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A green vehicle routing methodology for assessing optimal fleet mix and cost/emissions tradeoffs given environmental policy incentives

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Abstract

Transportation accounts for nearly one quarter of global greenhouse gas (GHG) emissions. A significant proportion of transportation emissions can be attributed to supply chain transport, which also represents the fastest-growing sector of emissions. As a way of addressing this challenge in the effort to combat global climate change, many local and national governments have leveraged public policy in the form of carbon taxes, emissions trading systems (ETSs), and subsidies for heavy goods electric vehicles (HGEVs). Firms affected by these policies are thus faced with higher costs for more emissions-intensive supply networks and a lower barrier to entry towards adopting HGEVs. However, the exact policy conditions under which firms would be most motivated to change their behaviors remains unclear. In this paper, we develop a novel methodology to address this obstacle in the form of a bi-objective green vehicle routing problem. The first objective is the minimization of the total cost of transportation over a set of vertices comprised of a depot, customers, and charging stations; the second objective is the minimization of total GHGs emitted during transportation. The proposed approach considers the three policy instruments and their effects on both fleet mix decisions (i.e., the conditions under which a firm is most motivated to adopt HGEVs) and cost- and GHG-minimizing routing options. Via an analysis of the change of the Pareto frontier given increasingly stringent carbon pricing and/or increasingly generous HGEV subsidies, firms may consider routing options that yield the most significant GHG emissions reduction at the lowest cost. To this end, we provide a survey of current and forecasted global trends related to carbon tax rates, ETS carbon allowance prices, and HGEV subsidy amounts.

Author summary

When firms design their supply chain transportation networks, they generally do so with the primary objective of minimizing the total transportation cost. Consequently,

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they reasonably maximize the profitability and long-term viability of their firm. However, this is often paired with the social cost of higher GHG emissions and thus a greater contribution to global warming. In an effort to reduce the social cost of these GHG emissions, government policymakers utilize various tools to increase the monetary cost of more emissions-intensive behaviors and remove barriers to “emissions-friendly” behaviors. With reference to road freight transportation, the most commonly implemented policies to encourage “greener” supply chains are carbon taxes, ETSs, and subsidies for HGEVs. Our research presents a methodology by which policymakers can assess the extent to which their manifold of policies in this area are likely to incentivize behavioral change amongst the firms they regulate. Conversely, this same methodology can be used by regulated firms to analyze how to respond to current or potential future policy conditions, and how they might decrease their emissions from road transport at the lowest possible cost.

1. Introduction

Transportation emissions accounted for 23% of all energy-related global greenhouse gas (GHG) emissions in 2019, equivalent to 8.7 $GtCO_2$-eq, making it the third most significant and fastest-growing emissions sector [1,2]. In 2021, road transport accounted for 78% of transportation emissions, with two-thirds of these emissions attributed to passenger transport and one-third to supply chain transport, respectively [3]. Consequently, GHG emissions from road freight supply chain transport alone comprises approximately 6% of total global emissions, representing 2.3 $GtCO_2$-eq. According to the International Energy Agency, achieving the target of Net Zero by 2050 set by the Paris Accords would necessitate a 3% annual *decrease* in transport GHG emissions, which can be contrasted with the historical 1.7% average annual *growth* rate of emissions in this sector between 1990 and 2022 [4,5]. Thus, it remains a priority for policymakers, executives, advocacy groups, and academia to deploy, advocate for the deployment of, or research a variety of efficacious political and organizational instruments towards climate change mitigation efforts. The objective of this paper is to develop a method for assessing how a few increasingly common governmental policies can modulate organizational incentives and decisions related to supply chain management.

One organizational instrument aimed at minimizing GHG emissions, which has gained broader interest in the most recent decade, is the Green Vehicle Routing Problem (GVRP). The GVRP is a variant of the Vehicle Routing Problem (VRP) first formulated by [6] in 1959. In the VRP, which has given rise to multiple variants and thousands of research articles since its inception, firms seek to determine the most efficient route for their fleet of vehicles to deliver goods or services to various locations. Firms may utilize a wide range of available models and mathematical programming techniques to solve these problems, depending on factors unique to their industry. Possible considerations include production constraints, capacity constraints (of warehouses and vehicles), timing constraints, the number of supply network nodes, uncertainty, and fleet characteristics. In contrast to the VRP, which seeks to minimize total costs, the GVRP arranges transportation routes to minimize environmental externalities [7]. Invariably, there is an association between lower supply chain transportation GHG emissions and lower costs, however, as many researchers have discovered in bi-objective programming models (cost minimization and GHG emission/fuel minimization objectives), there exists some amount of tradeoff between the two; a transportation network arranged to minimize GHG emissions will cost more than one so arranged to minimize costs [8]. The exact amount varies depending on circumstances unique to each problem, although several authors have found that vehicle routing networks optimized to minimize GHG emissions cost significantly more compared to their cost-minimizing counterparts [9–12].

Concurrent with recent developments in GVRP literature, governments have instituted a range of policy instruments aimed at compelling firms to transform their GHG-intensive supply chains in a manner that facilitates achieving the climate change goals of the Paris Agreement. Examples of such instruments include carbon taxes, emissions trading systems (ETS), and subsidies for electric vehicles (EVs). Carbon taxes set a direct price on GHGs by levying a fee/ton of GHG emissions. ETSs (also known as “cap and trade” systems) set a cap on the total allowable amount of emissions by covered firms; emissions caps are generally lowered over time, and firms may buy or sell emissions allowances in a market. As of 2024, there were 75 carbon taxes and ETSs in operation globally [13]. EV subsidies, which may include incentives such as purchase rebates, tax credits, reduced road taxes, and charging infrastructure subsidies, aim to reduce the upfront and operating costs of EVs [14]. Many nations, including China, India, several European countries, the United States (US), and Canada, have instituted EV subsidy programs to support a transition away from combustion engines [15]. Despite a preponderance of EV subsidies for personal vehicles, which have effectively stimulated EV uptake in this area, the adoption of heavy goods EVs (HGEVs) has thus far lagged behind [16]. The current lack of adoption of HGEVs remains a key barrier preventing progress towards Net Zero Emissions in the supply chain transportation sector [2,17].

The fundamental argument of this paper is that each of these policies has an effect on many of the variables utilized in standard formulations of the GVRP, and that an accurate understanding of these interactions would aid both policymakers and organizational leaders in their decision-making. Equipped with an application of the outcomes of this paper, policymakers would be better prepared to implement policy aimed at encouraging firms to create a greener supply chain; furthermore, firms would be better able to determine under which policy conditions modifying their fleet mix to include HGEVs would be most profitable, and how they might slightly adjust their vehicle routing assignments to generate the greatest reduction in GHG emissions at the least expense. With respect to the latter, the method explored towards reaching conclusions about this relationship (the cost/emissions tradeoff) is that of a Pareto frontier sensitivity analysis. Pareto frontier sensitivity analysis is a technique used in multi-objective optimization to examine how changes in input parameters, constraints, or system assumptions affect the Pareto frontier, which represents the set of optimal tradeoffs between conflicting objectives.

Recent directions in GVRP research have primarily focused on multi-objective optimization, integration of alternative fuel vehicle-specific (AFV, which includes EVs, hybrid EVs, hydrogen fuel cell vehicles, and more) characteristics into problem constraints, and designing more advanced algorithms that might better handle the uncertainty and complexity intrinsic to the GVRP [18–21]. Only a small amount of GVRP research has yet considered the implications of the fluctuating landscape of economic policies that potentially impact multi-objective GVRP solutions [22–26]. However, this segment of the research has not dealt with the topic comprehensively, with the referenced articles only considering a portion of the policies assessed in this paper, directing their research at model output rather than input parameter sensitivity, or failing to consider the important heterogeneous AFV and CFV (conventionally fueled vehicle) fleet condition. Additionally, the large volume of current transportation policy research has predominantly assessed the impacts of legislative initiatives focused on policies designed to reduce GHG emissions from personal transportation rather than supply chain transportation [27–30]. Finally, the capital investment required to begin using a fleet of HGEVs effectively is upwards of several million dollars, a fact that has not been integrated into similar decision-making models thus far [31]. Thus, the contributions of this paper are of interest to a few distinct literatures, notably those related to operations research, transportation policy, and environmental economics.

Section 2 of this paper highlights recent GVRP literature relevant to the present study and provides a brief review of the GVRP for readers with a policy and economic background; scholarship related to the tradeoff between cost-optimal and emissions-optimal routing is also summarized. Section 3 outlines a novel bi-objective cost and emissions minimizing model, which allows for a Pareto frontier sensitivity analysis of the three governmental policy instruments described above (carbon tax, ETS, and HGEV subsidies). Section 4 reviews literature associated with each of these policies to establish the appropriate parameter ranges for a sensitivity analysis. In Section 5, we discuss the broader implications of this work and outline promising directions for future research, concluding in Section 6.

2. The green vehicle routing problem

Since its initial description by [6], the VRP has undergone intense study and development, and has prompted dozens of different variants and solution methods as researchers continually attempt to bring approaches closer in their approximation to “real life” [32–34]. As discussed in the introduction, the GVRP is one of these extensions of the classical VRP that incorporates an environmental objective into supply chain transport planning [35]. The GVRP seeks to minimize energy use commonly expressed in terms of GHG emissions or fuel consumption (which is directly proportional to GHG emissions) over a set of arcs while observing constraints specific to the problem (time windows, fleet characteristics, charging policies, etc.). Section 2.1 provides a more thorough overview of the GVRP for readers unfamiliar with the topic. Section 2.2 offers further context surrounding multi-objective GVRPs, and Section 2.3 discusses recent findings in multi-objective GVRP research and their relation to the transport policies integrated into the model generated in the following section.

2.1. Overview and development of the GVRP

The first work to begin analyzing the VRP from a “green” point of view may be found in [36], who proposed a so-called “Energy Minimizing Vehicle Routing Problem” in which “energy” (emissions calculated as a product of distance travelled and vehicle weight) was minimized over the distribution network. In the following several years, the work of [36] was further developed by other researchers, who improved fuel consumption calculations, considered fleet heterogeneity, and increased model complexity to better resemble real-world applications [37–39]. In their 2014 review of the then-nascent GVRP literature, [40] defined three variants of the GVRP: (i) the Pollution Routing Problem (PRP) in which the GHG emissions of CFVs are minimized given the vehicle and payload characteristics, (ii) the Green-VRP, which addresses the additional challenges associated with operating a fleet of AFVs, and (iii) the VRP in reverse logistics. The GVRP classifications originating in [40] have endured, and all three variants first introduced in the latter half of the 2000s have since precipitated their own sprawling literatures [35,41]. Accordingly, recent areas of productive inquiry include the inclusion of supplementary problem characteristics, the integration of additional objective functions, and the development of more precise solution methodologies [42,43].

The characteristics included in a given GVRP model largely depend on vehicle/fleet specifications, the problem objectives, customer requirements, the data available to the firm/researcher, and the level of certainty surrounding this data. Some considerations found in recent publications include:

- Vehicle type and fleet specifications: The majority of GVRP research has considered models involving only CFVs; however, several dozen authors have generated studies reviewing GVRP approaches to fleets consisting of AFVs [24,44–46]. Further complexity may be added, dependent upon a variety of possible AFV recharging or refueling assumptions. For EVs, researchers have considered complete recharging, partial recharging, non-linear charging functions, and battery swapping [47–50]. Two-thirds of the current body of GVRP research has considered homogenous fleets comprised entirely of CFVs or entirely of AFVs [19]. However, many researchers have also developed solution approaches addressing mixed-fleet circumstances [51–53].

- Objectives: The type of objective function, which represents the goals of the researcher or firm, exerts an overriding influence on each problem. [19] classified the objective functions of 458 GVRP models according to three sustainability dimensions (economic, environmental, and social) and 28 categories. Total CO_2 emissions, total cost, and total cost including emission cost accounted for almost half of the objective function categories, while all categories identified in the social dimension accounted for only one-tenth of the objective function categories. Authors have integrated environmental objectives in a litany of ways, with applications to scheduling problems, cold-chain logistics, depot siting, and charging station siting, among others [54–57]. The amount of detail integrated into cost/emissions functions also varies, with, for example, some researchers considering only the operating costs (driver salary, fuel costs, etc.) of routing, and others integrating additional considerations for inventory holdings costs, early/late delivery penalty costs, capital expenditure-related costs, GHG emissions costs, and more to generate a comprehensive "total cost" function.
- Customer requirements, data availability, and data uncertainty: These represent possible constraints imposed on the problem due to "real-world" circumstances, leading to the integration of many other extensions of the VRP into GVRPs. Considerations include the incorporation of time windows, multiple echelons, stochasticity, location routing, pickup and delivery, inventory routing, and cold chain logistics [58–61]. For example, in a GVRP with time windows, the resulting transportation route assignments provide the lowest cost/emissions route that also adheres to specific time windows imposed by a customer (i.e., vehicles arriving neither too early nor too late). Readers may be referred to [62] and [63] for further information on VRP variants applicable to GVRP formulations.

Beyond the application of additional, more complex problem characteristics, another area of significant importance in the GVRP literature of late relates to the development of superior solution methods. To this end, several authors have provided recent and extensive summaries of the most commonly utilized methods [19,20,35,64–67]. The primary form of mathematical models designed to solve GVRPs is the mixed-integer linear program (MILP), as GVRP models almost always involve assigning a freight load to a route or node via the use of integer decision variables. Broadly, frequently used solution methodologies may be classified as exact, heuristic, meta-heuristic, and hybrid. Due to the large set of possibilities and constraints, as well as the general NP-hardness of GVRPs, exact methods are rarely employed. While hybrid and heuristic methods enjoyed greater popularity in the research literature published in the early 2010s, metaheuristic approaches, due to their flexibility, scalability, and robustness, have gradually supplanted hybrid and heuristic methods as the most prevalent approach [19].

2.2. The multi-objective GVRP

In multi-objective GVRP models, researchers identify two or more competing objective functions for their program to consider when assigning freight loads to transport vehicles, transport vehicles to customer nodes, and/or AFV transport vehicles to AFV fueling stations (i.e., charging stations for EVs, as an example). Objectives are often aligned with what has been termed the "triple bottom line" (TBL) framework, first proposed by [68]. Under the TBL framework, business success is measured not only by profit, the conventional metric for evaluating business performance, but also by equitable treatment of human capital and reduction of environmental footprint [69]. In accordance with the TBL framework, many researchers in the multi-objective GVRP space have sought to align their objective functions with economic, social, and/or environmental measures of performance. As noted above, the integration of social dimensions represents the least-studied of the three, although various authors have attempted to capture this metric through objective functions aimed at increasing employment, decreasing injuries, improving customer satisfaction, minimizing noise levels, and ensuring a more equitable distribution of overtime [70–73]. Far more commonly, economic and environmental measures are considered in the same multi-objective model [18]. Given that the subject of this paper is assessing how the implementation of common economic policies affects organizational decision-making in a manner that may enhance environmental performance, we now turn our attention to this segment of the literature.

2.3. Findings from cost and environmental impact-minimizing models

Bi-objective models, which aim to minimize both total route transportation costs and environmental impact, represent the most common multi-objective approach to the GVRP [18]. As explained in the introduction, a network arranged to minimize environmental impact (measured via fuel use, GHG emissions, or energy consumption) results in a greater cost to the business compared to a network arranged to minimize only costs. Table 1 presents a review of some recent bi-objective (cost/environmental impact minimization) GVRP models and their findings in reference to this tradeoff, as taken from each study's respective Pareto frontier.

Table 1 indicates that, in most cases, the tradeoff between cost and environmentally optimized vehicle routing is substantial. This is demonstrated by the first bullet point, which describes the general findings of each reference. The second bullet point merely provides a verbal depiction of the downward-sloping tradeoff curve of Pareto frontiers in bi-objective problems, wherein both objectives are minimized. The further one objective is valued, the more the other must be sacrificed. Given the growing emphasis surrounding corporate sustainability amongst consumers and the increasing number of firms providing public GHG-reduction-related sustainability commitments, many firms may derive benefit from organizing their supply network in such a way that incurs, for example, ~0.5% more cost, but emits 75% fewer GHGs, which was found to be possible in [79]. However, the amount of difference between environmentally-optimized and cost-optimized solutions is likely to differ if environmental policy parameters (carbon pricing and HGEV subsidies) are taken into account, as is the rate of change of the Pareto frontier, which may have important implications on the cost/emissions tradeoff decisions a firm may have now or in the future. In the following two sections, we address this problem by first generating a mathematical model that takes policy parameters into account and then providing a synopsis of data related to a more thorough analysis of the Pareto frontier through the application of sensitivity analysis.

3. Mathematical model

In this section, we present a generalizable GVRP model formulation for a bi-objective cost and emissions-minimizing problem with a heterogeneous fleet comprising HGEVs and CFVs (diesel trucks), with environmentally relevant transportation policies taken into account. This problem formulation will serve as the basis for discussion in Section 4, which, after reviewing the relevant literature, will establish the key range of scenarios most suitable for each policy parameter. S1 Appendix – Example Implementation is provided to demonstrate the model's feasibility and discuss solution methods. Key problem characteristics to note are as follows:

- Bi-objective: As previously noted, the greatest disincentive against adopting more sustainable business practices is often presented by an associated increase in cost, rather than a similar deterioration in social outcomes. The first objective (Equation 3) is to minimize the total cost of all tours, while the second objective (Equation 4) is to minimize the total GHGs emitted during all tours.
- Heterogeneous fleet: Given that the model is designed to indicate policy levels at which a firm would be incentivized to acquire a greater number of HGEVs, this is critical. The acquisition cost (A^k) and subsidy amount (S^k) for each vehicle k can be manipulated to suit various assumptions for each vehicle class. For example, the acquisition cost of CFVs is often assumed to be even lower than their retail price, given that most firms begin with a complete fleet of CFVs and study the possibility of integrating HGEVs, which would need to be purchased at the full retail price (less any subsidies).
- Capacitated with split deliveries: These are perhaps two of the most common variants of the classical VRP. The integration of these features (load updating at customers, replenishing load after each return trip to the depot, etc.) enables a greater degree of fidelity to "real-world" supply chain operations.

Table 1. Findings related to the cost/environmental impact tradeoff from recent bi-objective GVRP research.

Reference	Problem Characteristics	Cost Parameter	Environmental Parameter	Findings in Reference to the Cost/Environmental Impact Tradeoff
[9]	PRP; Fni; TW	Driving Time	Fuel Consumption	−Least-fuel routes are associated with ~8% lesser fuel consumption and ~5% greater driving time compared to their least-time counterparts. −~75% of possible fuel consumption reduction may be realized at a < 1% increase in driving time.
[74]	PRP; Fni; TW	Total Cost	CO_2 Emissions	−Least-emissions routes are associated with ~42% lower CO_2 emissions and ~100% higher total cost compared to their least-cost counterparts. −Approximately 50% of possible CO_2 emissions reduction may be realized at a cost increase of ~14%.
[75]	PRP; Fho; TW	Driver Wages	CO_2 Emissions	−Least-emissive routes are associated with ~26% lower emissions and ~32% higher wages compared to least-wages counterparts. −~50% of possible emissions reduction may be realized at the expense of a ~ 4% increase in driver wages.
[76]	PRP; Fho	Driving Time	Fuel Consumption	−Least-fuel routes are associated with ~76% less fuel consumption and ~375% more driving time compared to their least-time counterparts. −Approximately 40% of possible fuel consumption reduction may be realized at a slight increase of ~13% in driving time.
[77]	PRP; Fho	Total Distance	CO_2 Emissions	−Least-emissions routes are associated with ~4% lesser CO_2 emissions and ~4% greater travel distance compared to their least-distance counterparts. −~50% of possible CO_2 emissions reduction may be realized at a < 1% increase in total distance.
[78]	PRP; Fho	Distance Traveled	Fuel Consumption	−Least-fuel routes are associated with ~2% lesser fuel consumption and ~2% greater distance traveled compared to their least-distance counterparts. −~50% of possible fuel use reduction may be realized at a < .1% increase in travel distance.
[79]	G-VRP; Fhe; TW; Re	Total Cost	GHG Emissions	−Least-emissions routes are associated with ~87% lower GHG emissions and ~62% higher total cost compared to their least-cost counterparts. −~75% of possible GHG emissions reductions may be realized at a < 1% increase in total cost.
[80]	G-VRP; Fhe; TW; Re	Total Cost	Fuel Consumption	−Least-fuel routes are associated with ~15% less fuel consumption and ~12% higher total cost compared to their least-cost counterparts. −Approximately 40% of possible fuel consumption reduction may be realized at a cost increase of ~3%.
[81]	G-VRP; Fhe; TW	Delay Time	Pollutant Emissions	−Least-emissions routes are associated with ~35% lesser pollutant emissions and ~240% greater delay time compared against their least-delay time counterparts. −Approximately 60% of possible pollutant emissions reductions may be realized at a delay time increase of ~30%.

PRP – Pollution Routing Problem; Green-VRP – Green-Vehicle Routing Problem; Fni – Fleet composition not indicated; Fho – Homogeneous fleet composition; Fhe – Heterogeneous fleet composition; TW – Considers time windows; Re – Considers EV recharging.

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- Time windows: The time limitations imposed by shift work, vehicle maintenance, and production/delivery schedules are characteristic of almost every supply chain. Thus, time windows have been integrated into the model. Here, T_{max} indicates the maximum allowable service time for each vehicle on each day or shift (in each tour z, discussed in the following point). T_{stop} allows for additional time to be added to each tour for depot and customer stops. Finally, T^{kz} represents the total tour time for vehicle k in tour z, which must always remain below T_{max} and above the cumulative travel time plus stop time (see Equation 8 and Equation 9).

- Multi-tour: Due to their higher upfront, but lower maintenance costs, the decision to purchase HGEVs now is generally a long-term decision, which will often not pay for itself until some years in the future. Thus, seeing as the model's purpose is to aid long-term decision-making, a time horizon must be integrated into the model. Here, z denotes each tour, which may represent a shift, a day (for longer trips, for example), or an even longer period. In the case where z represents a day, 1,095 tours would indicate a decision horizon of three years. Such a trip index is also necessary for assessing the need to purchase or sell emissions credits (e^+ and e^- respectively), as carbon allowances (G) are usually distributed annually. Of course, such a trip index introduces combinatorial explosion almost immediately for even small datasets; this is discussed further in S1 Appendix – Example Implementation. Lastly, it should be noted that z provides a convenient way to account for expected seasonal or otherwise forecasted changes in any other parameter without adding appreciable complexity (for instance: grid emissions factor μ, customer demand p_i, driver wages C_w, etc.).
- Recharging assumptions: In contemporary research, a significant amount of complexity is added to models in attempting to account for various recharging policies. Partial recharging, non-linear recharging, and battery swapping are among the most popular assumptions [22]. Here, however, we depart from these approaches and assume *full recharging* during loading/unloading at the depot and at customers with charging stations. We justify this in several ways. Firstly, public charging infrastructure capable of supporting HGEVs is not widely available; thus, firms seeking to integrate HGEVs must typically install at least some of their own HGEV charging stations [82,83]. This assertion is empirically validated by the actions of several of the world's largest companies, who, amongst many others, have recently integrated HGEVs, including Amazon, PepsiCo, DHL, and Coca-Cola [84–87]. Secondly, it would be reasonable to assume that, given the installation of brand-new charging stations, firms would install these charging stations in such a way as to minimize HGEV downtime. This may be accomplished by "live charging," wherein trucks are charged while at the loading dock. Thirdly, given that median dock dwell time is over 2.5 hours for full truckloads, and this median coincides with the time to charge some of the most popular HGEVs fully, the assumption of full recharging at the depot/customers is now rendered reasonable [88–91]. Readers who still disagree may consider simply adding some constraints to include a longer T_{stop} for HGEVs when at a location with a charging station and in need of charge, or limiting the maximum charging amount after departing the depot (some common approaches found elsewhere in the literature).
- Integration of policy parameters: Parameters representing each of the three most common policies potentially affecting the GVRP (carbon tax, ETS carbon allowances, HGEV subsidies) are included (β, Υ and G, and S^k, respectively). This integration is a key factor that distinguishes this work from previous literature in the field.

The model is informed by the work of [80,92–96]. Many of the works referenced in Table 1 and previously in this work were also consulted.

Table 2 presents the notations used in the model. The set $K = K_e \cup K_c$ defines all available HGEVs and CFVs, respectively. The GVRP establishes optimal tours that start from the depot, visit all customers, may visit some charging stations, and return to the depot; this is defined by the set $N_{n+1}\left\{0, 1, \cdots, n+1\right\}$ with departure depot $\left\{0\right\}$, arrival depot $\left\{n+1\right\}$, customers D with their copies, and charging stations CS. Each vehicle k is associated with its acquisition cost (A^k), subsidy amount (S^k), load capacity (Q^k), operating cost per unit distance (O^k), and (for HGEVs) energy consumption per unit distance (h^k) and battery capacity (R^k). The recharging cost for HGEVs is denoted by r, and the reserve battery margin of safety by Ms. C_w represents the cost of driver wages, C_F the cost of diesel fuel, C_I the cost to build HGEV charging infrastructure at the depot, and C_E the cost to build an expanded network of charging stations at various customer locations. Each arc (i, j) has a related travel time (t_{ij}) and travel distance (d_{ij}), and each customer D has a given demand (p_i). G represents the carbon cap for the firm, the price of each additional carbon allowance denoted by Υ, and the unit cost of GHG emissions (the carbon tax) is defined as β. GHG emissions for HGEVs are calculated using μ, the electrical grid emissions factor. The model calculates total fuel consumption for diesel trucks and converts

Table 2. Notations for the mathematical model.

Sets	
K_e	Set of available HGEVs
K_c	Set of available CFVs
K	Set of all available vehicles $K_e \cup K_c$
D	Set of customers and their copies
CS	Set of charging stations
N	Set of customers, charging stations, and their copies $D \cup CS$
N_{n+1}	Set of customers, departure depot, charging stations, and their copies $D \cup (n+1) \cup CS$

Parameters			
A^k	Acquisition cost for vehicle k	ξ	Fuel-to-air mass ratio
S^k	Subsidy amount for vehicle k	f	Engine friction factor
d_{ij}	Distance between vertex i and vertex j	I	Engine speed
h^k	Energy consumption per distance by vehicle k	E	Engine displacement
t_{ij}	Travel time from vertex i to vertex j	ι	The efficiency parameter for diesel engines
p_i	The demand of customer i	κ	The heating value of typical diesel fuel
Q^k	The maximum load capacity for vehicle k	P	Engine power
m	Minimum delivery fraction	P_t	Total tractive power required by the vehicle
T_{max}	The maximum service time for each vehicle	P_l	Power related to the running losses of the engine
T_{stop}	Penalty time for stopping at customer or depot	W_T	Total weight of the vehicle
O^k	The operating costs for vehicle k	W_c	Curb weight
r	Recharging cost	W_l	Load weight
C_I	Cost of initial HGEV charging infrastructure	τ	The average acceleration of the vehicle
C_E	Cost of expanded HGEV charging infrastructure	g	Gravitational constant
C_w	Cost of driver wages	δ	Angle of road
C_F	Cost of diesel fuel	C_a	Aerodynamic drag coefficient
Ms	The battery level safety margin for HGEVs	C_r	Rolling resistance coefficient
R^k	The battery capacity of vehicle k	α	Effective frontal area of the vehicle
β	Unit cost of GHG emissions (carbon tax rate)	ρ	Air density
μ	Regional average grid emissions factor for electricity	ψ	Constant for converting *gram/s* to *litre/s*
Ω	GHG emissions coefficient for diesel fuel	υ	The average speed of the vehicle
G	Carbon cap for the firm	E_{cfv}	Total GHG emissions from CFVs
Υ	Carbon allowance cost	E_{hgev}	Total GHG emissions from HGEV charging
Z	Number of days in the planning horizon	$\lambda, \phi, \sigma, \in$	Terms used to simplify equations (see S2 Appendix)

Variables	
x_{ij}^{kz}	1 if vehicle k traverses arc (i,j) in tour z, 0 otherwise
q_{ij}^{kz}	The flow of load carried from vertex i to vertex j by vehicle k in tour z
y_i^{kz}	The current energy level of vehicle k when arriving at vertex i in tour z
U_i^{kz}	The remaining load capacity of vehicle k upon arrival at node i in tour z
l_j^{kz}	The amount of load delivered by vehicle k at node j in tour z
T^{kz}	The total route time for vehicle k in tour z
v_k	1 if vehicle k is selected to traverse any routes at all, 0 otherwise
EVu	1 if at least one HGEV is used to traverse any route, 0 otherwise
EVe	1 if the expanded HGEV charging infrastructure is activated, 0 otherwise
e^+	Emissions credits purchased
e^-	Emissions credits sold

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this to GHG emissions by using Ω, the GHG emission coefficient for diesel fuel. Approximately 20 of the parameters listed in Table 2 are utilized solely for the calculation of fuel consumption from CFVs as described by [9,97,98]. The use of these variables and their integration into the model's objective functions are explained in S2 Appendix – Calculation of Fuel Consumption from Diesel Trucks. Some researchers have relied on simpler methods, such as distance-based or weight-distance-based approaches, for calculating diesel truck fuel consumption; however, the modeling approach introduced by [97] is notably more accurate [99].

The binary variable x_{ij}^{kz} is used to determine the arc (i, j) that is traversed by vehicle k in tour z. Variable q_{ij}^{kz} represents the flow of load carried between vertex i and j by vehicle k in tour z. y_i^{kz} and U_i^{kz} indicate the remaining load capacity and energy level of vehicle k when arriving at node i in tour z. Binary variable v_k indicates if vehicle k was used to travel any route, while binary variable *Evu* triggers if an HGEV traverses any route at all, and variable *Eve* if an HGEV "wants" to take a route so long that recharging would be required at one of the potential charging stations at customer nodes. As noted previously, e^+ and e^- indicate emissions credits purchased or sold.

The term E_{cfv} is used to simplify the equation representing the total amount of GHG emissions from CFVs (in tonnes of CO_2-equivalents), which may be given as:

$$E_{cfv} = \frac{\Omega}{1,000} \sum\nolimits_{k \in K_c} \sum\nolimits_{z \in Z} \sum\nolimits_{i \neq j} \left[\left(W_c \varphi \sigma d_{ij} + flEt_{ij} + \in \varphi d_{ij} \left(d_{ij} / t_{ij} \right)^2 \right) \ \lambda x_{ij}^{kz} + \left(\varphi \sigma \lambda d_{ij} q_{ij}^{kz} \right) \right] \tag{1}$$

Similarly, E_{hgev} is the term utilized to simplify the total amount of GHG emissions associated with charging HGEVs. E_{hgev} is given as:

$$E_{hgev} = \left(\mu \sum\nolimits_{k \in K_e} \sum\nolimits_{z \in Z} \sum\nolimits_{i \neq j} h^k d_{ij} x_{ij}^{kz} \right) / 1,000 \tag{2}$$

The equations representing the objective functions and constraints for the model are now shown below. A description conveying the meaning of each equation is provided in Table 3.

Objective Function 1 (minimize total costs):

equation 3.1 calculates the HGEV charging costs, *3.2* fuel and diesel emissions costs, *3.3* operating and wage costs, *3.4* vehicle acquisition costs, *3.5* HGEV infrastructure costs, and *3.6* carbon credit costs or revenue.

$$MinZ_1 = \tag{3}$$

$$r \sum\nolimits_{k \in K_e} \sum\nolimits_{z \in Z} \sum\nolimits_{i \neq j} h^k d_{ij} x_{ij}^{kz} \tag{3.1}$$

$$+ C_F \beta E_{cfv} \tag{3.2}$$

$$+ \sum\nolimits_{k \in K} \sum\nolimits_{z \in Z} \sum\nolimits_{i \neq j} x_{ij}^{kz} \left(O^k d_{ij} + C_w T^{kz} \right) \tag{3.3}$$

$$+ \sum\nolimits_{k \in K} v_k \left(A^k - S^k \right) \tag{3.4}$$

$$+ \left(EVu \cdot C_I + EVe \cdot C_E \right) \tag{3.5}$$

$$+ \Upsilon \left(e^+ - e^- \right) \tag{3.6}$$

Objective Function 2 (minimize GHG emissions):

Emissions associated with CFVs plus those due to HGEV recharging.

$$MinZ_2 = E_{cfv} + E_{hgev} \tag{4}$$

Table 3. Description of objective function and constraints.

Equation Number	*Description*
Objective Functions	
(3)	*Total cost*
(3.1)	Total recharging costs for HGEVs.
(3.2)	Cost due to fuel use and carbon tax.
(3.3)	Operating and driver wages costs.
(3.4)	Vehicle acquisition costs minus subsidies.
(3.5)	Cost to erect HGEV infrastructure.
(3.6)	Cost of or revenue generated from the purchase/sale of carbon allowances.
(4)	*Total GHG emissions*
Constraints	
(5)	Each vehicle must depart from the depot.
(6)	The number of arcs leaving the depot must equal the number arriving.
(7)	Vehicle tours must be connected.
(8)	Service time must be greater than or equal to the travel time and stop penalty time.
(9)	The service time of each vehicle is limited to T_{max}.
(10)	A vehicle is triggered as "used" if it leaves the depot.
(11)	The load that flows across any arc is zero unless that arc is used.
(12)	Demand is satisfied for each customer in each tour.
(13)	Flow conservation at customer nodes.
(14)	If the vehicle starts at or returns to the depot, the vehicle's load is set to full.
(15)	When leaving the depot, the vehicle load is decreased by the amount that was dropped off at the first customer.
(16)	Between customers, the remaining vehicle load is reduced by the amount delivered at the next customer.
(17)	A delivery is only made if the customer is visited.
(18)	The minimum delivery amount is defined as the vehicle capacity multiplied by the minimum delivery fraction.
(19)	If any HGEV completes a tour, the initial HGEV infrastructure cost is triggered.
(20)	The battery level is set to full if the HGEV starts at or returns to the depot, or arrives at a customer with a charging station.
(21)	HGEV battery level is reduced based on travel distance.
(22)	If the expanded charging infrastructure is inactive, the HGEV must reserve enough battery to return to the depot.
(23)	If the expanded infrastructure is active, the HGEV must reserve enough battery to return to the depot or a charging station.
(24)	Total GHG emissions, plus emissions credits sold, must be less than the allowance for the period, plus those purchased.
(25)-(34)	Define variable types.

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Routing Constraints:

Every vehicle must depart from the depot.

$$\sum\nolimits_{z\in Z}\sum\nolimits_{j\in N_{n+1}} x_{0j}^{kz} \geq v_k,\ \forall k\in K \tag{5}$$

For each vehicle and tour, the number of arcs leaving the depot equals the number arriving.

$$\sum\nolimits_{j\in N_{n+1}} x_{0j}^{kz} = \sum\nolimits_{i\in N_{n+1}} x_{i0}^{kz},\ \forall k\in K,\ z\in Z \tag{6}$$

Vehicle tours must remain connected.

$$\sum\nolimits_{i\in N, i\neq j} x_{ij}^{kz} - \sum\nolimits_{i\in N, i\neq j} x_{ji}^{kz} = 0,\ \forall k\in K,\ z\in Z,\ \forall j\in D \tag{7}$$

Service time must be greater than or equal to the travel time plus stop penalty time.

$$T^{kz} \geq \sum\nolimits_{i\in N}\sum\nolimits_{j\in N, j\neq i} t_{ij}x_{ij}^{kz} + T_{stop}\left(\sum\nolimits_{i\in N}\sum\nolimits_{j\in N,\ j\neq i} x_{ij}^{kz} - v_k\right) \tag{8}$$

The service time for each vehicle k in tour z is limited to T_{max}.

$$\sum\nolimits_{z\in Z} T^{kz} \leq T_{max},\ \forall k\in K \tag{9}$$

If a potential vehicle k leaves the depot at least once, it is therefore purchased or activated and therefore marked as "used" ($v_k = 1$).

$$v_k \geq x_{0j}^{kz},\ \forall k\in K,\ \forall z\in Z,\ \forall j\in N_{n+1} \tag{10}$$

Capacity and Flow Constraints:

The load that flows across any arc is zero unless that arc is traversed by any vehicle.

$$q_{ij}^{kz} \leq Q^k x_{ij}^{kz},\ \forall k\in K,\ z\in Z,\ \forall i,\ j\in N,\ i\neq j \tag{11}$$

Demand is satisfied for each customer in each tour.

$$\sum\nolimits_{k\in K} l_j^{kz} = p_i, \forall i\in D, z\in Z \tag{12}$$

Flow conservation at customer nodes.

$$\sum\nolimits_{i\in N,\ i\neq j} q_{ij}^{kz} = l_j^{kz} + \sum\nolimits_{i\in N, i\neq j} q_{ji}^{kz} \tag{13}$$

Starting at the depot, or if a vehicle returns to the depot, the load capacity returns to full.

$$U_0^{kz} = Q^k \tag{14}$$

If a vehicle leaves the depot for customer j, then the remaining capacity is reduced by the amount of load delivered at node j.

$$U_j^{kz} = Q^k - l_j^{kz} \tag{15}$$

For consecutive visits, the remaining load capacity is reduced by the amount of load delivered at node j.

$$U_j^{kz} = U_i^{kz} - l_j^{kz} \tag{16}$$

A delivery is only made if the customer is visited.

$$l_j^{kz} \leq p_i \sum_{i\in N, i\neq j} x_{ji}^{kz},\ \forall k\in K,\ z\in Z,\ \forall j\in D \tag{17}$$

The minimum delivery at a node is the load capacity times the minimum delivery fraction.

$$l_j^{kz} \geq mQ^k \sum_{i \in N, i \neq j} x_{ji}^{kz}, \ \forall k \in K, \ z \in Z, \forall j \in D \tag{18}$$

HGEV-Specific Constraints:

If any HGEV traverses a route, then *EVu* is triggered.

$$EVu \geq v_k, \ \forall k \in K_e \tag{19}$$

The battery level is set to full if *j* is the depot or if *j* is a customer node with a charging station and the expanded charging network is active (i.e., if $Eve = 1$).

$$y_j^{kz} = R^k \tag{20}$$

Otherwise, the battery level is reduced by the energy consumed during travel.

$$y_j^{kz} = \ y_i^{kz} - h^k d_{ij} \tag{21}$$

If $Eve = 0$, then the vehicle must reserve enough battery plus a safety margin to return to the depot.

$$y_i^{kz} \geq h^k d_{i0} + Ms \tag{22}$$

If $Eve = 1$, then the vehicle must reserve enough battery plus a safety margin to return to the depot or nearest charging station.

$$y_i^{kz} \geq h^k \cdot min\left\{d_{i0}, \min_{j \in CS} d_{ij}\right\} + Ms \tag{23}$$

Carbon Cap Constraint:

Total GHG emissions plus emissions credits sold must be less than the carbon cap allotted for the period.

$$E_{cfv} + \ E_{hgev} \ + \ e^- \leq G \cdot \frac{Z}{365} + e^+ \tag{24}$$

Variable Type Constraints:

$$x_{ij}^{kz} \in \left\{0, 1\right\}, \qquad \forall (i,j) \in A, i \neq j, \forall k \in K, \forall z \in Z \tag{25}$$

$$v_k \in \left\{0, 1\right\}, \qquad \forall k \in K \tag{26}$$

$$EVu \in \left\{0, 1\right\} \tag{27}$$

$$EVe \in \left\{0, 1\right\} \tag{28}$$

$$q_{ij}^{kz} \geq 0 \qquad \forall (i,j) \in A, i \neq j, \forall k \in K, \forall z \in Z \tag{29}$$

$$I_j^{kz} \geq 0 \qquad \forall j \in D, \forall k \in K, \forall z \in Z \tag{30}$$

$$y_i^{kz} \geq 0, \ \ 0 \leq y_i^{kz} \leq R^k, \qquad \forall i \in N_{n+1}, \forall k \in K_e, \forall z \in Z \tag{31}$$

$$U_i^{kz} \geq 0, \ \ 0 \leq U_i^{kz} \leq Q^k, \qquad \forall i \in N_{n+1}, \forall k \in K, \forall z \in Z \tag{32}$$

$$T^{kz} \geq 0, \ \ \forall k \in K, \forall z \in Z \tag{33}$$

$$e^+, e^- \geq 0 \tag{34}$$

4. Establishing a basis for policy assumptions

Many economists have argued that the most effective policy tools for combating global climate change are carbon pricing, combined with subsidies for green technological innovation [100–102]. As such, we have integrated into our model the two most common pricing instruments (carbon taxes and ETSs) and incentives for the most relevant green innovation in the transportation sector (HGEVs) with the parameters β, Υ, and S^k, respectively, and variables e^+ and e^-. The next step in arranging for an adequate Pareto frontier sensitivity analysis involves conducting a literature review to establish evidence-based ranges for the relevant parameters.

4.1. Carbon pricing

Carbon pricing is designed to reduce GHG emissions by applying the "polluter pays" principle, which holds that those responsible for emitting GHGs should bear the costs of their environmental impact. Carbon pricing instruments may be considered direct or indirect. Direct carbon pricing provides a price signal closely linked to actual emissions (i.e., linked to the carbon content of a specific type of fuel, for example). In contrast, indirect carbon pricing involves instruments that change the price of related products in a way not directly proportional to the emissions of those products (i.e., applying a tax to the volume of gasoline or diesel) [103]. Carbon taxes and ETSs are direct instruments for pricing carbon. Under a carbon tax, governments levy a fee on covered firms for their GHG emissions. In an ETS, limits are placed on the amount of GHG emissions from all covered firms. These firms must give up their emissions allowances to cover the emissions within a compliance period. Allowances are generally issued annually, and firms may purchase additional allowances or sell their excess in the market.

The first carbon pricing instruments were carbon taxes implemented in the early 1990s by several Nordic countries, including Finland, Sweden, Norway, and Denmark [104]. Market-based cap and trade programs were first introduced in the US in the 1980s to phase out chlorofluorocarbons in response to the Montreal Protocol, and then again in the 1990s through the US Acid Rain Program, a cap and trade program for sulfur dioxide emissions. This proof of concept contributed to the Kyoto Protocol of 1997, which was the first major international agreement to recognize and endorse market-based mechanisms for reducing GHG emissions [105]. Following the Kyoto Protocol, several pilot programs were developed in the UK, the US, Denmark, and Canada. These pilot programs informed the development of some of the large ETSs still in effect today, including the EU ETS established in 2005, regional ETSs throughout North America, China's national ETS launched in 2021, and many others.

The prevalence of carbon taxes and ETSs has increased rapidly since their introduction. As of April 2024, there exist 39 carbon taxes and 36 ETSs in operation worldwide covering ~24% of global GHG emissions [13]. The introduction of new carbon pricing instruments has demonstrated prolonged momentum, with an average of 4 pricing instruments being introduced per year since 2010. Furthermore, there are currently 18 nations and 7 subnational organizations that have ETS or carbon tax policies either under consideration or under development [13]. Many countries that presently only impose a carbon tax have an ETS under consideration and vice versa [106]. Fig 1 shows the current global coverage of carbon taxes and ETSs.

In the preceding paragraphs, we have provided a summary of the mechanisms and history of carbon pricing tools. We have also conveyed the rapid implementation of these tools since the mid-2000s and demonstrated that it is likely this trend will continue, bringing a greater share of global emissions under the carbon pricing umbrella. As a result, wise firms should maintain an interest in their local/national carbon pricing policies. Given information about current and forecasted carbon tax and carbon allowance prices (β and Υ), firms can implement the methodology outlined in Section 3, combined with the array of assumptions outlined in Fig 2, to optimize their supply networks.

Other important values to consider may include the following:

- $\beta = 63$ \$USD/tCO_2-e: High-Level Commission on Carbon Prices Estimate to Limit Warming to 2˚C (Low End)
- $\beta = 127$ \$USD/tCO_2-e: High-Level Commission on Carbon Prices Estimate to Limit Warming to 2˚C (High End)
- $\beta = 226$ \$USD/tCO_2-e: IPCC Estimate to Limit Warming to 1.5˚C (Low End)
- $\beta = 385$ \$USD/tCO_2-e: IPCC Estimate to Limit Warming to 1.5˚C (High End)
- $\Upsilon = 134$ \$USD/tCO_2-e: Projected 2040 EU ETS Carbon Price

4.2. Heavy goods electrical vehicle subsidies

HGEV subsidies primarily aim to accelerate market adoption of HGEVs by lowering upfront costs and stimulating production efficiencies, thereby moving HGEVs toward price parity with CFVs. They also address environmental and public

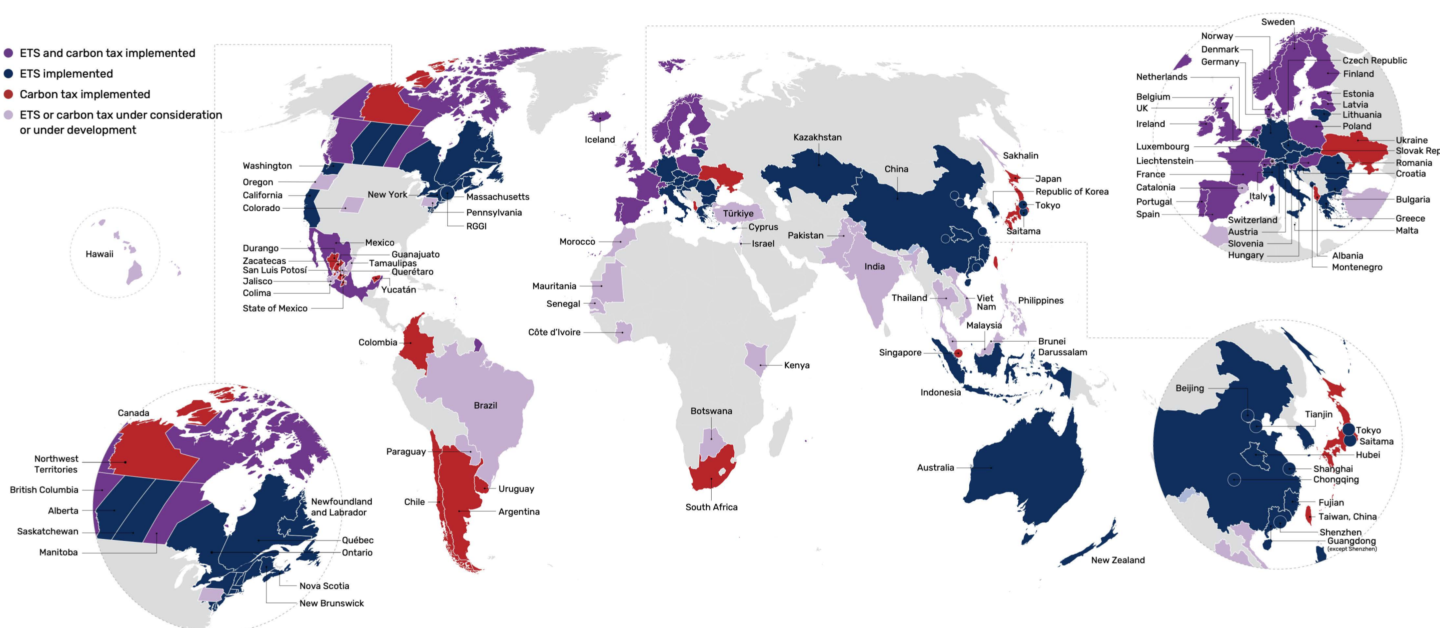

Fig 1. A global map of carbon taxes and ETSs as of April 2024. From [13].

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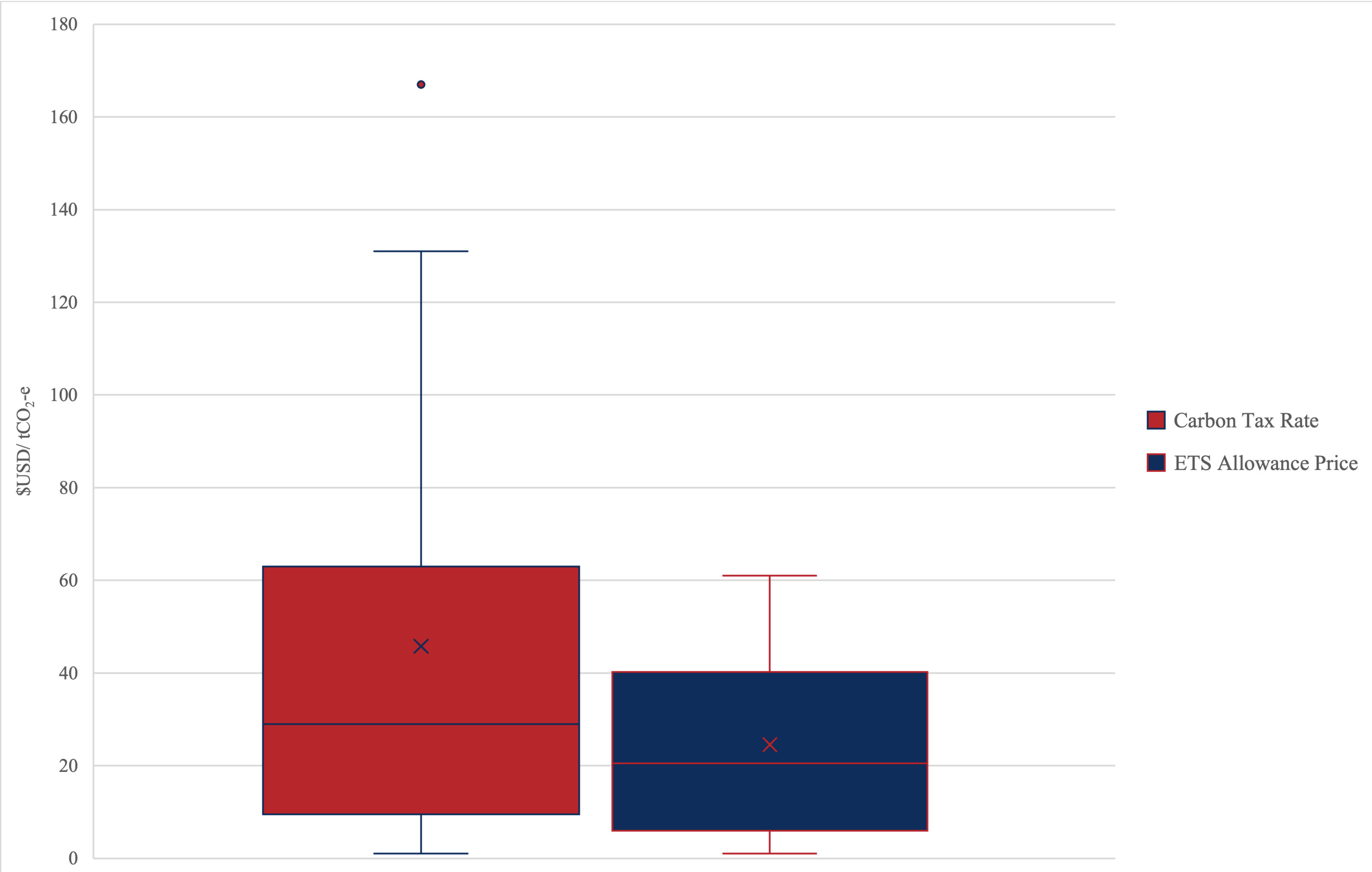

Fig 2. Proposed parameters to use in a Pareto frontier sensitivity analysis. Created with information found in [13,107–110].

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health concerns by reducing GHG and pollutant emissions, contributing to cleaner air and fulfilling climate targets. From an economic standpoint, these incentives foster job creation, encourage technological innovation, and support energy security by promoting electricity from local or renewable sources instead of imported oil [111]. Ultimately, such incentives are designed as short to medium-term policy levers to propel EVs into mainstream acceptance until costs naturally decline and the market no longer requires direct financial support.

Since the 1990s, many nations have offered EV subsidies in various forms. Some common approaches include purchase incentives (such as purchase grants, purchase vouchers, tax credits, and import tax reductions or exemptions), ownership cost incentives (reduced registration taxes, toll exemptions, and free parking), charging infrastructure support, and subsidies for manufacturers [112]. Starting in the late 2000s, China began to introduce a generous mix of EV-promoting policies [113]. Many authors agree that this assemblage of policy initiatives has contributed significantly to China's current position as the world's leading EV manufacturer and EV user [114–116]. Prior to 2020, nearly all HGEVs produced were sold in China, and, while sales elsewhere started to gain momentum in 2020, Chinese HGEVs accounted for 70% of global sales even in 2023 [14]. Norway represents another benchmark case of EV subsidy success. One of the earliest adopters of EV subsidy programs in the 1990s, Norway now boasts an 80% market share for EVs, the highest in the world [117].

In addition to Norway and China, many other nations currently operate or are considering implementing various subsidy initiatives. As of 2024, 104 nations have policy measures and targets related to future EV adoption, and upwards of 50 national and subnational subsidy programs are active around the world [15,16]. According to the International Energy Agency, the global EV fleet is projected to grow twelvefold by 2035 under the "stated policy scenario," which reflects the most likely outcome given current national commitments [14,118]. Under this scenario, the International Energy Agency expects that an excess of 20% of new heavy-goods vehicles will be EVs in 2035, while the Net Zero Emissions scenario by 2035 would necessitate that nearly 60% of new heavy-goods vehicles be EVs [119]. Fig 3 showcases the current state of *EV* purchase and ownership subsidies or incentives around the world.

So far, we have reviewed the purpose of EV subsidies, briefly discussed two successful case examples of EV subsidy implementation, and highlighted some key facts to indicate the likely continuation and expansion of EV subsidy measures globally. Armed with the importance of these insights in validating the assumptions made about our mathematical model formulated in the previous section, we now continue to establish reasonable assumptions for S^k, the subsidy amount parameter. In the model, the subsidy amount S^k is deducted from the vehicle acquisition cost A^k for HGEVs (see equation 3.4). This implies that S^k may only account for capital expenditure-related subsidies (purchase grants, purchase vouchers, tax credits, purchase tax exemption, import tax exemption, etc.) and not operating expenditure-related subsidies (toll exemptions, reduced registration taxes, etc.). However, we view this association of the subsidy amount with capital expenditures as justified only because the vast majority of EV subsidies (both in terms of the number of policies and the total monetary value of subsidies) are directed at reducing the upfront rather than operating costs [109]. Table 4 provides a summary of some national policies as well as the recommended range for S^k based on the identified policies.

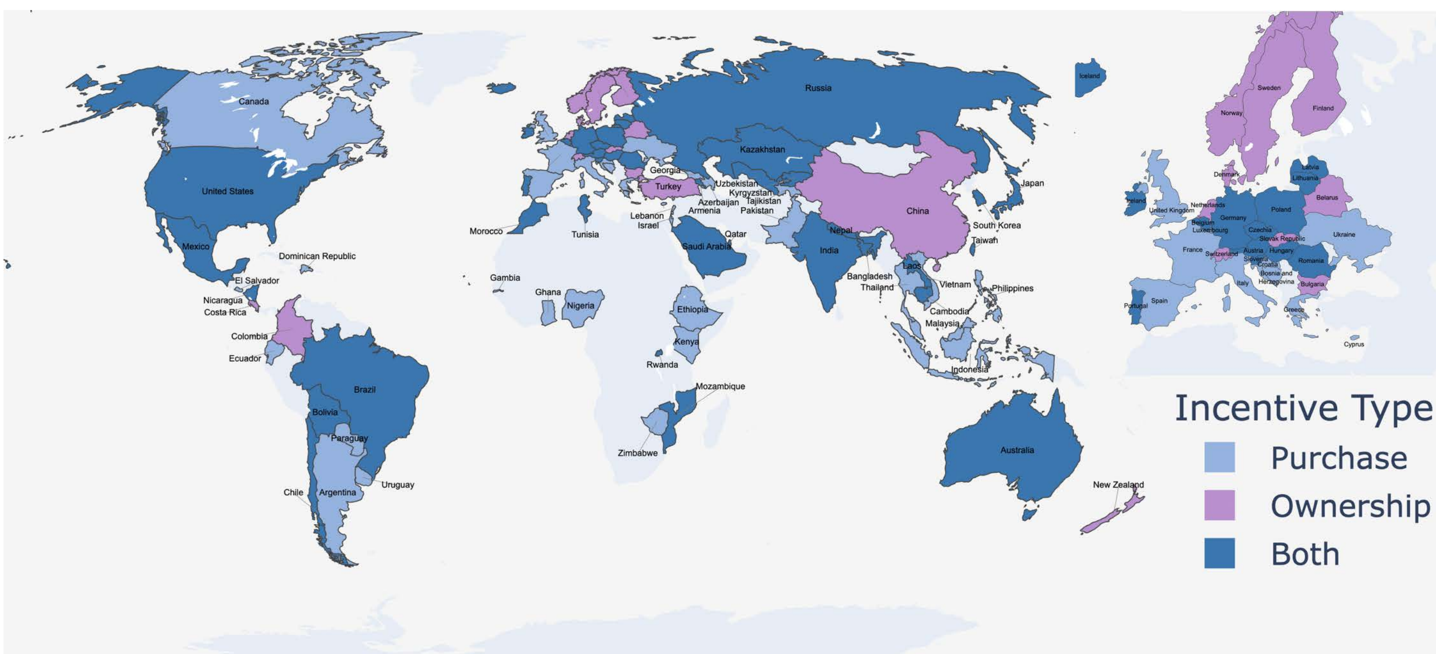

Fig 3. A global map of EV purchase and ownership subsidies. Cases in which national policy provides only one policy type but some subnational policies provide the other are classified as "both." Due to a lack of English-language resources detailing the exact nature of HGEV-specific policies in many nations, we elected to showcase EV subsidies overall; however, even some brief research reveals that the two are highly intertwined. Manufacturing subsidies are not included. Created via use of information provided by [15].

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Table 4. List of HGEV incentive policies relevant to estimating appropriate S^k values.

Nation	Subsidy Type	Amount
United States, Federal, and California (US incentives are not mutually exclusive)	Federal purchase grant (for vehicles 19,501lbs to 33,000lbs) Federal tax credit (for vehicles above 14,000lbs) California purchase voucher (for approved vehicles above 10,000lbs)	Federal grant: 65% of new vehicle + charging infrastructure cost ($190,000 USD/ vehicle max) Federal tax credit: $40,000 USD California purchase voucher: $45,000 USD, $60,000 USD, or $120,000 USD (size dependent)
United Kingdom	Purchase grant	Ranging from $3,050 USD to $30,500 USD
Canada	Purchase rebate	Ranging from $28,000 USD to $140,000 USD
Norway	Purchase grant (ended 2025)	Up to 40% of the extra costs associated with purchasing AFV trucks
China	Purchase grant (ended 2022) Purchase tax exemption	Grant: $4,000 USD purchase grant Tax exemption: exemption from 10% purchase tax for vehicles with a selling price of up to $46,000 USD
Netherlands	Purchase grant (starting 2026)	Up to 30% of the vehicle purchase price
Suggested range of values for S^k: $5,000 USD to $300,000 USD		

Taken from [120–127].

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5. Discussion

In this paper, we have presented a novel GVRP model and methodology that will aid organizations and policymakers in their decision-making. Both the model approach and research questions addressed by the model set it apart from previous works in this area. The model approach captures all three environmental policy initiatives with the most significant impact on green vehicle routing, whereas the limited previous research in this direction has primarily focused on the impact of only one of these initiatives. Previous research has also viewed integration of these policies merely from the perspective of "how will this addendum to the objective function affect optimal routing?" Instead, we ask "how will this addendum to the objective function impact organizational fleet composition decisions, organizational routing cost, and GHG minimizing tradeoff options, and governmental decision-making with respect to policy selection?" With this in mind, we believe this to be a pragmatic and impactful addition to previous work. Moreover, this model provides a method of integrating HGEV infrastructure costs into management decisions, a characteristic not found in other GVRP models thus far. This is critical, as often the price differential between a CFV and the equivalent HGEV ranges from $75,000 to $250,000, which, as demonstrated in the previous section, may be made up for in many areas with strong subsidy incentives [128]. However, given that HGEV charging infrastructure may cost up to several million dollars, a simple comparison of subsidy levels and purchase prices would represent an insufficient analysis [31].

To elaborate on some of the possible applications of this approach from an organizational perspective, we argue that it could provide key insights and answers to the following questions:

- Would it be cost-effective to purchase HGEVs to replace the fleet of CFVs, given the current regulatory landscape? How many should be purchased?
- Given the regulatory authority's stated intentions in reference to future environmentally-related transportation policies (carbon tax rates, HGEV subsidy program duration/ amounts) and ETS market projections (the expected future cost of carbon allowances), will the answer to the previous question change in the short or long term?
- Given the sustainability-related commitments the organization has made to its shareholders and the public, how can the organization adjust its vehicle routing to achieve the greatest reduction in GHG emissions with the lowest increase in cost?

- Would the magnitude of the current cost/GHG tradeoffs change under likely future carbon pricing or HGEV subsidy scenarios?

Conversely, government policymakers may find this model and methodology valuable for answering such important questions as:

- Which policy levers would have the greatest impact on reducing supply chain transportation GHG emissions?
- To what extent would a particular policy mix under consideration modulate the overall transportation costs for firms covered by carbon pricing or HGEV subsidy schemes?
- Which policy or set of policies would encourage the greatest amount of change (i.e., conversion of current CFV fleets to zero-emission EVs) in supply chain transportation?

In addition to laying out a model that organizations and governments can utilize to support their strategic decision-making, we have provided parameter assumptions for HGEV subsidies, carbon taxes, and carbon allowance prices in Section 4. These parameters are based on historical, current, and projected future rates and prices. Differing parameter assumptions may be easily integrated into the model generated in Section 3 to determine relevant changes to HGEV adoption and cost/GHG emission tradeoff decisions. Finally, numerous classical VRP variants are integrated, including capacitated, time window, multi-tour, split delivery, and heterogeneous fleet models; when combined with depot and customer recharging, the model provides an adaptable and realistic basis for modeling complex supply chain scenarios.

The chief limitation of this work lies in the fact that, for now, it remains a theoretical framework, and not yet a model that has been applied to a large dataset representing the depot, delivery nodes, vehicle characteristics, and recharging stations of an actual firm. S1 Appendix demonstrates the feasibility of the model by deriving exact solutions to the problem, as formulated using a small dataset based on Walmart's supply chain in Eastern Ontario, and on the CFVs and HGEVs commonly used by Walmart. Implementation of the model to a larger dataset may yield (and has yielded) challenges that require implementation of simplifications, advanced decomposition, and/or metaheuristic approaches. However, the general approach would still be valid regardless of these potential modifications. As large organizations have only recently begun to integrate HGEVs into their supply chain networks at a larger scale, it seems likely that usable datasets may emerge or (with some reasonable assumptions) be created in the near future [129–132]. To this end, we have attempted to contribute by providing a larger dataset for Walmart's supply network in Eastern Ontario (one distribution center and ~120 stores) in the supplementary material. Future research would benefit from a larger application of the model (or similar model/approach) described herein, followed by consideration for additional complexities posed by HGEV distribution networks, such as non-linear recharging functions and battery swapping. In a forthcoming work, we seek to transform this theoretical framework into an applied one, thus providing greater insight into many of the questions posed earlier in this discussion.

6. Conclusion

As highlighted in the introduction, road freight supply chain transport accounts for a large share of global GHG emissions and represents the sector with the most rapidly increasing carbon footprint. Without a concerted effort to curb these emissions, achieving the important targets outlined in the Paris Accords will not be possible. Critical elements of recent emissions-reduction efforts in road freight include incentivizing the faster uptake of zero-emissions HGEVs through HGEV subsidies and increasing the cost of more emissions-intensive supply networks, as best demonstrated by ETSs and carbon taxes. We have highlighted that all of these programs have become increasingly pervasive in recent years, and that this trend is likely to continue, with a greater number of national governments and municipalities offering subsidy programs and passing legislation to increase the share of global GHG emissions covered under carbon pricing schemes. Regulators have an interest in introducing the optimal policy mix with the ultimate aim of attaining Net Zero emissions as quickly as is reasonably practical. Regulated organizations have an interest in responding to their regulatory obligations in a way that ensures the maximum profitability and long-term viability of their firms. The bi-objective GVRP model developed in this paper aids both regulators and regulated parties in best pursuing their interests while more accurately representing those aspects of the supply chain that are critical to the decisions of each party.

Supporting information

S1 Appendix. Text discussing an exact solution implementation of the problem discussed in the main paper. The code for this implementation is provided in the data availability statement.
(DOCX)

S2 Appendix. Text reviewing details surrounding the instantaneous fuel consumption model and derivation of Equation 1**.**
(DOCX)

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Investigation: Griffin Mosher Wilson.

Methodology: Griffin Mosher Wilson.

Project administration: Griffin Mosher Wilson, Richard T. Stone.

Resources: Griffin Mosher Wilson, Richard T. Stone.

Supervision: Richard T. Stone.

Validation: Griffin Mosher Wilson.

Visualization: Griffin Mosher Wilson.

Writing – original draft: Griffin Mosher Wilson.

Writing – review & editing: Griffin Mosher Wilson, Richard T. Stone.

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