycle cost of battery-powered electric vehicles. *Transport. Res. Transport Environ.* 6, 371–404. [https://doi.org/10.1016/S1361-9209\(00\)00031-6](https://doi.org/10.1016/S1361-9209(00)00031-6).
- Directive (EU), 2023. 2023/959 of the European parliament and of the council of 10 may 2023 amending directive 2003/87/EC establishing a system for greenhouse gas emission allowance trading within the union and decision (EU) 2015/1814 concerning the establishment and operation of a market stability reserve for the union greenhouse gas emission trading system (text with EEA relevance). *OJ L* 130, 134–202.
- Ellram, L.M., 1995. Total cost of ownership: an analysis approach for purchasing. *Int. J. Phys. Distrib. Logist. Manag.* 25, 4–23. <https://doi.org/10.1108/09600039510099928>.
- Ellram, L.M., 1993. A framework for total cost of ownership. *Int. J. Logist. Manag.* 4, 49–60. <https://doi.org/10.1108/09574099310804984>.
- European Commission, 2024. Green transition [WWW Document]. URL: [https://reform-support.ec.europa.eu/what-we-do/green-transition\\_en](https://reform-support.ec.europa.eu/what-we-do/green-transition_en).
- European Commission, 2023. CO2 emission standards for heavy-duty vehicles [WWW Document]. European Commission - European Commission. URL: [https://ec.europa.eu/commission/presscorner/detail/en/qanda\\_23\\_763](https://ec.europa.eu/commission/presscorner/detail/en/qanda_23_763).
- Forrest, K., Mac Kinnon, M., Tarroja, B., Samuelsen, S., 2020. Estimating the technical feasibility of fuel cell and battery electric vehicles for the medium and heavy duty sectors in California. *Appl. Energy* 276, 115439. <https://doi.org/10.1016/j.apenergy.2020.115439>.
- Gunawan, T.A., Monaghan, R.F.D., 2022. Techno-econo-environmental comparisons of zero- and low-emission heavy-duty trucks. *Appl. Energy* 308, 118327. <https://doi.org/10.1016/j.apenergy.2021.118327>.
- Gustafsson, M., Svensson, N., 2021. Cleaner heavy transports – environmental and economic analysis of liquefied natural gas and biomethane. *J. Clean. Prod.* 278, 123535. <https://doi.org/10.1016/j.jclepro.2020.123535>.
- Hagman, J., Ritzén, S., Stier, J.J., Susilo, Y., 2016. Total cost of ownership and its potential implications for battery electric vehicle diffusion. *Research in Transportation Business & Management, Innovations in Technologies for Sustainable Transport* 18, 11–17. <https://doi.org/10.1016/j.rtbm.2016.01.003>.
- Haywood, L., Jakob, M., 2023. The role of the emissions trading schemes in the policy mix to decarbonize road transport in the European union. *Transp. Policy* 139, 99–108. <https://doi.org/10.1016/j.tranpol.2023.06.003>.
- International Organization for Standardization, 2023. ISO 14083:2023 - quantification and reporting of greenhouse gas emissions arising from transport chain operations. ISO Standard No. 14083:2023. URL: <https://www.iso.org/standard/78864.html>. (Accessed 9 April 2025).
- Izadi, A., Nabipour, M., Titidezh, O., 2019. Cost models and cost factors of road freight transportation: a literature review and model structure. *Fuzzy Information and Engineering* 11, 257–278. <https://doi.org/10.1080/16168658.2019.1706960>.
- Jahangir Samet, M., Liimatainen, H., Pihlatie, M., van Vliet, O.P.R., 2024. Levelized cost of driving for medium and heavy-duty battery electric trucks. *Appl. Energy* 361, 122976. <https://doi.org/10.1016/j.apenergy.2024.122976>.
- Ji, D., Gan, H., 2022. Effects of providing total cost of ownership information on below-40 young consumers' intent to purchase an electric vehicle: a case study in China. *Energy Policy* 165, 112954. <https://doi.org/10.1016/j.enpol.2022.112954>.
- Jones, J., Genovese, A., Tob-Ogu, A., 2020. Hydrogen vehicles in urban logistics: a total cost of ownership analysis and some policy implications. *Renew. Sustain. Energy Rev.* 119, 109595. <https://doi.org/10.1016/j.rser.2019.109595>.
- Katreddi, S., Thiruvengadam, A., Thompson, G.J., Schmid, N.A., 2023. Mixed effects random forest model for maintenance cost estimation in heavy-duty vehicles using diesel and alternative fuels. *IEEE Access* 11, 67168–67179. <https://doi.org/10.1109/ACCESS.2023.3290994>.
- Krause, J., Yugo, M., Samaras, Z., Edwards, S., Fontaras, G., Dauphin, R., Prenninger, P., Neugebauer, S., 2024. Well-to-wheels scenarios for 2050 carbon-neutral road transport in the EU. *J. Clean. Prod.* 443, 141084. <https://doi.org/10.1016/j.jclepro.2024.141084>.
- Lévay, P.Z., Drossinos, Y., Thiel, C., 2017. The effect of fiscal incentives on market penetration of electric vehicles: a pairwise comparison of total cost of ownership. *Energy Policy* 105, 524–533. <https://doi.org/10.1016/j.enpol.2017.02.054>.
- Mojtaba Lajevardi, S., Axsen, J., Crawford, C., 2019. Comparing alternative heavy-duty drivetrains based on GHG emissions, ownership and abatement costs: simulations of freight routes in British Columbia. *Transport. Res. Transport Environ.* 76, 19–55. <https://doi.org/10.1016/j.trd.2019.08.031>.
- Noll, B., del Val, S., Schmidt, T.S., Steffen, B., 2022. Analyzing the competitiveness of low-carbon drive-technologies in road-freight: a total cost of ownership analysis in Europe. *Appl. Energy* 306, 118079. <https://doi.org/10.1016/j.apenergy.2021.118079>.
- Pääkkönen, A., Aro, K., Aalto, P., Kontinen, J., Kojo, M., 2019. The potential of biomethane in replacing fossil fuels in heavy transport—A case study on Finland. *Sustainability* 11, 4750. <https://doi.org/10.3390/su11174750>.
- Padder, S.A., Khan, R., Rather, R.A., 2024. Biofuel generations: new insights into challenges and opportunities in their microbe-derived industrial production. *Biomass Bioenergy* 185, 107220. <https://doi.org/10.1016/j.biombioe.2024.107220>.
- Palmer, K., Tate, J.E., Wadud, Z., Nellthorpe, J., 2018. Total cost of ownership and market share for hybrid and electric vehicles in the UK, US and Japan. *Appl. Energy* 209, 108–119. <https://doi.org/10.1016/j.apenergy.2017.10.089>.
- Pellegrini, L.A., De Guido, G., Langé, S., 2018. Biogas to liquefied biomethane via cryogenic upgrading technologies. *Renewable Energy, SI: Waste Biomass to Biofuel* 124, 75–83. <https://doi.org/10.1016/j.renene.2017.08.007>.
- Rajashankara, K., 1994. History of electric vehicles in general motors. *IEEE Trans. on Ind. Applicat.* 30, 897–904. <https://doi.org/10.1109/28.297905>.
- Roosen, J., Marneffe, W., Vereeck, L., 2015. A review of comparative vehicle cost analysis. *Transp. Res.* 35, 720–748. <https://doi.org/10.1080/01441647.2015.1052113>.
- Wang, Z., Acha, S., Bird, M., Sunny, N., Stettler, M.E.J., Wu, B., Shah, N., 2024. A total cost of ownership analysis of zero emission powertrain solutions for the heavy goods vehicle sector. *J. Clean. Prod.* 434, 139910. <https://doi.org/10.1016/j.jclepro.2023.139910>.
- Wu, G., Inderbitzin, A., Bening, C., 2015. Total cost of ownership of electric vehicles compared to conventional vehicles: a probabilistic analysis and projection across market segments. *Energy Policy* 80, 196–214. <https://doi.org/10.1016/j.enpol.2015.02.004>.
- Zhang, X., Lin, Z., Hao, H., Hao, X., Wang, Z., Li, S., 2024. Environment-economic comparison of potential alternative fuel heavy-duty trucks in China. *Transport. Res. Transport Environ.* 131, 104206. <https://doi.org/10.1016/j.trd.2024.104206>.
- Zhou, H., Chen, B., Han, Z.X., Zhang, F.Q., 2009. Study on probability distribution of prices in electricity market: a case study of Zhejiang Province, China. *Commun. Nonlinear Sci. Numer. Simulat.* 14, 2255–2265. <https://doi.org/10.1016/j.cnsns.2008.04.020>.