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ORIGINAL ARTICLE

Assessing scope 3 transportation emissions: A calculation tool for sustainable manufacturing

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Abstract
Scope 3 emissions, particularly those arising from transportation activities, pose a substantial challenge for manufacturing organisations seeking to reduce their carbon footprint. This study presents the development of a carbon dioxide emissions estimation tool designed to enhance the accuracy and practical application of emissions measurement for inbound transport within the supply chain. The tool integrates key variables, namely vehicle type, distance travelled, and load carried and employs Monte Carlo simulation to account for data uncertainty. Using empirical data from a manufacturing firm, the study evaluates the emissions impacts of various transportation scenarios. Results indicate that distance travelled and vehicle load are the primary determinants of emissions magnitude. While larger vehicles offer improved efficiency when fully utilised, emissions per unit of goods transported depend on load optimisation and vehicle selection. The analysis further reveals the considerable variability introduced by multi-stop routing and uneven load distribution, underscoring the complexity of real-world logistics. These insights underscore the value of scenario-based modelling for emissions estimation and provide a foundation for developing more effective decarbonisation strategies in transport logistics.

Keywords Carbon accounting tool · Scope 3 emissions · Transportation emissions · Monte carlo simulation · Sustainable manufacturing

1 Introduction

Climate change and environmental sustainability have become critical challenges for the global manufacturing sector, necessitating comprehensive carbon accounting across entire value chains. The Greenhouse Gas (GHG) Protocol classifies emissions into three scopes: Scope 1 (direct emissions from owned or controlled sources), Scope 2 (indirect emissions from purchased electricity, heat, or steam), and Scope 3 (all other indirect emissions occurring within the supply chain and product life cycle) [1]. While many manufacturing organisations have developed methodologies to quantify and mitigate their Scope 1 and 2 emissions, Scope 3 emissions remain a significant challenge due to their complexity, data availability issues, and the involvement of multiple stakeholders.

Scope 3 emissions are divided into fifteen distinct categories under the Greenhouse Gas Protocol, including Purchased Goods and Services, Capital Goods, Fuel- and Energy-Related Activities, Upstream Transportation and Distribution (Category 4), Waste Generated in Operations, Business Travel, Employee Commuting, and Downstream Distribution and Processing. This study focuses explicitly on Category 4: Upstream Transportation and Distribution, which encompasses emissions generated from the transportation of products purchased by the reporting company, in vehicles not owned or operated by the reporting company.

Within Scope 3 emissions, Category 4: "Upstream Transportation and Distribution", represents a challenging area for manufacturing companies to quantify, as it depends on multiple interrelated factors, including transportation modes, fuel types, distances travelled, vehicle efficiency, and logistics strategies [2]. Accurate accounting of Category 4 emissions is critical because they often represent a substantial portion of a manufacturing company's total Scope 3 footprint. However, they are challenging to quantify due to data

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complexity and operational variability. This is especially so as many manufacturing firms are increasingly outsourcing their own transportation operations to third-party warehouse logistics providers. As for inbound logistics, it is not common practice to control the type and size of vehicles that deliver raw materials, components and assemblies to the factory doors. However, given that transportation emissions contribute significantly to a company's overall carbon footprint, their accurate measurement is becoming necessary for effective sustainability strategies towards net-zero [3]. A notable issue is that existing carbon accounting tools often lack precision, fail to incorporate uncertainty, or do not consider real-world logistical variations, leading to inconsistent or unreliable emissions reporting [4]. For example, EcoACT ACTR (Accountability, Carbon Tracking, and Reporting) provides businesses with structured methods for measuring and managing their carbon footprint across different activities, including transportation. However, while comprehensive in emissions reporting [5], it does not provide scenario-based modelling with detailed uncertainty, nor do the tools provided by the GHG protocol, which prioritise simplicity, comparability, and ease of use for general emissions reporting. EcoTransIT World is another tool that models and calculates the environmental impact of freight across different transport modes. Although it incorporates some scenario modelling capabilities, it primarily relies on predefined assumptions without customisable uncertainty simulation [6].

To address this gap, this study developed a data-driven tool for calculating CO_2 emissions to enhance the accuracy of Scope 3 transportation emissions measurement. The tool integrates key transportation variables—vehicle type, load capacity, and travel distance—while employing Monte Carlo simulations to model uncertainty and assess emissions variability under different logistical scenarios. By applying this tool to real-world transportation data from a manufacturing supply chain, the study identifies the primary determinants of transportation-related CO_2 emissions. Furthermore, it evaluates the efficiency of different vehicle types under varying loading conditions.

2 Related work

In the context of the energy crisis and climate change, most countries consider the transition to low-carbon development and growth essential [7]. Among the sectors responsible for emissions, the transport industry plays a pivotal role in the battle against climate change, given the high level of CO2 generated by the consumption of fossil fuels [8]. Nevertheless, the high energy demand of the sector represents a significant challenge to achieving carbon neutrality [9]. It is therefore highly desirable to gain a comprehensive understanding of the drivers of transport emissions to effectively identify reduction strategies and their relevance for economic development [10].

In response to this challenge, numerous tools have been developed in recent years in the field of carbon accounting that facilitate the decision-making process on adopting carbon mitigation strategies [11]. Such tools may assist companies in reporting their emissions and, more importantly, in understanding the key factors that contribute to emissions in their specific context. This will ensure that the efforts made to identify avenues for carbon reduction can be both targeted and effective [12].

Tools capable of measuring carbon emissions can also contribute to transparency and consistency in sustainable reporting, aligning with regulations and standards [13]. Such openness can enable businesses and consumers to make informed and responsible decisions [2], whilst it has been shown that reductions in carbon emissions are often accompanied by reductions in costs and an increase in operational efficiency within companies [14].

According to the International Energy Agency (IEA), CO2 emissions from road transport have increased significantly and were predicted to be almost 60% higher in 2022 than in 2019 [15]. Today, transport accounts for around 25% of total greenhouse gas emissions in the European Union (EU), central to economies and trade connectivity [16]. However, the current transport model has its challenges. In addition to its significant contribution to CO2 emissions, the transport sector has negative environmental impacts, including air and noise pollution and habitat fragmentation. Accurate quantification of these emissions is crucial for developing effective mitigation strategies and promoting sustainable practices in the transportation sector, thereby addressing economic and environmental challenges [17].

Addressing these challenges requires a multifaceted approach. For instance, the need for standardisation is a foundational step. In 2019, Kellner and Schneiderbauer proved that there is no globally accepted standard for allocating greenhouse gas (GHG) emissions to shipments in road freight transport. Most methodologies often focus on specific regions, single transport modes or are complex to use [18]. As a result of this inconsistency, and since the prevailing standard of EN 16258:2012 [19] was not rigorous in accounting for the Well-to-Wheel requirement of Scope 3, Wild [20] proposed the development of a harmonised and universal CO2 calculation standard for the transport and logistics sector. Such a global standard must be comprehensive, globally applicable, and practical. However, challenges remained, such as data availability, verification and auditing, or accounting for uncertainty [20].

Another critical challenge in measuring CO2 emissions is the collection of accurate data. The lack of reliable, standardised and high-quality data is an obstacle to correctly measuring Scope 3 emissions. It can lead to a lack of information needed to make informed decisions about reducing carbon emissions from the supply chain [21]. Furthermore, since supply chains are intricate networks comprising multiple nodes and tiers of suppliers, accurate Scope 3 emissions data necessitate access to information from all these tiers. This is challenging, given that companies may not control, have access to, or indeed be obliged to share data, even if they do possess it. As a solution, Stenzel and Waichman proposed a combination of technology solutions, regulatory support, and collaborative efforts between companies to enable accurate and efficient reporting of Scope 3 emissions [22]. This was pertinent to the ISO 14083:2023 [23] standard that came into effect, replacing EN 16258:2012, which, although it offers a framework for data collection, does not resolve data-sharing access challenges across the multiple tiers of the upstream supply chain [24].

In addition to data collection, variability in emissions is a crucial factor to consider. Transport emissions depend on several factors, including distance travelled, vehicle type, load, traffic conditions, and driving style, which introduces considerable variability into the calculations [25]. For this reason, given that the new, improved global standard of ISO 14,083 does not provide a new set of emission factors, it is essential to incorporate uncertainty into any modelling tool to obtain more realistic results by considering a variety of scenarios.

Finally, another significant challenge is accurately allocating GHG emissions along distribution routes. In complex supply chains, this task can be a considerable challenge. Currently, approaches such as the star method often assign equal CO2 emissions to each customer on a route, regardless of location or order size. This approach does not account for the varying contributions of each customer to the total emissions generated along the route. Naber et al. address this issue by exploring alternative methods that consider factors such as distance and order size to more fairly allocate CO2 emissions on distribution routes [26]. Existing models tend to prioritise operational variables such as fuel consumption or distance travelled. For instance, Lagou-dis and Shakri developed a model that calculates transportation and distribution carbon emissions based on several factors, providing a series of scenarios to help companies achieve their sustainability goals. While these models are undoubtedly helpful, they often lack a comprehensive approach to the entire lifecycle of emissions [27]. To address the lifecycle aspect, a project titled Lumbreras et al. proposed a methodology for calculating the total GHG emissions related to the road transport fleet. It considers vehicle manufacturing, fuel production, transportation, vehicle use, and end-of-life. This approach provided a more holistic view of emissions but could be complex to implement due to the extensive data required [28].

EmiTRANS is another tool designed to calculate future emissions from road transportation and evaluate emission reduction strategies. It provides users with the capacity to comprehend future emission trends and evaluate the impact of implemented emission reduction strategies within the road transport sector [29]. However, its accuracy depends heavily on the quality of input data and assumptions about future developments.

In GHG emissions modelling, several approaches have also emerged to address uncertainties. For example, CAT v1.0, developed in 2018, assesses GHG emissions in managed forests, though it was limited to forestry. This indicates a need for similar models tailored to the transport sector [30]. Similarly, a study proposed advanced methods, including the Delphi method, neural networks, and Monte Carlo simulation, to quantify carbon emissions in China's civil aviation sector. However, restrictions such as limited data and subjective methods highlighted the need for further refinement of the research [31].

Shin Hee Baek and Jong Soo Kim integrated carbon emissions and quantity discounts into optimisation. This framework provides a foundation for sustainable supply chain decision-making, yet it necessitates precise data on emissions and discounts, which may prove challenging to obtain [32]. Wang et al. [33] explored the inclusion of carbon emissions in supply chain decisions. Their study presented an Analytic Network Process-Integer Programming (ANP-IP) model for supplier selection and order allocation, incorporating both economic factors and carbon emissions within a carbon emission trading scheme (ETS). The study demonstrated that a stricter ETS could promote low-carbon supply chains.

The reviewed literature highlighted numerous models that have been applied to project CO2 emissions in the transport echelons of supply chains. However, these models do not account for uncertainties in the carbon emission factors, which can lead to potential inaccuracies in carbon accounting. Figure 1 places the studied models in a "design space" about their inclusion of uncertainty and data collection and integration complexities, thus highlighting a current gap in analytical rigour.

By incorporating uncertainty in critical transport parameters such as distance or load conditions, a new tool has been developed to model stochastic scenarios of these parameters to help companies more accurately manage and reduce their category 4, Scope 3 supply chain carbon footprint.

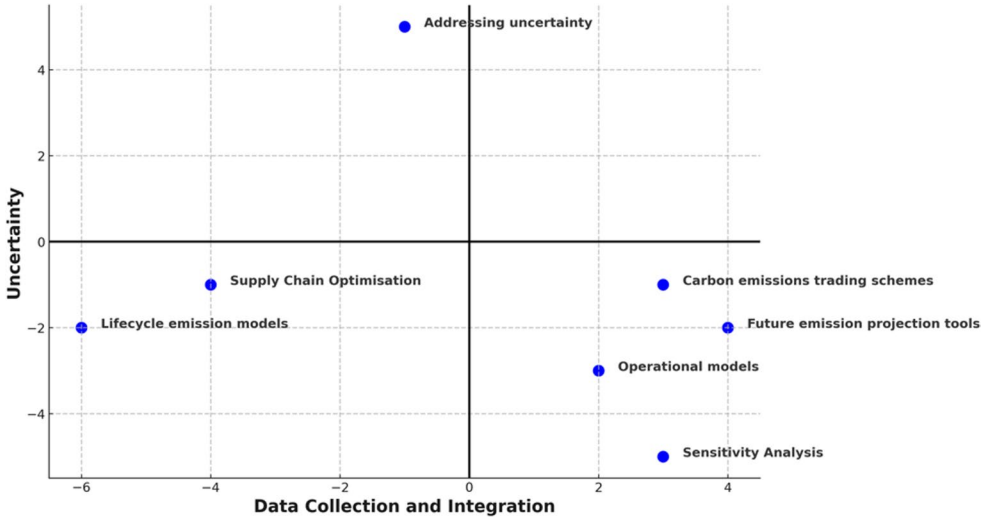


Fig. 1 Design space of existing models

3 Model development

The literature review highlighted the need for a simple decision-making model that also considers uncertainty. To ensure simplicity and wide applicability, the tool was developed using Microsoft Excel with the @RISK Monte Carlo simulation add-in (Palisade Corporation). @RISK integrates seamlessly with Excel to perform Monte Carlo simulations by allowing users to define uncertain input variables with specific probability distributions and automatically propagate these uncertainties through thousands of randomised simulations to produce probability distributions of outputs, sensitivity analyses, and confidence intervals.

The user interface is designed to facilitate data entry and display complete results. Key features include:

- Data entry: Simple forms for manual input of distance, vehicle weight, and vehicle load.
- Calculation of results: The calculations' results are displayed immediately, and the CO2 emissions based on the parameters entered can be viewed.
- Uncertainty analysis visualisation: The tool also visually represents the uncertainty analysis results, including histograms and sensitivity analysis graphs.

There are three main approaches to calculating emissions from transportation, as highlighted by a comprehensive literature review:

- *Fuel-based method* that determines the amount of fuel consumed (i.e., Scope 1 and Scope 2 emissions of transport providers) and applies the appropriate emission factor to the specific fuel used [3].
- *Distance-based method* that involves determining the mass, distance, and mode of each shipment, and then applying the appropriate mass-distance emission factor for the vehicle used [3].
- *Spend-based method* that involves determining the amount of money spent on each mode of business travel transport and applying secondary emission factors [3].

The primary objective of this model was to incorporate uncertainty into the calculation of CO2 emissions, particularly in relation to distance and vehicle load, so the distance-based method was employed. Fuel-based and spend-based methods depend on accurate fuel consumption or financial records, which can be hard to obtain from third parties. The distance-based method, however, relies on the distance covered that companies can typically access more easily, thus simplifying data collection and usage. Figure 2 depicts the methodology used in the development of the tool.

3.1 Key model factors and parameters

The model includes the following key parameters for calculating CO_2 emissions:

- *Distance travelled D*: This represents the total distance travelled by the vehicle during the transportation activity, measured in kilometres (km). It was modelled as a random variable using a Gaussian (normal) distribution with a standard deviation changing depending on the scenario analysed. This reflects the typical variability in transport distances resulting from traffic, detours, and logistical routing issues [25]. The normal distribution is additionally well-supported by the central limit theorem when the distance is an aggregate of many small random

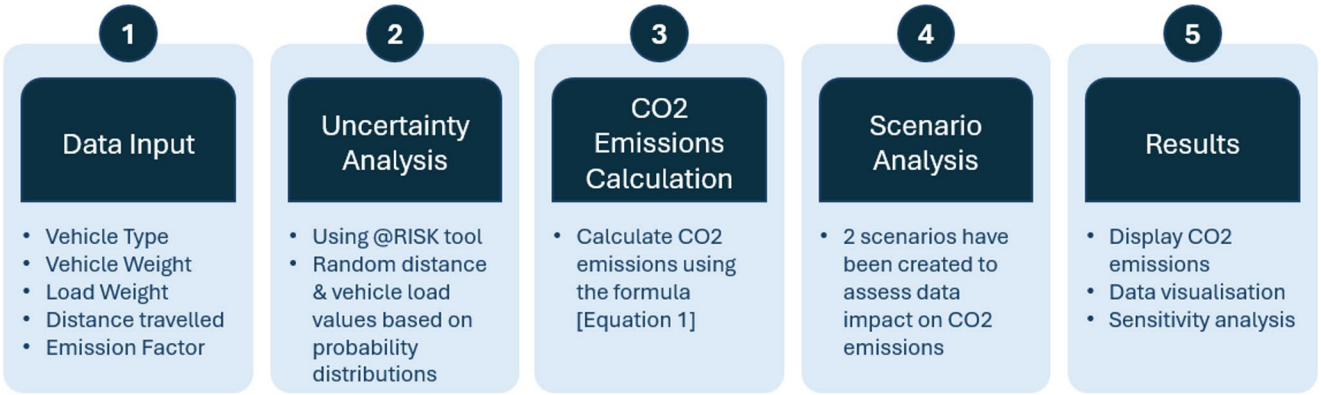


Fig. 2 Methodology framework

variables. Finally, the data collected from companies supported this, as for the same destinations, the actual tracked distances fitted a Gaussian distribution, most likely due to the drivers' attempts to avoid traffic jams.

- *Vehicle Weight W*: This refers to the vehicle's tare weight, excluding any load it carries. It is measured in kilograms and was modelled as a constant for each truck type. The data collected from vehicle manufacturers also supported this.
- *Vehicle Load L*: This value refers to the weight of the goods being transported, measured in kilograms (kg). It was modelled as a random variable using a triangular distribution with minimum, most likely, and maximum values based on actual operational records. This was to reflect asymmetric variability; whereby fully loaded trips are less frequent than underloaded or almost empty trips [26]. Triangular distribution works well when empirical load distributions are not available, but simultaneously accounts for the fact that loads are bound between 0 and a maximum value, with the aim of the operators being always to maximise the load. Finally, triangular data can help quantify expert knowledge from the operators, allowing for a quick, realistic approximation that respects real-world constraints.
- *Vehicle Type*: Fuel efficiency and emission factors depend on the type of transport vehicle. In this model, three different types of road transport were considered: commercial vans, referred to as pickup trucks, rigid trucks, and articulated trucks. Table 1 shows that there are different values for load capacity, tare weight, and emission factor for every kind of vehicle and percentage of laden use.
- *Vehicle Fuel*: In this model, only diesel fuel has been considered.
- *Emission Factor EF*: Emission factors translate activity data quantities into greenhouse gas emissions. They are derived from the emissions associated with the production of materials and fuels, transport operations, waste management and other processes [27]. They are measured in grams of CO2 released per km. EF were assumed to be constant in the model (fixed values from established databases), and thus not treated as stochastic variables in the model.

Table 1 Values considered for each vehicle type

Vehicle Type	Load Capacity (kg)	Tare Weight (kg)	Fuel type	Laden	CO2 Emission Factor (g CO2/km)
Pickup Truck	1,000–1,500	1,500–2,500	Diesel	100%	231.56
Rigid Truck	5,000–12,000	7,500 − 12,000	Diesel	0%	692.15
				50%	823.68
				100%	955.22
Articulated Truck	20,000–30,000	16,000–18,000	Diesel	0%	65.3
				50%	867.5
				100%	1,078.7

Once all model elements were identified, the formula used to calculate the final emissions becomes:

$$CO_{2\,e} = D^{*}(W + L)^{*}EF \tag{1}$$

3.2 Data quality and validation

To ensure model accuracy and relevance to real-world conditions, actual data from the inbound shipment logs of a medical products SME manufacturing company operating in the UK were utilised. Data cleaning involved cross-verifying shipment records, removing outliers (defined as load weights beyond three standard deviations), and resolving missing entries by conservative imputation where necessary.

Although basic cross-validation against recorded shipment weights and distances was conducted to ensure plausibility, the dataset's size and structure did not permit a formal train-test split or independent validation. Consequently, at this level, the model is considered exploratory

and indicative for the SME under consideration, rather than fully predictive. Further validation with larger, independent datasets remains an objective for future research. Nevertheless, uncertainty in the distance parameter was considered for real-life data, as variations in travelled distance can arise due to actual traffic and route conditions, the number of stops a vehicle makes, and other logistical factors. The @ RISK software was employed to simulate a range of possible outcomes, thereby incorporating uncertainty into the emission calculations.

3.3 Modelling uncertainty

A total of 10,000 Monte Carlo iterations were performed for each scenario. This was determined sufficient after convergence analysis showed stabilisation (<1% variation) in key output metrics beyond 8,000 iterations. Uncertainty was propagated through random sampling across 10,000 iterations. Output metrics included full probability distributions, means, standard deviations, confidence intervals, and sensitivity charts, providing quantification of emissions variability.

It would be reasonable to assume that vehicle type and typical load are naturally related (e.g. a pickup truck rarely carries a 10-tonne load). However, limitations in the available real-world data precluded robust estimation of correlation coefficients. Hence, correlations between uncertain variables were not explicitly modelled. Therefore, the Monte Carlo simulation treated each input variable (e.g. distance travelled, vehicle load) as statistically independent. While this simplified the modelling process, it may have underestimated or overestimated uncertainty in combined outputs. Future work could incorporate correlations where data availability permits, further refining the realism and accuracy of emissions projections.

3.4 Risk simulation scenarios

By varying the key parameters, it is possible to analyse how changes in load, distance, vehicle type, or fuel affect CO_2 emissions and identify areas where actions can be taken to reduce CO_2 emissions. Thus, many forward-looking scenarios can be proposed that can facilitate a quantitative interpretation of future emissions [34]. Two scenarios were examined with the real transportation data: The first was to assess the impact of direct (point-to-point) inbound freight load and distance on emissions, and the second was to study the effects of multi-stop vehicle routings. These two scenarios were chosen as they represent the most common approaches to inbound transport logistics that seek to maximise delivery efficiency through vehicle route scheduling optimisation.

3.4.1 Scenario 1

Initially, the baseline scenario considered three types of vehicles, which vary in size, capacity, and fuel consumption, as shown in Table 1. Most shipments necessitate the utilisation of smaller vehicle types, which were frequently observed to be approximately half-empty for the data donor company. In this scenario, it was assumed that the vehicles travel directly from the point of origin (usually from a supplier's premises or a 3rd party logistics consolidator) to the company in question and then return to their departure point without making any additional stops. This direct route enables a straightforward evaluation of CO_2 emissions, bypassing the complexities of additional logistics. Considering this, a 10% uncertainty in the distance travelled was assumed to account for possible variations in the route taken, such as minor detours due to traffic or road conditions (which was reflected in the model as a Gaussian distribution with a standard deviation set at 10% of the mean).

3.4.2 Scenario 2

This scenario modelled the objective to maximise vehicle utilisation by assuming that each vehicle trip consisted of four stops: three delivery points and a return to the origin. This approach would distribute the carbon emissions of each vehicle across multiple companies (drop-off points), but the additional stops would likely result in longer travel distances. Thus, the 3rd stop was designated as our data donor's delivery point, while the other stops were randomly generated using Excel and @RISK to simulate real-world conditions. Random variables included the distance between stops and the load delivered at each point. Crucially, each vehicle was assumed to begin each trip with a full load and gradually decrease its cargo with each subsequent delivery at a stop point. In this scenario, the uncertainty for the distance varied between 30% and 50%, accounting for the potential complexity of routes with multiple stops, such as the need for refuelling, mandatory rest stops, or adapting to weather and road conditions that may alter estimated distances and times.

4 Results

For the 1 st scenario, CO_2 emissions are plotted in Fig. 3 against the distance travelled for each truck category, with a linear trend line to illustrate the distribution of the collected data. The graphs demonstrate a correlation between distance travelled and CO_2 emissions across all three categories of vehicles. However, the data distribution varies in terms of linearity according to truck size. In the case of the pickup

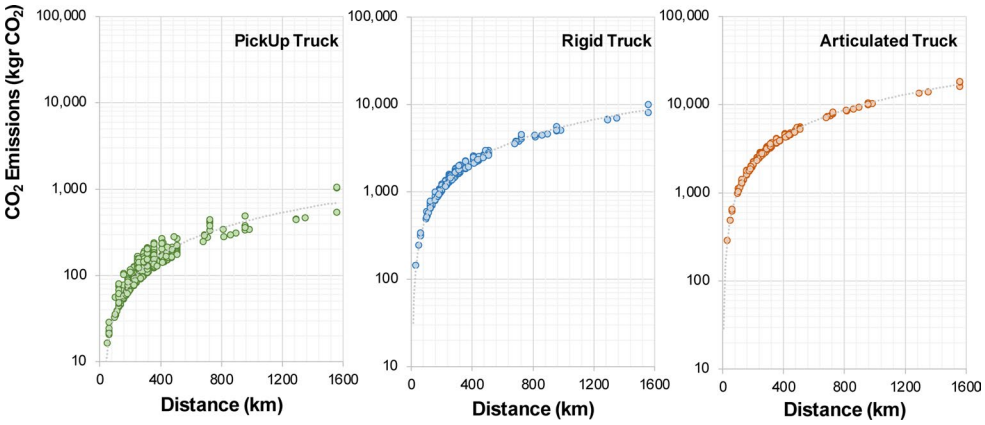


Fig. 3 CO_2 emissions against distance for three different types of vehicles under the baseline scenario 1

truck, the data points are more scattered, particularly at shorter distances and lower emission levels. Conversely, as the truck size increases, the relationship between CO_2 emissions and distance becomes more linear, with data points aligning more closely to the trend line, especially for the articulated truck.

Further analysis of these results can highlight the CO_2 emissions variances for each vehicle type. Using a box-plot distribution in Fig. 4, the variability of emissions across vehicle types is presented. This was generated based on the distribution of simulated CO_2 emissions per kilometre for each vehicle type, using outputs from the Monte Carlo simulation. Each box shows the interquartile range (25th to 75th percentiles), with the median represented by a central line. Whiskers extend to show the range of data, excluding outliers, which are plotted individually. The graph reveals that in the case of pickup trucks the emissions are lower and tightly clustered, indicating minimal variability, while for rigid and articulated trucks the emissions are more varied with several high outliers, indicating occasional high emissions. The emissions results for each vehicle type were accompanied by 95% confidence intervals, derived from the Monte Carlo simulation output. For example, for the pickup truck category under direct shipment conditions, the mean emissions were estimated at 0.28 kg CO_2/km with a 95% CI of (0.25–0.31 kg CO_2/km).

A further parameter that appears to have a substantial impact on the calculation of CO_2 emissions is the quantity transported by each truck. As the company in question does not always order enough orders to fill a vehicle fully, this variable has been analysed using relative efficiency, which is calculated by considering the CO_2 emissions per km travelled and the number of kg transported.

A truck loaded with less than a full load or transporting light loads may be anticipated to operate at a capacity below that which could be achieved with a fully laden vehicle. This will result in greater emissions per unit of load than optimal, while excessive weight may cause resistance to progress and lead to increased energy costs. The scatter plots in Fig. 5 illustrate the relationship between load and CO_2 emissions, independently of the distance travelled.

The results demonstrate that the relationship between emissions per distance and load is linear, exhibiting variation according to vehicle size. The data indicate that smaller vehicles, such as pickup trucks, show a steeper slope, suggesting that an increase in load has a more pronounced impact on fuel consumption. In contrast, larger trucks have more gradual inclines, indicating they are better suited to transporting substantial loads. This discrepancy can be attributed to different factors, including load efficiency and empty weight.

Linear regression analyses on the scatter plots of distance versus emissions yielded the R^2 values included in Fig. 5. These values indicate strong linear relationships between distance travelled and CO_2 emissions, particularly for larger vehicle types.

The model's emissions outputs were qualitatively compared to average emissions factors from the DEFRA (UK

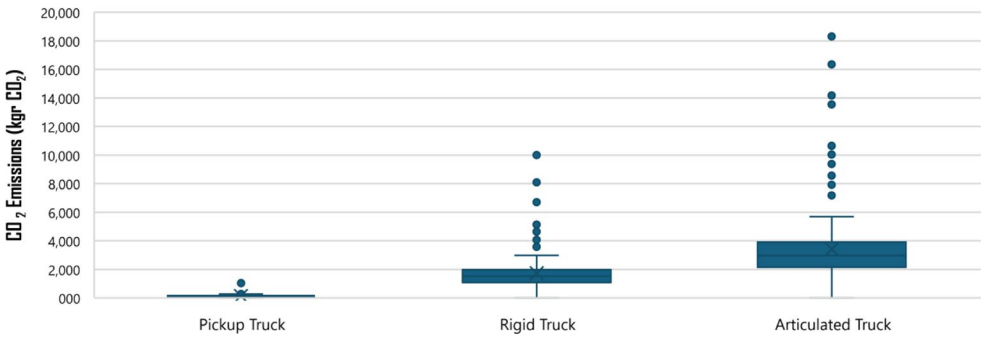


Fig. 4 Emissions distribution for each vehicle type

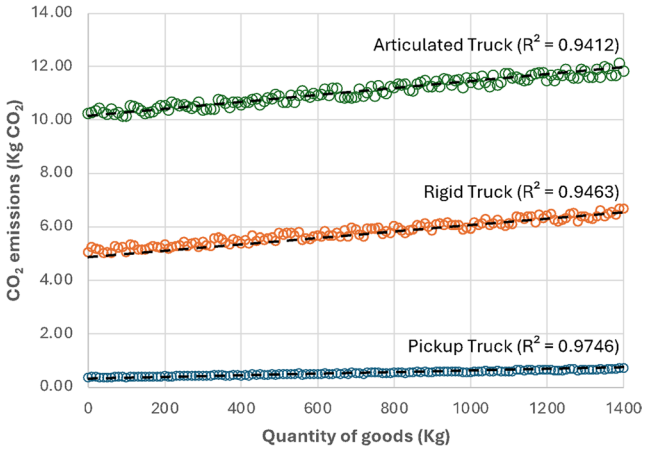


Fig. 5 CO_2 emissions against loaded weight for three different types of vehicles under the baseline scenario 1

Government) freight data. Results for direct shipment scenarios were within 10% of DEFRA's reported averages for similar vehicle types, lending preliminary external validity to the tool's projections. Considering these results, Fig. 6 shows that the Pickup truck is the most efficient for like-for-like transported load as it emits less CO_2 per km travelled.

To validate the observed differences in CO_2 emissions across vehicle types presented in Fig. 6, a one-way Analysis of Variance (ANOVA) was conducted on the simulated emission data. The ANOVA results indicated statistically significant differences between vehicle groups (p-value < 0.01), confirming that the observed differences in emissions efficiency between pickup trucks, rigid trucks, and articulated trucks are unlikely to have occurred by chance. This reinforces the conclusion that vehicle type selection is predominant in emissions optimisation.

Additionally, as shown in Fig. 6, compared to the pickup truck, the other vehicles are less efficient in terms of freight transport because they emit more CO2 per unit load.

Finally, a sensitivity analysis derived from regression coefficients in the @RISK simulations ascertained the variables with the greatest impact on CO_2 emissions. In each case, the distance travelled was the highest and most dominant factor, explaining 70–85% of the variability in emissions. Vehicle loading variability accounted for 15–30%. Emission factors, being constants, contributed no variability. These results were visualised through importance charts generated by @RISK, supporting the prioritisation of distance optimisation strategies for emissions reduction.

For the 2nd scenario, a route involving four consecutive stops with the company receiving its goods at the 3rd truck stop was analysed to demonstrate a linear relationship with a positive slope, as shown in Fig. 7, indicating that the greater the distance travelled, the greater the amount of carbon emitted.

Figure 8 shows that the truck emits more carbon dioxide during the origin and the first stop than during the rest of the journey. After the first stop, the emissions per km drop progressively. This clearly demonstrates the impact of the transported weight on emissions. Although the higher the weight, the higher the carbon emissions, there is a weight that generates far more emissions than would be the case if the reduction were not progressive over the entire route and for the entire weight transported.

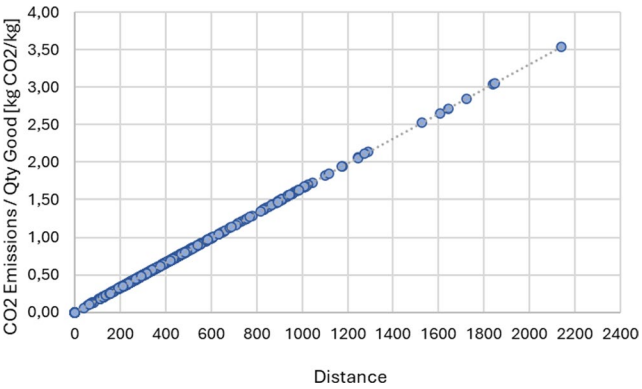


Fig. 7 Multiple stops scenario– emissions against distance

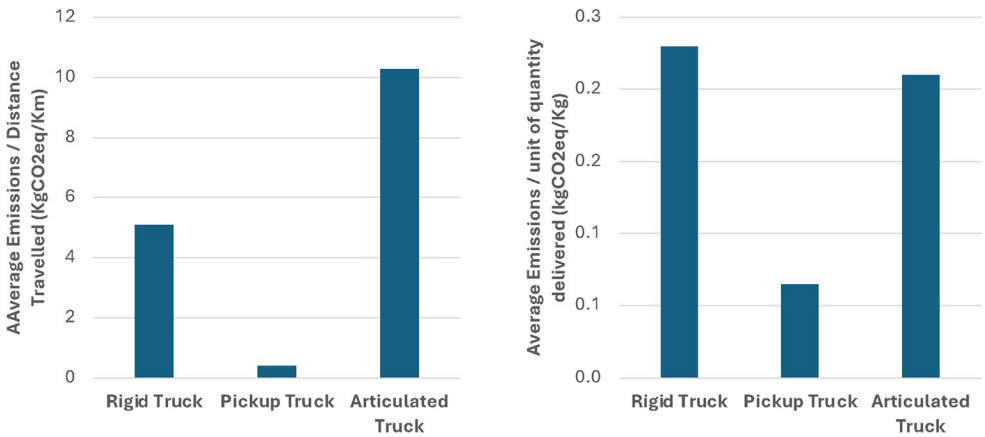


Fig. 6 Average CO2 emissions by distance travelled by vehicle type (left) and by unit of quantity delivered (right)

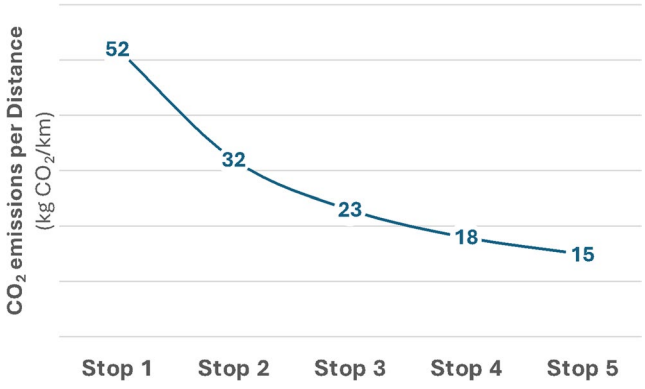


Fig. 8 CO_2 emissions per distance at each stop

5 Conclusion

This study aimed to develop a methodological tool capable of incorporating relevant and reasonable degrees of uncertainty in the assessment and projection of emissions associated with Category 4 (inbound transport logistics) under Scope 3 carbon dioxide emissions. The aim was to enhance the accuracy of carbon accounting within the supply chain. The modelling framework was constructed using accessible and cost-effective tools, enabling the incorporation of uncertainty and the simulation of scenarios that realistically reflect the upstream logistics of a typical medical company.

Quantitative analysis demonstrated that, under direct shipment scenarios, pick-up trucks emitted an average of 0.28 kg CO_2/km (95% Confidence Interval: 0.25–0.31 kg CO_2/km). The implementation of multi-stop routing led to an estimated 12% increase in total emissions relative to direct point-to-point deliveries. Sensitivity analysis indicated that the distance travelled accounted for approximately 70–85% of the variability in emissions, while vehicle load contributed between 15 and 30%.

The findings yielded two principal insights. First, regardless of vehicle type, distance travelled emerged as the predominant factor influencing road freight emissions, suggesting its suitability as a heuristic for prioritising optimisation strategies. Second, for organisations similar in operational profile to the one used to model the tool, particularly those that frequently procure less-than-truckload consignments, it is advisable, where feasible, to specify the use of pick-up trucks (or delivery vans) rather than rigid or articulated trucks. In scenarios involving round-robin deliveries, it is advantageous for goods to be received towards the latter part of the route, provided this sequencing does not compromise service levels and simultaneously supports freight cost optimisation.

Nevertheless, despite incorporating uncertainty into the tool, the inherent assumptions and simplifications necessitate a cautious interpretation of the results, especially when extrapolating to real-world logistics systems that are typically more dynamic and complex. The model may underestimate emissions in such settings, potentially leading to sub-optimal decisions in carbon management strategies if applied without contextual adjustments.

The current version of the tool is limited to diesel-powered vehicles and does not accommodate alternative-fuel or electric vehicle types. Furthermore, correlations between uncertain variables, such as vehicle type and load, were not incorporated due to data limitations. Multi-stop routing was modelled using randomised stop generation rather than optimised algorithms.

Consequently, when employing this model, companies are encouraged to adapt the input data to more accurately reflect their specific operational contexts. This is readily achievable, as the tool, implemented in Excel and supported by @RISK, remains both affordable and user-friendly. Through such customisation, organisations can begin to model their own extended supply chains and construct tailored scenarios that elucidate optimal trade-offs. This, in turn, enables proactive reduction of inbound logistics emissions and supports broader Scope 3 emission reduction efforts, using company-specific data supported by robust graphical and numerical outputs to inform decision-making.

Future research may focus on extending the tool's capabilities to incorporate a wider range of vehicle powertrains (e.g., electric and hybrid), implementing vehicle routing optimisation algorithms for multi-stop simulations, and integrating correlations between transport variables using larger and more diverse datasets to enhance the model's robustness and generalisability.

Author contributions All authors contributed to the conception and design of the study. Cristina Garcia Llubia performed material preparation, data collection, and analysis. Cristina Garcia Llubia and John Patsavellas wrote the first draft of the manuscript, and all authors reviewed and edited the final version. Konstantinos Salonitis supervised the project. All authors read and approved the final manuscript.

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Declarations

Competing interests The authors have no relevant financial or non-financial interests to disclose.

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