Adoption of Electric Trucks in Freight Transportation

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Abstract

Transportation sector is the largest contributor of global greenhouse gas emissions in the USA. Disruptive technological changes in this sector, such as alternative fuel vehicles, are crucial for emission reduction. We analyze how a cost-minimizing strategic transition plan can be developed for a transportation firm that aims to adopt electric trucks in their fully diesel fleet, over time. We consider the case in which the firm needs to invest in charging infrastructure required to support this transition, as the public charging infrastructure is currently inadequate. The congestion effect at the charging stations, the charging times, and the potential loss of productive driving time due to detours to reach charging stations are explicitly considered. By developing an independence property, we are able to model this problem as a linear integer program without any need to explicitly specify origins and destinations. We illustrate the resulting transition plan with a realistic data set. Our results indicate that a transportation firm that operates with high demand density over a given service region significantly benefits from adoption of electric trucks, while also enjoying substantial carbon emissions savings. High demand density also favors smaller battery capacity with shorter ranges under the optimized charging network capacity, even though larger battery capacity would increase productivity with extended ranges. Our analysis also offers insights for governments and regulators regarding the impact of several influential factors such as carbon cost, content of renewable energy in electricity mix, diesel engine efficiency, and subsidizing the charging infrastructure.

Keywords : Sustainability, Transportation, Investment Decisions, Electric Vehicles

1 Introduction

Technological change is necessary if we are to meet the aggressive emission targets of the 2016 Paris accord[1]. This is particularly true for the transportation sector, one of the largest contributors to global greenhouse gas (GHG) emissions. As of 2017, the transportation sector generated the largest share (28.9%) of all U.S. GHG emissions (EPA, 2019). Globally, the estimate is close to 25% (IEA, 2017a). Moreover, road transport accounts for approximately 80% of all such emissions (IEA, 2017a).

Under current trends, energy demand and emissions related to transportation are predicted to double by 2050 (IEA, 2016). Therefore, disruptive—rather than progressive—change is needed to meet emission targets in the sector (Girod et al., 2012). Some estimates indicate that an adoption of alternative fuel vehicles (AFV) in the order of 50% for overall traffic is required, by 2050, to stay within the 2-degree climate target (UNFCCC, 2010). Other estimations are equally radical.

On the commercial front, the International Energy Agency has developed two scenarios for the evolution of energy demand from freight vehicles (IEA, 2017b). The first scenario estimates the evolution of the sector solely based on advances in current technologies[2]. This scenario leads to an increase in GHG emissions in the order of 55% by 2050. The second scenario, however, explicitly considers the adoption of a new type of "modern truck" based on radical technological change; it achieves a reduction in GHG emissions in the order of 60%. In this scenario, the penetration of AFVs in commercial fleets is in the order of 85% for light vehicles, 75% for medium freight vehicles, and 70% for heavy freight vehicles.

Currently, the adoption of AFVs in the commercial space is virtually zero[3]. As of the end of 2018, the number of AFVs on the road was around 5 million, the vast majority of which were consumer vehicles (IEA, 2019). Of these, 3 million are battery electric vehicles. (This is equivalent to approximately 0.1% of the total number of consumer vehicles on the road.)

The lack of adoption of AFVs in the industrial sector can be attributed to a number of reasons. Limited range, high cost of fixed assets, and a lack of fueling infrastructure are consistently listed

[1] Some countries even consider the Paris agreement too conservative. The Netherlands, for example, recently passed legislation to cut 95% of carbon emissions by 2050.

[2] Based on policies and measures that are currently adopted or announced, e.g., improvements in fuel efficiency, vehicle utilization, and routing.

[3] Particularly in the medium/heavy freight space. A number of hybrid and electric vehicles for urban light commercial use are in the piloting and early deployment stages in several areas.

as the primary factors holding firms back (IEA, 2017b). In contrast to the consumer space, an investment in AFVs can potentially represent a significant portion of a firm's total investment, particularly for logistic service providers. A change in the technology basis of their largest asset base is non-trivial. Thus, it is understandable for firms to take a wait-and-see approach, allowing for the market to become less uncertain (i.e., allowing for the different technologies to mature) before formulating an alternative-fuel strategy (Courtney et al., 1997).

From a technological perspective, however, we are currently at the verge of maturity. Electric vehicles (e-vehicles) specifically targeted at the consumer sector deliver outstanding performance (Lambert, 2017, 2018; Coppola and Kharif, 2018; Evarts, 2019). Recent research suggests that battery technology is now at a stage where, even though they are still more expensive upfront, the total ownership cost (considering maintenance costs and tax rebates) of consumer e-vehicles is lower than the total ownership cost of internal combustion vehicles (IC-vehicles) (Wu et al., 2015; Letmathe and Suares, 2017; Danielis et al., 2018). Moreover, forecasts estimate that the purchase cost of consumer e-vehicles will be competitive with IC-vehicles as soon as 2025 (Deloitte, 2019).

Developments in the commercial space are slower, but several truck and e-vehicle manufacturers such as Daimler, Mack, Tesla, Nikola, Volvo, Navistar, and DAF have announced plans to deliver long-haul electric trucks (e-trucks) (Extremetech, 2019).

Trucks based on other alternative-fuel technologies are also under development. The question in the transportation sector is, therefore, not whether the current standard for commercial applications will be replaced by new vehicle technologies. Rather, the question is how to implement the upcoming technology change in the best way possible. This question motivates our research.

In this paper, we study whether e-trucks can become a feasible alternative for a firm that currently operates a fully diesel fleet. In particular, we analyse the way in which a firm can optimize this (potential) transition over the years. We develop a model to optimize the investment and salvaging decisions of a transportation firm for its fleet together with the required investment for the charging infrastructure associated with its e-trucks. We contribute to the literature by formulating a linear model that considers the vehicle and the infrastructure investment problems simultaneously. Our model avoids a-priori assumptions regarding the fleet composition (e.g., we allow new investments to be made on electric, diesel, or a combination of both types of vehicles in each period) and on the assignment of vehicles to customers.

The argument for considering vehicle and infrastructure decisions simultaneously is threefold. First, there is no existing infrastructure for refueling AFVs on the scale necessary for commercial use (Extremetech, 2019). Thus, early adopters must also invest in infrastructure. Second, even for a sufficient coverage area of publicly available charging infrastructure, fleet owners might want to avoid potential congestion, uncertain waiting times, and unavailability due to maintenance and breakdowns. Third, the choice of charging technology and the density of the charging infrastructure have a substantial impact on the effective utilization of trucks and, hence, on the level of customer service provided.

Our approach is generic and can thus be applied to alternative scenarios through different parameter settings. We illustrate the use of our model by performing a numerical study based on parameter settings inspired in real life use, reflecting strategies for e-vehicle adoption in a small and a large area with dense and sparse demand, respectively. From our numerical study, we obtain the following insights:

- Adopting e-trucks does not only have environmental appeal, but it may also be the cost-optimal strategy. This result, however, relies on optimizing the infrastructure density as well as the fleet composition. Unproductive time becomes too costly if charging stations are located too far apart; the infrastructure itself becomes too costly if stations are located too close together.

- The attractiveness of e-trucks, as well as the robustness of the solutions, are also tightly linked to the density of demand: e-trucks become more cost-effective as the customer concentration increases within a given area.

- Firms should opt for the optimal trade-off between battery capacity and infrastructure density, rather than investing in the largest batteries providing longer ranges. Indeed, it turns out that high demand density favors smaller battery capacity.

- While the transition to e-vehicles may occur without the need for governmental intervention, higher carbon costs accelerate the adoption of e-trucks in the optimal fleet composition.

- Increasing the efficiency of diesel engines can be counterproductive in the long run. This is due to the fact that cleaner diesel vehicles are not green enough to significantly reduce emissions, but are clean enough to avoid or delay the adoption of the greener technologies.

The rest of this paper is structured as follows. In Section 2 we provide a survey of the literature related to sustainable transportation and fleet replacement issues. Then, in Section 3 we introduce our mathematical formulation and describe the parameters chosen for our model. Section 4 shows the results of our numerical study and scenario analysis. We conclude with Section 5.

2 Literature Review

Our research is motivated by the sustainability-driven requirement for technological change in commercial transport. Our paper is therefore positioned in the intersection of two literature streams: sustainable operations (in particular, green transportation) and asset management (and fleet composition).

2.1 Sustainable transportation

Within the general field of sustainable operations (see Drake and Spinler, 2013, for an overview), much attention has centered around sustainable transportation and, in particular, on the need to transition from internal combustion vehicles (ICV) to alternative fuel vehicles (AFV), both as means of personal (see, e.g., Sun et al., 2010; Propfe et al., 2012) and commercial transportation (e.g., Chocteau et al., 2011; Kleindorfer et al., 2012). Existing research ranges from engineering considerations (Finesso et al., 2016) to economic issues, including fiscal incentives (Lévay et al., 2017) and total cost of ownership (Hagman et al., 2016). The particular challenges facing commercial operators in adopting AFVs are most relevant to our paper. In this context, Schneider et al. (2014) and Pelletier et al. (2016) provide in-depth discussions of the challenges firms face and of future research perspectives of goods distribution using AFVs. Note that, while there is no universal consensus as to the optimal alternative fuel technology (see IEA, 2017b), electric vehicles (EV) are typically considered the default AFV, with the current state of technology. Within the vast literature on sustainable transportation, the electric vehicle routing problem (E-VRP) and facility location problems (FLP) for optimal location of charging infrastructure have gathered considerable attention, on which we elaborate further below.

Afroditi et al. (2014) trace the early appearance of the electric vehicle routing problem (E-VRP) to the beginning of the decade and suggest trends and insights for future research: a call for real-world, industry-based solutions. In subsequent years, the topic has sparked considerable interest from the research community. Given that the problem is NP-hard, hybrid heuristics are typically used to solve problem instances. Among others, extensions to the E-VRP include addition of time windows and recharging stations with or without mixed fleet and fleet size considerations, and full or partial charging. We refer the reader to Macrina et al. (2019) for a complete survey of the related literature in this domain.

Goods distribution using EVs poses a double challenge: limited range and long recharging times. This challenge requires explicit modeling of the charging technology and infrastructure, e.g. Sari (2017) considers adopting battery swapping stations, which has not emerged as a viable technology for e-vehicles compared to the plug-in counterpart. Another approach in this domain is to decompose the problem: identify a route and find the optimal station location among a set of candidate locations (e.g., Wang, 2007). Within the facility location problems, Zhu et al. (2016) develop a genetic-algorithm-based method to solve the charging station location and size problem, and Zhang et al. (2017) incorporate demand dynamics in a multi-period capacitated fast-charging infrastructure location planning model. We refer the reader to Karakitsiou et al. (2018) for a recent review of the models and challenges in this domain.

A number of recent papers consider integrated location-routing problems. Schiffer and Walther (2017) recognize the “chicken and egg” nature of the problem, in which the adoption of EVs is hindered by a lack of infrastructure, and infrastructure investment is hindered by a lack of EV adoption. They formulate the electric location routing problem with time windows and partial recharging as a mixed integer programming model and allow for simultaneous routing and infrastructure decisions, considering partial recharging and recharging at customer sites. Schiffer and Walther (2018) later extend this model to incorporate demand uncertainty with robust optimization.

In contrast to the short-term focus of the FLP and E-VRP, we account for the characteristics of electric vehicles from a strategic perspective, focusing on the investment decisions for the fleet assets and the charging infrastructure. We estimate the required capacity of the refueling infrastructure based on the total driving times of vehicles scattered over a given region, without needing to identify their exact routes. We also do not identify the exact locations of charging facilities, but confine our analysis to the design of a charging network defined in terms of the maximum distance between the facilities. Rather than optimizing the routing, location, and sizing decisions based on a given infrastructure, we optimize the timing of the capacity investment decisions for a desired density of the infrastructure network at a strategic level. When a strategic decision lays out a transition plan as an outcome of our model, desired FLP and E-VRP models can be used by the decision maker to convert this plan into tactical and operational decisions for locating charging facilities and for identifying vehicle routes and charging schedules.

Similar to our approach, Koç et al. (2018) consider investment decisions in the charging infrastructure. The authors consider an E-VRP problem with shared charging stations by allowing multiple firms to invest jointly in the infrastructure of the charging stations. In addition to the investment in the charging infrastructure, we also optimize for the investment in fleet assets.

2.2 Asset management, technology adoption, and equipment replacement.

The classical asset management/replacement problem considers the tradeoff between increasing operating, maintenance, and depreciation costs of aging equipment against the salvage value and replacement cost of new equipment (Hartman and Tan, 2014). A large literature on the subject considers deterministic (Howe and McCabe, 1983) and stochastic factors (Adkins and Paxson, 2017). Extensions to the pure replacement problem are the replacement problem with new technology adoption (Karaca-Mandic, 2011), the renewal problem (Adkins and Paxson, 2011; Reindorp and Fu, 2011), and the combined replacement and renewal problem (Stutzman et al., 2017). When adopting a new technology, a decision maker faces the additional uncertainty of future technological change, its associated attributes, and cost (Yatsenko and Hritonenko, 2015, 2017). Operationally, sustainability can be incorporated by framing the issue as a multi-objective problem, with, e.g., energy consumption and GHG emissions as additional objectives (Liu et al., 2017).

From a strategic perspective, the timeframe for technological change is aligned with the timeframe over which environmental policies are evaluated (Jaffe et al., 2003). Thus, the problem of strategic asset replacement with sustainable technologies has started to gain traction in the literature (Drake et al., 2016; Aflaki and Netessine, 2017).

2.2.1 Strategic fleet replacement

A number of papers study the different strategic aspects of the replacement of a fleet of ICVs by EVs. Ansaripoor et al. (2016) use a risk-type analysis to optimize the expected conditional value at risk (RECVaR) metric, Kleindorfer et al. (2012) formulate a stochastic dynamic programming model with uncertain battery and fuel acquisition prices to support the fleet renewal decision at the French postal operator (La Poste), and Cortés-Murcia et al. (2019) propose taking advantage of mandatory lunch breaks for recharging.

Wang et al. (2013) and Patricksson et al. (2015) are closest in spirit to our paper. The former present a dynamic capacity investment model for two competing technologies: "green" and conventional. The authors assume stochastic demand and operating costs, formulating a dynamic programming model in which the decision to invest/divest or do nothing is taken every period for a certain time horizon. They illustrate an application of their model with a case study of the diesel/electric vehicle fleet for Coca-Cola. The authors, however, consider a 1-to-1 replacement of the diesel fleet with electric vehicles, thus foregoing the interaction effect between infrastructure capacity and waiting times—and the associated impact on the required fleet size. Patricksson et al. (2015) study the problem of fleet composition with regional emission limitations using RoRo shipping as a case study. While they consider several technological characteristics in their model, there is no infrastructure component in their analysis.

We consider the specific strategic issue of the transformation of an entirely diesel fleet into an electric fleet within a given time horizon. The aim of our model is to assist with strategic decision-making by finding the optimal investment decision in terms of truck technology and charging infrastructure. We optimize over the entire planning horizon; thus, our solution implies a time-varying investment strategy. We make general assumptions regarding the demand for transportation and the location of origins, destinations, and charging infrastructure. In contrast to prior research, the number of facilities and charging instruments installed in a given period are treated as decision variables; this allows us to trade off infrastructure investment against unproductive time (i.e. deviations from route and queueing time prior to recharging).

3 Problem Environment and Settings

We consider a freight-moving firm operating with a fleet of diesel trucks (d-trucks) in a given geographical region. The firm aims to minimize the investment and operational costs associated with its fleet (composition) over a certain planning horizon. We also incorporate a carbon emission cost component in the objective function, which can be a carbon tax, the cost of permits in a cap-and-trade system, the cost of carbon offsets, or simply an internal proxy for the firm to account for the environmental impact of its operations (zero being a special case, if the environmental effect is to be neglected). The firm might reduce the carbon footprint of its transportation operations by adopting a 'greener' fleet containing e-trucks. Given the current state of the technology, we assume that the charging infrastructure required to operate the e-truck fleet is not readily available, hence, the firm must also invest in the charging infrastructure to materialize this transition. Operational cost components are 'fuel' (diesel or electricity), carbon emissions, driver wages, and maintenance of trucks and charging outlets. Investment cost comprises procurement costs and salvage values associated with trucks and charging infrastructure. We introduce a metric for measuring the 'sustainability' of the fleet composition: the Green Ratio (GR), which we define as the fraction of e-trucks that the firm owns in its current fleet. We assume that the firm initially operates with $GR = 0$ and might adopt e-trucks at any time until the end of the planning horizon.

We adopt a strategic level analysis of the freight movement operations. We do not predicate our analysis on the exact locations of origins, destinations, and the routes traversed, which might differ on a daily basis. Instead, we assume that the trucks are continuously traversing roads, destined for a drop-off, pick-up, refueling, or parking location in a given service region defined at a city, country, or continent scale. Our analysis considers a dense road network over which origins and destinations are randomly scattered, implying that the traversing trucks are also randomly dispersed over the service area at any given time, without any condensed mass at a particular region. This topology fits well to Europe, where the road network is not sparse, and origins and destinations can be anywhere, due to a large and dispersed population. It also fits to highly populated areas such as the North American coasts, as well as Asian, Latin American, and African metropolitan areas. The problem under concern applies to any firm that owns and operates a fleet of trucks, whether in-house or for-hire.

Currently, the charging infrastructure for e-trucks is not available on a sufficiently large scale to support the industrial adoption of e-trucks. Hence, we concurrently plan for the establishment of the charging infrastructure that will support a green transition. We define a "charging facility" as a charging station that contains one or more charging outlets, which we call "charging instruments". We treat the number of facilities and instruments installed as design variables to be optimized. Depending on the invested charging capacity, e-trucks may need to detour to access a charging facility by deviating from their main route and may also need to wait for an available instrument, due to congestion at the facility. In contrast, we assume that d-trucks can find a refueling station along their main route whenever necessary and start refueling without delay, as gas stations are ubiquitous and with abundant capacity.

3.1 Definition of Demand and Productive Driving Time

A typical trucking operation consists of productive and non-productive work elements. Productive work elements are driving times to reach a drop-off, pick-up, or parking location. Non-productive elements include loading, unloading, and refueling times. The non-productive element associated with the refueling of e-trucks includes the duration of the detour required to reach a charging facility and to return to the main route after receiving the service, potential waiting time at the facility for an available charging instrument due to congestion, and the recharging time; whereas that of the d-trucks includes only the fueling time at the gas station. We denote the total working time of a truck, excluding the non-productive work elements, as the "productive driving time". Depending on the number and locations of the destinations to be visited in a given time period, we define the transportation demand in terms of

W_t: total productive driving time required to satisfy the demand for the trucking operations in year t.

Let τ_e be the non-productive work element of e-trucks due to recharging, ν be the average speed of the truck, and R_e be the driving range of an e-truck. Then, the productive driving time of an e-truck, D_e^p, can be estimated by

$$D_e^p = \frac{R_e/\nu}{R_e/\nu + \tau_e}. \tag{1}$$

3.2 Charging Infrastructure Design

Transitioning to a greener fleet can be viable only if the operations are backed up with sufficient charging capacity. The two variables that dictate this capacity are

F_t: number of charging facilities installed in the service area in year t, and

γ_t: number of charging instruments installed in each facility in year t.

Recall that we consider the demand to be homogeneous across the service region, meaning that the charging facilities are spread uniformly within that region with identical capacities. The charging capacity will factor in when estimating the non-productive working time of e-trucks, which is their main operational adversity compared to d-trucks. Obviously, installing more charging capacity will decrease the non-productive driving times of e-trucks, while increasing their investment requirements.

Rather than setting F_t and γ_t as independent decision variables, we adopt a service level target aimed by the decision maker through the following design variables:

δ: distance between any two charging stations, and

ω: maximum average waiting time at a charging facility due to congestion.

Note that δ and ω imply how much time a driver will spend to recharge an e-truck. Based on the target service level pair (δ, ω) set by the decision maker, investment decisions can be optimized.

We model the congestion at a charging facility via a $G/D/\gamma_t$ queueing system, in which the 'customers' are e-trucks arriving at charging facilities equipped with γ_t charging instruments. Even though the state-of-charge (SoC) might differ for arriving trucks in general, we assume in our analysis that the SoC of the arriving trucks will be consistently low, as the drivers would be instructed to maximize their battery usage before recharging. This implies that the service delay at a charging instrument will be degenerate with a service time equal to the recharging time of an e-truck battery, denoted by μ_e. The design parameters (δ, ω) will dictate the arrival rate and the required γ_t value.

Estimating the Number of Facilities: Let G be the total area (in km^2) of the region served by the transportation firm. Assuming that the charging facilities can be located anywhere in the service region on a continuous domain, the maximum number of charging facilities, $\overline{F}$, required to ensure

δ kilometers between any two charging facilities can be estimated by

$$\overline{F} = \frac{G}{\delta^2},$$

supposing that charging stations are installed at the centers of $\delta \times \delta$ grids that span all service areas on a continuous scale. This estimation warrants the maximum detour length to access a charging station and return to the main route to be δ kilometers from anywhere on the road, by using rectilinear metric. Note that this estimation is merely an upper bound, as it ignores the topology of the network. More realistic values can be estimated by solving a coverage problem on a given network. However, we use this upper bound in our analysis, because we conduct a strategic analysis to generate generic insights about the transformation process.

If the firm operates with a mixed fleet of diesel and electric trucks at any point in time, a decision should be made regarding the allocation of each type of truck to different regions and customers. As the adoption of e-trucks requires investment in charging infrastructure, allocating e-truck fleet to satisfy the customer demand in a continuous sub-region as a whole is more efficient than splitting the fleet to satisfy multiple separate regions. As we assume that the trucks are scattered randomly over the service area at any given time, the service area allocated to the e-truck fleet must be proportional to the demand satisfied by e-trucks. With this in mind, F_t can be estimated by

$$F_t = \frac{V_{te} D_e^p H_e}{W_t} \overline{F}, \tag{2}$$

where V_{te} is the number of e-trucks in the fleet of year t, and H_e is the number of operating hours of an e-truck in one year.

Under this construct, the total non-productive time for recharging an e-truck, τ_e, to be used in Equation (1) is given by

$$\tau_e = 2\delta/\nu + \omega + \mu_e.$$

Note that there can also be non-productive times other than τ_e, due to loading and unloading operations, but we ignore them, because they apply to both d- and e-trucks.

Estimating the Arrival Rate: Under the settings described above, we have the following proposition that enables us to develop an efficient solution approach. In particular, the proposition allows us to formulate the problem as a linear optimization problem, as explained in the next section.

Proposition: The arrival rate of e-trucks to a charging facility is independent of the size of the e-truck fleet V_{te} and is given by

$$\lambda_t = \frac{\nu W_t}{R D_e^p H_e \overline{F}}.$$

Proof:

$$\lambda_t = \frac{\eta V_{te}}{F_t} = \frac{\eta V_{te}}{\frac{V_{te} D_e^p H_e}{W_t} \overline{F}} = \frac{\eta W_t}{D_e^p H_e \overline{F}},$$

where $\eta = \nu / R$. □

Estimating the Number of Instruments: For any $G/D/\gamma_t$ queue with an arrival rate of λ_t and service time of μ_e, the γ_t value that ensures the service level target ω can approximately be estimated by using the waiting time in the queue as follows:

$$\gamma_t = \min \left\{ m : \omega \leq \frac{C_a^2}{2} \frac{(\lambda_t \mu_e / m)^{\sqrt{2(m+1)}-1}}{m - \lambda_t \mu_e} \mu_e \right\} \quad \forall t, \tag{3}$$

where C_a is the coefficient of variation of the arrival time. See Whitt (1983) and Hopp and Spearman (2011) for discussions on estimating the waiting time in the queue.

3.3 Problem Formulation

In this section, we present a linear mathematical programming formulation of the problem under concern. Table 1 summarizes the parameters. We use the following indices:

t: year index; 0, ..., T

k: truck type index; d: diesel truck, e: electric truck

h: age index; 0,..., L,

where T denotes the total number of years in the planning horizon, and L is the maximum useful life of a truck. The decision variables are

P_t^i: Number of charging instruments purchased at the beginning of year t

P_{tk}^v: Number of type k vehicles purchased at the beginning of year t

Q_{ht}^i: Number of charging instruments of age h owned at the beginning of year t

Q_{htk}^v: Number of type k vehicles of age h owned at the beginning of year t

S_{ht}^i: Number of charging instruments of age h salvaged at the beginning of year t

S_{htk}^v: Number of type k vehicles of age h salvaged at the beginning of year t.

For any given service level target pair (δ, ω), one can estimate $\overline{F}$ and γ_t values by using (2) and (3), respectively, for each year t. Then, the Sustainable Fleet Management Problem, SFMP, can be formulated as a function of $\overline{F}$ and γ_t as follows:

A:	Annualized fixed cost of a charging facility
c^i_t:	Purchasing cost of one charging instrument in year t
c^v_{tk}:	Purchasing cost of one type k vehicle in year t
D_k:	Driving hours of type k vehicle in one working hour
D^p_k:	Productive driving hours of type k vehicle in one working hour
e^d_{htk}:	CO_2 emissions in kg per hour of driving by a type k vehicle of age h in year t
e^m_k:	CO_2 emissions in kg due to the manufacturing process of a type k vehicle
f_{htk}:	Fuel cost of a type k vehicle of age h in year t for one hour of driving
$\overline{F}$:	Minimum number of charging facilities required to have an access within δ kilometers from anywhere on the road network
GR:	Green Ratio; fraction of e-trucks in the fleet
H_k:	Number of operating hours of a type k vehicle per day
m^f_t:	Annual maintenance cost required in a charging facility per year
m^v_{htk}:	Maintenance cost of a type k vehicle of age h for one hour of driving in year t
$\overline{Q}^v_{h0k}$:	Number of vehicles of type k of age h owned at the beginning of the planning horizon
R_k:	Range of a type k vehicle in kilometers, with a full tank or battery
s^v_{htk}:	Salvage value of a type k vehicle of age h in year t
s^i_{ht}:	Salvage value of one charging instrument of age h in year t
u_t:	Driver cost per hour in year t
W_t:	Daily productive driving hours necessary to satisfy the annual demand in year t
Y:	Number of working days in a year
β_t:	Discount factor for year t
γ_t:	Number of charging instruments kept in each charging facility in year t
δ_k:	Average distance that a type k vehicle deviates from its route to reach a charging facility
ϵ_t:	Cost of emissions in year t per kilogram of CO_2 emissions
η:	Number of times that an e-truck must visit a charging facility per day
λ_t:	Arrival rate of e-trucks per hour to a charging facility in year t
μ_k:	Average recharging or refueling time for a type k vehicle
ν:	Average speed of the truck
τ_k:	Total time spent for refueling/recharging including the back-and-forth access time to the charging facility
ω_k:	Average waiting time in the queue allowed at the charging facility for a type k vehicle

Table 1: *Summary of Notation*

SFMP$(\overline{F}, \gamma_t | \delta, \omega)$:

$$\text{Min.} \quad \sum_{t,k} c_{tk} P^v_{tk} \beta_t - \sum_{h,t,k} s^v_{htk} S^v_{htk} \beta_t + \sum_{h,t,k} (f_{htk} + m^v_{htk}) Y H_k D_k Q^v_{htk} \beta_t + \sum_{t,k} \epsilon_t e^m_k P^v_{tk} \beta_t$$
$$+ \sum_{h,t,k} \epsilon_t e_{htk} Y H_k D_k Q^v_{htk} \beta_t + \sum_{h,t,k} u_t Y H_k Q^v_{htk} \beta_t + \sum_t (A + m^f_t) F_t \beta_t + \sum_t c^i_t P^i_t \beta_t - \sum_{ht} s^i_{ht} S^i_{ht} \beta_t$$

$$\text{s.to} \quad Q^v_{0tk} = P^v_{tk} \qquad \forall t, k \tag{4}$$
$$Q^v_{h0k} = \overline{Q}^v_{h0k} - S^v_{h0k} \qquad \forall h \geq 1, k \tag{5}$$
$$S^v_{h0k} \leq \overline{Q}^v_{h0k} \qquad \forall h \geq 1, k \tag{6}$$
$$Q^v_{htk} = Q^v_{h-1,t-1,k} - S^v_{htk} \quad \forall h \geq 1, t \geq 1, k \tag{7}$$
$$S^v_{htk} \leq Q^v_{h-1,t-1,k} \qquad \forall h \geq 1, t \geq 1, k \tag{8}$$
$$Q^i_{0t} = P^i_t \qquad \forall t \tag{9}$$
$$Q^i_{h0} = \overline{Q}^i_{h0} - S^i_{h0} \qquad \forall h \geq 1 \tag{10}$$
$$S^i_{h0} \leq \overline{Q}^i_{h0} \qquad \forall h \geq 1 \tag{11}$$
$$Q^i_{ht} = Q^i_{h-1,t-1} - S^i_{ht} \qquad \forall h \geq 1, t \geq 1 \tag{12}$$
$$S^i_{ht} \leq Q^i_{h-1,t-1} \qquad \forall h, t \tag{13}$$
$$W_t \leq \sum_k H_k D^p_k \sum_h Q^v_{htk} \quad \forall t \tag{14}$$
$$F_t = \frac{D^p_e H_e \sum_h Q^v_{hte} \overline{F}}{W_t} \qquad \forall t \tag{15}$$
$$\sum_h Q^i_{ht} = \gamma_t F_t \qquad \forall t \tag{16}$$
$$Q^v_{htk}, P^v_{tk}, S^v_{htk}, Q^i_{ht}, P^i_t, S^i_{ht} \in \mathbb{Z}_{\geq 0}. \tag{17}$$

The objective function calculates the present value of all operational costs and benefits, which include the purchasing cost of trucks; salvage value of trucks; fuel and electricity costs; maintenance costs of trucks; carbon emission costs due to manufacturing and transportation operations; cost of the driver; fixed cost of installing charging facilities; and purchasing cost, salvage value, and maintenance costs of charging facilities, in the respective order. Parameter D_k measures the driving time of each truck type and can be calculated as $D_k = \frac{R_k/v}{R_k/v + \omega_k + \mu_k}$, where ω_e is the service level target for e-trucks and $\omega_d = 0$ for d-trucks, by assumption.

Constraint sets (4) – (8) are the balance equations for each type of truck through acquisition and salvaging. Constraint sets (9) – (13) are similar balance constraints for the charging instruments. Constraint set (14) ensures that the size of the fleet is adequate to satisfy the demand, considering the available working time of each truck. Constraint set (15) defines the auxiliary decision variable, F_t, which is the required number of charging facilities in period t to serve the e-truck fleet in that period. Constraint set (16) ensures that an adequate number of charging instruments are installed in each charging facility. Note that γ_t is a parameter in this constraint given by (3). Constraint set (17) are the nonnegativity and integer constraints.

3.4 Operational Constraints

We extend the base model to include operational constraints that can originate from internal or external mandates.

Budget Constraint. An obvious operational constraint in practice is having budget limitations for new investments. Let B_t^a and B_t^o be the available budget in year t for investment in assets and for operational expenses, respectively. Then, the following two constraints can be added to SFMP:

$$\begin{aligned} \sum_k c_{tk} P_{tk}^v + \sum_t AF_t + \sum c_t^i P_t^i &\leq B_t^a && \forall t \\ \sum_{h,k} (f_{htk} + m_{htk}^v) YH_k D_k Q_{htk}^v + \sum_{h,k} \epsilon_t e_{htk} YH_k D_k Q_{htk}^v + \sum_t m_t^f F_t &\leq B_t^o && \forall t. \end{aligned}$$

Green Ratio. An internal constraint can be imposed to achieve a (potentially progressive) target level of "green ratio" in year t. Let G_t be the minimum green ratio that the decision makers want to attain in year t. Then, the following constraint can be added to SFMP:

$$\sum_h Q_{hte}^v \geq G_t \sum_{h,k} Q_{htk}^v \qquad \forall t.$$

Emission Constraints. As discussed above, there can be emission targets mandated by governments that should guide the optimal investment plan. Such mandates can be in the form of a single absolute or relative target within a given number of years (e.g. net-zero within 10 years or 50% savings in emissions within the next five years, respectively) or in the form of progressive savings over the years (e.g. at least 10% annual savings over the next 10 years). Let

E^a_τ: Maximum CO_2 emissions to be achieved by year τ, and

E^p: Minimum percentage of CO_2 savings compared to the previous year until reaching net-zero.

An absolute target of E^a_τ can be achieved by adding the following constraints to SFMP:

$$
\begin{aligned}
\sum_{h,k} e_{h\tau k} Y H_k D_k Q^v_{h\tau k} &\leq E^a_\tau \\
\sum_{h,k} e_{htk} Y H_k D_k Q^v_{htk} &\leq \sum_{h,k} e_{h,t-1,k} Y H_k D_k Q_{h,t-1,k} \qquad \forall t \geq \tau + 1.
\end{aligned}
$$

Progressive savings targets can be achieved by adding the following constraints to SFMP:

$$
\sum_{h,k} e_{htk} Y H_k D_k Q^v_{htk} \leq \left(\frac{100 - E^p}{100}\right) \sum_{h,k} e_{h,t-1,k} Y H_k D_k Q^v_{h,t-1,k}.
$$

3.5 Technology related costs and parameters

We present relevant costs and parameters in three categories: Trucking, charging infrastructure, and energy and technology.

Trucking related costs: *Purchasing Cost.* In our numerical study, we consider heavy duty Class 8 trucks that can accommodate about 15 tons. The average price of a Class 8 diesel truck in 2017 was $118,000 (USD), and the average price increase since 2011 was 5% (Statista, 2019). Accordingly, we set the base procurement price of a diesel truck to $120,000 in the first year of our analysis and inflate the price by 0.8% until the end of the planning horizon. There are no e-trucks available in the market as of 2019, but several manufacturers like Daimler, DAF, and Tesla have announced plans to produce and sell functionally comparable e-trucks with varying prices and technological characteristics in the near future (Lambert, 2017, 2018; Coppola and Kharif, 2018). Because these announcements are in the form of marketing initiatives to create public interest, the announced price information is speculative. Rather than relying on these prices, we set the price differential between d-trucks and e-trucks as much as the battery price (along with the suggestion of IEA, 2017b), which is roughly the case for consumer vehicles in the current market.

Salvage Value. The useful life of industrial trucks is accepted as seven years, even though many trucking firms prefer to renew their fleets more frequently. We assume that both d- and e-trucks depreciate based on sum-of-the-years method (cf. Danielis et al., 2018, who report that the battery EVs retain 10% of their value after 6 years).

Maintenance Costs. During the course of this study, we contacted two North American large-sized carriers: an in-house and a for-hire fleet operator. Both firms reported that their maintenance and repair costs are around $0.2 per mile. We use this quantity as the base for d-trucks in Year 1 and increase it by the inflation rate over the planning horizon. Maintenance and repair costs of e-trucks are expected to be lower than d-trucks, as electric engines are much simpler than combustion engines (Morris, 2015). Such potential savings reported in literature vary between 18 – 45% (Danielis et al., 2018; Letmathe and Suares, 2017; Weldon et al., 2018). In our analysis, we use an average savings of 30% for e-trucks over the maintenance and repair costs of d-trucks, in every year. With the wider adoption of EVs in general, it is reasonable to expect a decrease in maintenance costs, with increased practice and experience in the sector. Therefore, we assume an annual 3% decrease in the maintenance costs of an e-truck of a particular age. Obviously, the maintenance costs of a truck will increase as it ages, and this raise is taken as 20% in our study both for d- and e-trucks (Martin, 2016).

Charging Infrastructure Related Costs. *Charging Facility*: Charging instruments can be housed in existing facilities, such as gas stations, or at locations that might require new construction. Hence, establishment costs of charging facilities may vary significantly from one facility to another. We assume that the installation cost is somewhere between $50,000 (e.g. modifications required at an existing facility) and $350,000 (maximum installation costs estimated by Smith and Gonzales, 2014). Consequently, we assume an annualized fee of $15,000 which corresponds to an investment requirement of $175,000 with an 8% rate of return over 30 years. *Charging Instruments*: Level 3 charging is the current industry standard. These chargers operate with 480 volts of energy, providing much faster charging time, but requiring an elevated upfront cost of procurement and installation, compared to its Level 1 and 2 counterparts. As high utilization is desired in industrialized applications, we assume the adoption of Level 3 charging instruments. The list prices of

Level 3 chargers sold by a North American EV charging station installation company vary between \$12,500 for single-headed chargers to \$35,800 for two-headed chargers, depending on the power provided (SCA, 2019). Referencing to this seller, we assume that the procurement and installation cost of one charging instrument is \$15,000 in the base scenario, with an annual increase by the inflation rate. We take the useful life as seven years, with linear depreciation for salvage value calculations. *Maintenance*: We assume \$10,000 of annual maintenance cost requirements to keep up the charging instruments and related infrastructure per each charging facility, with an annual increase by the inflation rate.

Energy and Technology Related Costs and Parameters. *Fuel Prices*: The price of diesel fuel depends on volatile oil and gas prices in the global commodity market, whereas electricity prices are driven by the demand/supply dynamics of a given regulated market, which might differ from region to region. The US Department of Energy (DoE, 2019) projects that retail prices of diesel oil will increase in 2018 dollars by 13% from 2020 to 2030, in their reference scenario. We set the diesel price as \$2.5 per gallon in Year 1 and assume that the retail price will increase annually by the inflation rate plus 1.2%. DoE (2019) projects that electricity prices will stay about the same in 2018 dollars from 2020 to 2030, in their reference scenario. Based on the current price, we set the electricity price at \$0.1 per kWh in Year 1, which will increase by the inflation rate over the years through the planning horizon. *Consumption Rates*: The US Environmental Protection Agency has recently proposed Phase II standards for fuel efficiency—which include Class 7 and 8 trucks for the first time—that will take effect starting in the model year 2021 (Stone, 2016). According to these standards, average fuel economy for 2018 is 6.24 miles per gallon (mpg) for diesel Class 7-8 trucks and is expected to rise to 8.55 mpg by the year 2050 (DoE, 2019), with a 1.6% increase from 2020 to 2030. Our contact carrier firms reported their current consumption rate around 7 mpg, with the help of their recent sustainability initiatives. We set the fuel efficiency as 7 mpg in the first year and assume that it will increase by 1.5% every year, for new trucks purchased. The electricity consumption rate per kilometer for e-trucks depends on the capacity of the battery used in kWh and the driving range that the battery provides. In our numerical analysis, we used a 300 kWh battery with a 350 km range (announced by Daimler) and a 1000 kWh battery with a 800 km range (announced by Tesla) as base parameters that dictate the battery prices and electricity consumption rates. *Battery price*: The current battery price is around \$200 per kWh, with a projected 8% rate of decrease per year (Letmathe and Suares, 2017; UCSUSA, 2018). *Charging Times*: Battery charging times rely on the battery capacity, charging voltage, and power of the charger. There are several other environmental factors that affect the charging times and efficiencies. For Level 3 chargers, also known as rapid chargers, the manufacturers aim for almost-full charging in 30 minutes, as an industry standard (EVConnextions, 2019; PodPoint, 2019). Consequently, we assume that whatever the battery capacity is, the manufacturer will provide a charger that can charge 80% of the battery in 30 minutes (which we consider as our base case) and 100% in 60 minutes. This is in line with current expectations behind Tesla's upcoming semi-truck charging solutions (Teslarati, 2018).

Carbon price: The cost of carbon can be a direct tangible cost for transportation operations in regions where a carbon tax is implemented and is directly reflected in fuel prices. Currently, a carbon tax is in effect in 24 national jurisdictions around the world (WorldBank, 2019). Canada has one of the most ambitious carbon tax programs, in which the current per-ton price is around \$15, and the projected price for 2022 is \$38 (Plumer and Popovich, 2019). Some firms internalize a carbon cost to improve their corporate social responsibility performance, even when there is no carbon pricing regulation in effect. EDF (2019) estimates that the intangible social costs of carbon emissions add up to \$40 per ton. Some countries adopt an Emission Trading System (ETS) to control carbon emissions (37 national jurisdictions, according to WorldBank, 2019), but transportation is typically not included in this system. The average price of CO_2 European Emission Allowance per ton in 2018 was 15.48 Euros, which is almost triple the average 2017 price (BusinessInsider, 2019), and the price as of August 2019 is around 27 Euros per ton, continuing the increasing trend since mid-2017. Consequently, we set the price of carbon to \$20 per ton and analyze various scenarios. *Carbon Emissions*: The combustion of one liter of diesel fuel emits 2.64 kg of CO_2. We estimate the carbon emissions of a d-truck based on this value, the fuel efficiency of the engine, and the average speed of 80 kilometers per hour. The CO_2 emissions of an electric engine depend on how much CO_2 is emitted in the production phase of the electricity. We assume that 0.456 kilograms of CO_2 is emitted on average per generation of 1 kWh of electricity (Carbonfund, 2019). This amount is based on the latest figures reported by the EPA, which represent the overall average emissions in the USA (see EPA, 2018, for detailed data). The generation mix is approximately 67% fossil and biomass, 20% nuclear, and 14% renewables; emissions would be lower with more renewable content. DoE (2019) projects that the percentage of renewable energy in the total electricity generation capacity will increase from 19.56% in 2020 to 24.12% in 2030, in their reference scenario. Accordingly, we assume that an electric engine emits about 456 grams of CO_2 per kWh in Year 1 and will emit 0.5% less in every year thereafter. Another source of carbon is due to the manufacturing process of the trucks. We follow the approach adopted by Zhou et al. (2017) and assume that the main difference between total CO_2 emissions in the manufacturing process of a diesel and electric vehicle is largely due to the difference between the energy storage systems. Sen et al. (2017) report the total GHG emissions due to the manufacturing of one d-truck as 0.35 tons of CO_2e. Hao et al. (2017) estimate the GHG emissions of a battery during the manufacturing stage as 0.1 t CO_2e per kWh of capacity. Consequently, we set e_1^m to 350 for d-trucks and e_2^m to 350 plus 100 times the battery capacity for e-trucks.

4 Numerical Study

In this section, we present the results of a numerical study to demonstrate how our model can be used to analyze a strategic transition plan to a sustainable fleet, which gives insights into identifying the key technological, economical, and political factors that influence this transition. The results of this numerical study should not be considered a plug-and-play solution that necessarily applies to all; but it is an illustration of how our model would help a decision maker under given operational characteristics and parameter estimations over time. We used Gurobi Optimizer to solve the model by relaxing the integrality constraints.

In addition to the base parameters presented in Section 3.5, we conduct the numerical study with the following values for the remaining parameters. We consider the demand for transportation operations to be 2400 daily productive driving hours, with an annual increase of 3% for a small and a large region[4] over which the trucks operate, the small region being 160,000 km^2 representing a high demand density case and the large one being $640,000$ km^2 representing a low demand density case, which we refer to as "dense" and "sparse" cases, respectively. We consider a carbon cost that increases annually by 20% and set the planning horizon to 15 years. The inflation and the discount rates are set to 2% and 10%, respectively. We assume that a d-truck can be refueled in 15 minutes, and the range of a full tank is 800 km. We also set ω, the maximum allowed waiting time due to congestion for e-trucks, as 15 minutes and assume zero waiting time for d-trucks. Finally, we set the number of working days in a year as 250 and the number of operating hours per day for both type of trucks as 12 hours.

Figure 1 provides the optimal solution for two types of batteries: 300 kWh and 1000 kWh. Under our current battery cost assumptions, an e-truck equipped with a 300 kWh battery has a purchasing cost of $180,000, and one equipped with a 1000 kWh battery has a purchasing cost of $320,000. Note, however, that Tesla has announced the intention of selling 1000 kWh e-trucks at a price in the order of $180,000 – 200,000 (Lambert, 2017). This price implies a battery cost of $60 per kWh: less than half the current estimates. Therefore, we analyze this scenario separately, as a third ba

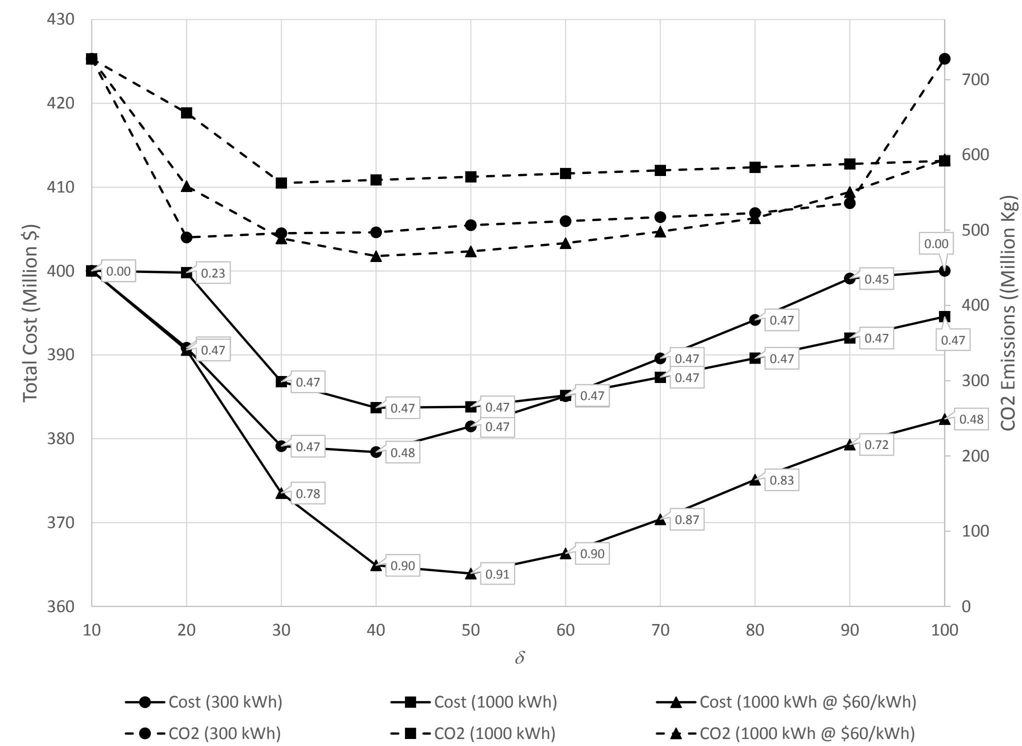

Figure 1: *Total Cost and Total CO_2 Emissions for Varying δ values for 300 and 1000 kWh batteries in Dense Demand Scenario*

We observe that neither too closely nor too widely placed charging facilities are preferable from a cost perspective. This is because the charging facility costs are dominant in the former case, and detouring to recharge the e-trucks becomes excessive in the latter case (which also results in

[4]For reference, the large region selected has a total area roughly comparable to the combination of France and Benelux.

a lower green ratio in the optimal solution). For the parameter set that we consider, the optimal δ is 40 or 50 kilometers, depending on the cost of the battery. Despite the extended driving range of 1000 kWh batteries, the optimal choice is a 300 kWh battery under our regular cost assumptions. Observe that this optimal result also lowers carbon emissions. What might seem intuitive—that one would be better off with larger batteries, due to the extended driving range resulting in higher productive hours and less detouring to recharge—only holds if the cost of the battery decreases, as is the case for the battery cost of $60/kWh in our numerical setting. This would also result in a much higher green ratio, i.e. 0.91 instead of 0.48. Even though the reduced cost of a large battery makes this option attractive cost-wise, the saving in emissions is less significant, because of the higher manufacturing emissions associated with larger batteries.

Table 2 compares the characteristics of the optimal solutions for sparse and dense demand under the 300 kWh battery option and different charging choices. We show the effect of waiting until the battery is fully charged (recall that the base scenario assumes 80% at 30 mins).

Table 2: *Characteristics of optimal solution for sparse/dense demand with small battery under different charging choices (base scenario in boldface).*

Demand	Charging Choice	δ^* (Km)	Total Cost ($)	Total CO_2 (Ton)	Green Ratio
Dense	**30 Min/80%**	**40**	**378**	**497**	**0.48**
	60 Min/100%	40	387	505	0.47
Sparse	30 Min/80%	60	395	512	0.47
	60 Min/100%	-	400	728	0

The results show that the optimal infrastructure investment depends strongly on the demand density, with higher demand density associated with higher infrastructure density. Furthermore, the optimal solution involves quickly charging batteries to "almost full" status, rather than waiting for a full charge. In the sparse demand case, the charging choice has a particularly significant influence, inasmuch as no investment in electric vehicles is made, if the charging policy is to fully charge the batteries (cf. rapid charging to 80%). The average green ratio in all scenarios that adopt e-vehicles is close to half.

Table 3 shows the absolute increase or decrease in Cost (million $) and CO_2 Emissions (million kg) associated with opting for the optimal solution over the status quo (i.e., all d-trucks) and the increase/decrease associated with two "fully green" policies: (1) adopting 100% e-trucks at time 0 with the infrastructure density derived from the optimal policy, and (2) adopting 100% e-trucks at time 0 with a high infrastructure density (δ = 10). Numbers in parentheses show the percentage increase or decrease.

Table 3: *Absolute Increase (+) or Decrease (-) in Cost and Emissions with respect to Status Quo.*

Demand	Measure	Optimal Strategy (δ^*)	All Green at δ^*	All Green at $\delta = 10$
Dense	Cost	-22 (5%)	-10 (2.5%)	+310 (77.5%)
	CO_2	-231 (32%)	-417 (57%)	-455 (62.5%)
Sparse	Cost	-5 (1%)	+40 (10%)	+1,488 (371%)
	CO_2	-216 (30%)	-391 (54%)	-455 (63%)

The optimal strategy achieves lower costs and emissions in both demand scenarios. For additional emissions savings, decision-makers can opt for an "all green" strategy, in which the entire diesel fleet is replaced at time zero with an electric fleet. When this strategy is compounded with the optimal infrastructure density, it can still achieve cost savings (in the dense demand scenario) or be made at a moderate cost penalty (sparse demand scenario), with respect to the status quo. Going all green and investing heavily in the infrastructure density to maximize productive driving times introduces significant cost penalties for relatively incremental savings in emissions.

Increasing the green ratio has a large direct effect on emissions and a relatively minor effect on cost. Increasing infrastructure density, on the contrary, has a large direct effect on costs and diminishing returns on emissions; additional infrastructure only affects the non-productive time per truck.

These results suggest that firms may realize a large portion of the potential emissions and cost savings by moving a relatively low percentage of transportation demand to e-vehicles. Fleet composition decisions, however, cannot be dissociated from infrastructure decisions; optimizing both fleet size and charging infrastructure appears critical for the success of e-vehicle adoption.

Table 4 shows the effect of a change in the carbon cost under dense and sparse demand conditions.

These results show that an increase in the carbon cost is followed by an increase in the green

Table 4: Effect of carbon cost on the optimal solution (base scenario in boldface).

ϵ_1 ($/Ton CO_2)	Dense Demand δ^* (Km)	Cost ($)	CO_2 (Ton)	GR	Sparse Demand δ^* (Km)	Cost ($)	CO_2 (Ton)	GR
10	40	370	501	0.47	-	385	729	0
20	**40**	**378**	**497**	**0.48**	**60**	**395**	**512**	**0.47**
40	40	392	393	0.75	60	412	511	0.47
100	40	428	343	0.88	50	462	481	0.55

ratio. This is consistent with prior research, which suggests that increasing these costs is an effective way to incentivize the move to more sustainable transport modes (i.e., from air/truck shipping towards barge and deep sea, see Hoen et al., 2013). Whereas said research shows that carbon costs need to increase drastically to affect the transport mode, our results show that the carbon cost that doubles the green ratio for the dense demand scenario is within the order of magnitude of the current carbon price. Accordingly, carbon taxes can be effectively used to steer existing truck fleets towards electric alternatives. These results also show that, in the dense demand scenario, carbon tax achieves the desired effect through increasing the attractiveness of converting additional vehicles to electric; the infrastructure investment remains unchanged in all scenarios. When demand is sparse, however, carbon taxes have an effect on the infrastructure investment.

Table 5 shows the effect of the assumptions behind the adoption rate of renewable electricity generation and the initial proportion of renewable content in the electricity mix. As discussed in §3.5, the base scenario is derived from the average energy mix in the USA and an increase in renewables of 5% per year. The next scenario considers an energy mix with half the emissions of the base scenario. (For reference, this is close to the average emission values in California of 0.206 kg/kWh.) Finally, we also consider a fully renewable scenario, with zero emissions from electricity generation.

The results show that the source of electricity has a significant effect on the total emissions. All else equal, a greater percentage of renewables is directly related to fewer emissions. In the dense demand scenario, the energy mix also shows a second order effect; the greener the power source, the larger the average green ratio becomes, because the energy mix plays a significant role in the dynamics of e-vehicle adoption. Renewable energy generation offsets the (relatively high)

Table 5: Effect of renewable content in electricity generation (base scenario in boldface).

		Dense Demand				Sparse Demand			
CO_2 Release (kg/kWh)	Annual Increase	δ^* (Km)	Cost ($)	CO_2 (Ton)	GR	δ^* (Km)	Cost ($)	CO_2 (Ton)	GR
0.456	**5%**	**40**	**378**	**497**	**0.48**	**60**	**395**	**512**	**0.47**
	10%	40	375 (1%)	409 (18%)	0.57	60	392 (1%)	455 (11%)	0.47
	25%	40	372 (2%)	274 (45%)	0.67	60	389 (2%)	394 (23%)	0.47
0.228	5%	40	375 (1%)	360 (28%)	0.63	60	392 (1%)	447 (13%)	0.47
0	–	40	371 (2%)	209 (58%)	0.73	60	388 (2%)	383 (25%)	0.47

emissions related to the production of e-vehicles—a large proportion of renewables speeds up the adoption of e-vehicles. For the sparse demand case, the energy mix only has a first order effect. The trade-off in this scenario is such that the infrastructure cost limits the density of the charging infrastructure, which, in turn, limits the adoption of e-vehicles.

Table 6 shows the effect of technological advances in diesel engines.

Table 6: Effect of the increase in diesel engine efficiency (base scenario in boldface).

	Dense Demand				Sparse Demand			
Annual Increase	δ^* (Km)	Cost ($)	CO_2 (Ton)	GR	δ^* (Km)	Cost ($)	CO_2 (Ton)	GR
1.50%	**40**	**378**	**497**	**0.48**	**60**	**395**	**512**	**0.47**
2.50%	40	377	491	0.47	-	393	683	0
5.00%	40	372	463	0.46	-	376	576	0

For the dense demand scenario, there is a relatively minor change in the fleet composition, with the average GR decreasing slightly with a change in diesel technology. In these scenarios, the increased (emission) savings from more efficient diesel engines compensate the relatively small decrease in the number of e-vehicles. As this technology change is assumed to be independent of price, the larger proportion of diesel trucks is related to a decrease in costs. Note, however, that the charging infrastructure does not change. For the sparse demand scenario, however, an increase in the diesel efficiency is enough to negate the potential benefits of e-vehicle adoption. Thus, when diesel vehicles become "good enough", it is optimal not to invest in any charging/e-vehicle infrastructure. The side effect is that the optimal solution with higher diesel efficiency is outperformed (in terms of carbon emissions) by the optimal solution with lower diesel efficiency.

These results suggest that, even though an increase in diesel efficiency can be rightly viewed as a positive development, there is a risk that efficiency increases are such that diesel trucks become "good enough" to postpone investments in electric trucks, but not "good enough" to bring about a substantial decrease in emissions. In such cases, policy-makers may have to intervene (see Table 4) to ensure the transition to green technologies.

Governments can facilitate the transition by providing certain incentives. One possibility could be to subsidize all of the facility installation and maintenance costs by designating a place for the transportation firms to install their charging network. These designated facilities can be used by more than one transportation firm, and each firm can install their own charging network at these locations—for the firm not to risk longer waiting times. Such an initiative taken by public authorities will eliminate the charging facility installation and maintenance costs for the transportation firm. When designing this incentive mechanism, the public authority should decide on the number of facilities provided in the service area. This variable can be controlled by the δ parameter in our setup. For any given value of δ, the transportation firm will solve SFMP by setting $A = 0$ and $m_t^f = 0 \ \forall t$. Obviously, smaller δ values will entice a transportation firm to switch to e-trucks earlier, resulting in lower CO_2 emissions; however, the total installation and maintenance costs for the public authority will be higher. The decision should be made by resolving this trade-off. Figure 2 depicts the trade-off between emission savings obtained and the corresponding cost for the public with this initiative, considering a single transportation firm. On this graph, each point is an efficient solution, and the point $(0, 0)$ denotes the default action of not providing this subsidy. If the public authority solves this problem for the firm with the densest demand, the resulting charging facility network will enable longer productive driving times for the firms with sparser demand (in comparison to the optimal charging network that the firm would have invested on its own), benefiting the whole transportation sector operating in the region. Therefore, the emission savings reported in Figure 2 for a particular public cost will be (much) higher. The figure shows that for higher levels of subsidy, the green ratio increases, as might be expected. Moreover, the "biggest bang for the buck" materializes in the dense demand case.

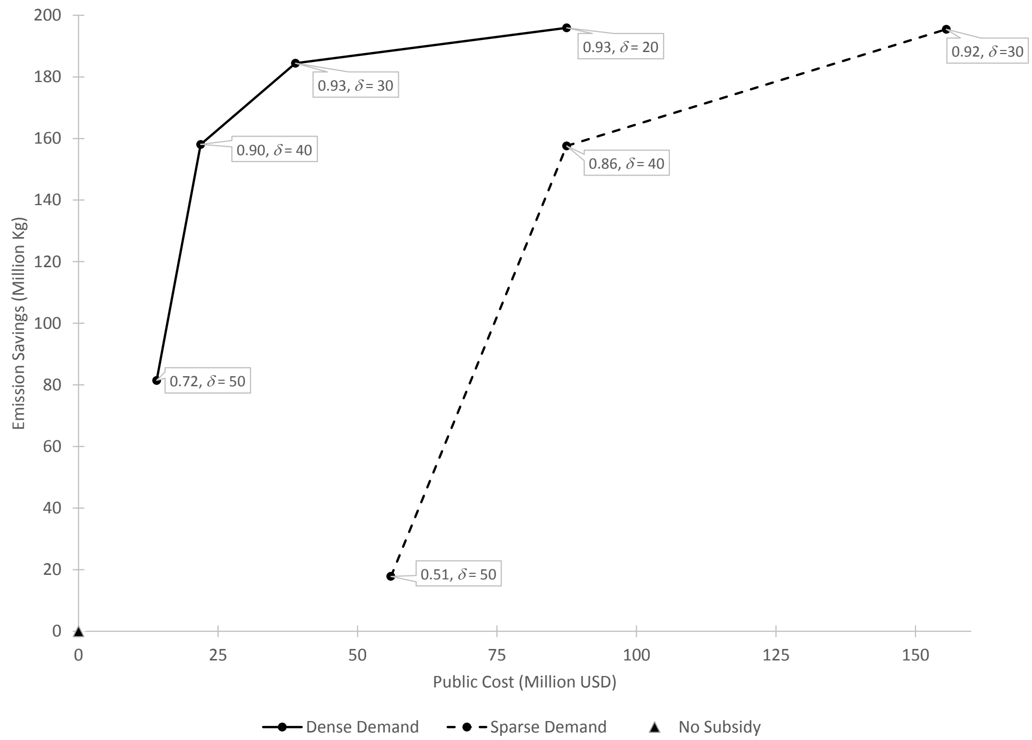

Figure 2: *Efficient Frontier for Emission Savings versus Public Cost. First numbers in the boxes indicate the Green Ratio at that efficient solution.*

5 Conclusions

In this study, we model the adoption of electric vehicles in the context of an existing fleet of commercial diesel trucks. In contrast to prior research, our model explicitly considers sequential investment decisions within a time horizon and includes charging infrastructure costs, as part of the investment strategy of a firm that explores the possibility of adopting electric trucks. Our model also distinguishes itself from prior research by considering the effect of infrastructure density on the fleet size itself. Infrastructure is not only required to enable access to a larger service area, but a denser charging infrastructure also implies shorter unproductive driving times (driven by shorter detours and queueing times) and, thus, affects the total capacity requirements. Our model, therefore, enables firms to evaluate medium to long-term investment strategies by simultaneously considering the effects of the adoption of e-trucks and the required infrastructure.

Through a numerical experiment based on a realistic data set, we generate a number of insights.

First, in most of the scenarios we consider, it is cost-optimal to invest in e-trucks. Considering that e-trucks are also generally more environment-friendly, this result suggests that the adoption of e-trucks has the potential to bring about the disruptive change required, if emission targets are to be met. However, the adoption potential of e-trucks depends to a large extent on the demand density in the area they are assigned to serve. The optimal fleet for scenarios with a dense demand is consistently greener than that for a sparse demand, mainly due to the infrastructure requirements. Infrastructure needs to be developed regardless of whether demand is dense or sparse, thus, all else equal, a dense demand area will utilize a given charging instrument to a higher degree and thus result in less unproductive time. In the case that firms can introduce/pilot the fleet changes in different areas, denser demand areas appear to be particularly well suited for this technology shift. Our results suggest that when demand is dense enough, the optimal policy of investing in e-trucks seems to be quite robust to parameter changes; whereas in sparse demand areas, the optimal solution can shift from no investment in electric technology towards the majority of the fleet being e-trucks, as particular problem parameters change. Moreover, our results suggest that, in such dense environments, e-trucks need not have a comparable range to d-trucks to become attractive. E-trucks can therefore be equipped with smaller (cheaper and lighter) batteries. In fact, our results show that fast charging small batteries to 80% capacity provides enough autonomy to the trucks. In particular, we see that 300 kWh batteries with charging stations spaced 40Km apart are the sweet spot for the demand density we analyzed.

Our results demonstrate the importance of coupling the e-truck adoption strategy with the charging infrastructure investment decisions. In particular, over-investing in infrastructure with the aim of minimizing emissions results in relatively low emission savings at the expense of severe increases in total costs, in comparison to the coupled optimal solution.

Given that we compare diesel vehicles to electric ones, it stands to reason that the fuel used in the electricity generation plays a decisive role. We show that even a relatively clean energy mix such as the one implemented in California results in higher e-truck adoption and brings about substantial reductions in total transportation emissions.

Our results also show that for a large number of settings, the optimal policy is a gradual shift towards electric trucks resulting in a mixed fleet, during the transition to a greener fleet. Thus, even though regulators are already envisioning a hard cut-off point after which all vehicles should be zero-emissions, the decision itself need not be “all at once”.

Concerning regulatory intervention, if the charging infrastructure is to be subsidized to entice the transition, the usual suspect is to invest in dense-demand regions. Our results show that even pricing the transport emissions at moderate levels has a significant impact on the adoption of the cleaner transport alternative, unlike previous findings in literature concerning the transition to cleaner transport modes.

Our motivation to study electric trucks as the contending green technology stems from the current developments in truck manufacturers. However, there are other green technologies in preparation, lab, or idea phase making the future of electric trucks precarious. Our model is generic enough to analyze the adoption of any given truck fueling technology, barring a fundamentally different freight transporting technology, such as hyperloop. An interesting problem is which technology to invest in, given multiple promising contenders with inherent uncertainty, which requires future research attention.

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