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PII: S0305-0483(22)00004-4
DOI: https://doi.org/10.1016/j.omega.2022.102595
Reference: OME 102595

To appear in: *Omega*

Received date: 9 April 2021
Accepted date: 7 January 2022

Please cite this article as: Osman Alp, Tarkan Tan, Maximiliano Udenio, Transitioning to Sustainable Freight Transportation by Integrating Fleet Replacement and Charging Infrastructure Decisions, *Omega* (2022), doi: https://doi.org/10.1016/j.omega.2022.102595

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Highlights

- E-truck adoption must be coupled with investment planning for charging infrastructure.
- E-trucks are already cost-attractive and a very long-range battery is not necessary.
- The optimal fleet under dense demand is greener than that under sparse demand.
- Cleaner energy mix results in higher e-truck adoption.
- Charging infrastructure investment can be jointly made with public or private partners.

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Transitioning to Sustainable Freight Transportation by Integrating Fleet Replacement and Charging Infrastructure Decisions

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January 12, 2022

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Abstract

The transportation sector is the largest contributor to global greenhouse gas emissions. Disruptive technological changes in this sector, such as alternative fuel vehicles, are crucial for emission reduction. We show how a cost-minimizing strategic transition plan to adopt electric trucks over time can be developed for a firm that owns and operates a fleet of diesel trucks. We consider the case in which the firm decides to invest in the charging infrastructure required to support this transition, either because the public charging infrastructure is currently inadequate or for strategic reasons. 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 specifying origins and destinations. We illustrate the resulting transition plan with realistic parameter configurations. Our results indicate that a firm with high transportation demand density over a given service region significantly benefits from adoption of electric trucks, while also enjoying substantial carbon emissions savings. High

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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. Additionally, we present an extension to the model that allows for different modalities of partnership in the infrastructure investment; notably public-private and private-private partnerships. While in general our results suggest that such partnerships are beneficial to all involved, the amount and relative distribution of the potential gains depend on the topography and on the density of 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 accords. This is particularly true for the transportation sector, one of the largest contributors to global greenhouse gas (GHG) emissions. As of 2017, this 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 (see, e.g., EEA, 2019).

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 (i.e., based on policies and measures that are currently adopted or announced, e.g., improvements in fuel efficiency, vehicle utilization, and routing). 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

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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; particularly in the medium/heavy freight space. 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 as the primary factors holding firms back (IEA, 2017b). Moreover, the lack of full-scale adoption of AFVs also impacts the uncertainty of their resale value, further limiting adoption. 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 (ICVs; 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 that of ICVs as early as 2025 (Deloitte, 2019). Developments in the commercial space are slower, but several truck and e-vehicle manufacturers such as Daimler, Mack, Tesla, Volvo, Scania, and DAF have announced plans to deliver long-haul 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, but how to

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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 fleet of ICVs – typically, diesel trucks (d-trucks) – for its own operations or as a service. We develop a model to optimize the investment and salvaging decisions for a truck fleet (composed of d- and/or e-trucks) together with the investment for the charging infrastructure associated with e-trucks. We explicitly factor-in the congestion effect at the charging stations due to scarce resources and lengthy charging times, which curtails the utilization of e-trucks. 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 may 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. Moreover, fuel costs are of strategic importance for road freight transport; estimates suggest that they comprise in the order of 30% of total costs (SuproÅ, 2018; Sternad, 2019). Therefore, fleet operators may want to maintain control of this significant cost component and thus invest in their own refueling infrastructure for strategic reasons. Even though there are not many e-trucks on roads as of yet, other kinds of AFVs are getting increasingly more popular and we already observe a recent spike in the number of providers offering charging infrastructure solutions to companies for their (and their customers') electric vehicles, see e.g., ChargeUp Europe (https://www.chargeupeurope.eu), which is a coalition of electric vehicle charging infrastructure providers. Deutsche Post DHL, for example, has come to an agreement already back in 2018 with Innogy to provide charging infrastructure for its growing electric vehicle fleet at DHL locations in 10 different countries in Europe (Cleantechnica, 2018). Kullman et al. (2021) report that French company ENEDIS chose to invest in their own charging infrastructure when replacing their fleet with EVs due to the uncertainty at public charging infrastructure. We find that, among other insights, e-trucks can indeed become a feasible alternative for firms in the near future if the density of the charging infrastructure is also optimized collectively.

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We develop a high-level strategic model that can provide valuable insights for the decision makers and the governing bodies. By using our model, the decision makers can identify when and if they are ready to invest in e-trucks and the type of e-truck (in terms of battery capacity) that best suits to their market structure. The governing bodies can benefit from our approach in developing policies to accelerate the transition of the industry to sustainable transportation. With the help of a numerical study inspired by real-life parameter settings, our approach is also instrumental in developing insights some of which may be counter to the common sense: (i) Investing in e-trucks can be optimal only if the decision maker also invests in their own charging infrastructure in an optimal manner, (ii) larger battery capacity is not always the best option compared to smaller battery capacity, and (iii) improvements in diesel engine efficiency can be counterproductive in the long run and can thwart the efforts to attain net-zero emission targets.

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 present our modeling approach that let us formulate a linear model to solve the problem efficiently. Section 4 contains the results of our numerical study and scenario analysis that we conducted based on a realistic data set. 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 at the intersection of two literature streams: sustainable operations (in particular, green transportation) and asset management / 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 ICVs to AFVs, 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; Rinaldi et al., 2020). Existing research ranges from engineering considerations (Finesso et al., 2016) to economic issues, including fiscal

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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 given 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.

Goods distribution using EVs poses a double challenge: limited range and long recharging times. This challenge requires explicit modeling of the charging technology, infrastructure, and policy. Even though there are several different charging technology standards (see Appendix A and B), the majority of studies in the literature model generic power and cost parameters. In our analysis, we use the American SAE standard and adopt the speed of Level 3 charging system. We refer the reader to Das et al. (2020) for a thorough review of the different standards and charging technologies of EVs and Appendix A for a summary of existing charging technologies.

Afroditi et al. (2014) trace the early appearance of the 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. The charging schedule and timing can also be an important factor for different applications and analysis. For example, studies within the E-VRP literature usually assume that the vehicles are charged overnight in a depot so that vehicles start their routes fully charged (e.g., Erdoğan and Miller-Hooks, 2012); a number of studies also foresee the use of en-route charging stations with fast chargers (Schiffer and Walther, 2018) as a top-off charge whenever necessary. Several extensions to the E-VRP also consider different charging and/or routing policies; for example, the inclusion of delivery time windows (Schiffer and Walther, 2017), minimizing emissions (Figliozzi, 2010) or energy consumption instead of costs (Kucukoglu et al., 2013), adopting battery-swapping instead of charging-stations (Mak et al., 2013; Sari, 2017; Sun et al., 2019b), and using the driver's lunch hour for partial recharging (Cortés-Murcia et al., 2019). There are also studies that consider long

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term planning and expansion of charging stations. Koç et al. (2018) allow for shared charging stations with a joint investment of multiple firms in charging infrastructure, Xie et al. (2018) deal with the long-term strategic planning of inter-city fast-charging infrastructure to satisfy the growing e-vehicle adoption in inter-city use, and Quddus et al. (2019) integrate use of renewable energy and vehicle-to-grid mechanisms in their problem settings. In recent works, Keskin et al. (2019) and Keskin et al. (2021) extend the E-VRP with stochastic waiting times in a recharging queue. They model the queues as M/G/1 systems and introduce heuristic and simulation-based solution methodologies. The authors argue that modeling the waiting times may be crucial, and should be taken into account, for routing decisions. Finally, Kullman et al. (2021) extend the E-VRP by explicitly considering a private-public recharging strategy and modeling congestion at the charger through M/M/C/∞ queues. They set the problem as an approximate dynamic programming model, and propose a number of static and dynamic routing policies. They find that with good dynamic routing policies, strategies considering public-private charging infrastructure consistently outperform private-only solution strategies. We refer the reader to Macrina et al. (2019) and Keskin et al. (2019) for up-to-date surveys of the related literature in this domain. In this study, in addition to charging infrastructure expansion decisions, we also consider fleet expansion and replacement decisions in an integrated manner.

A different modeling approach is the FLP, which decomposes the problem by first identifying a route and then finding the optimal station location among a set of potential candidates (e.g., Wang, 2007). In contrast to the E-VRP, the FLP typically uses the demand between origin-destination pairs to model the flow of vehicles, and treats the charging station location as a decision variable (Zhu et al., 2016; Zhang et al., 2017; Brandstätter et al., 2020). Finally, several assumptions can be made regarding the charging function itself. The majority of studies assume either deterministic charging times (Erdoğan and Miller-Hooks, 2012) or linear charging times, where every minute of charging time increases the charge of a vehicle by a constant (Felipe et al., 2014). Montoya et al. (2017), however, argue that in real life, battery charging is non-linear: the charging rate for the first 80% is significantly faster than the remainder.

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

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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 extended 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. 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.

This study is, to the best of our knowledge, the first to explicitly include the relationship between the fleet size, the capacity of charging stations, and the expected waiting time. As we know from queuing theory, the higher the capacity utilization, the longer the waiting times. In the type of application that concerns us, a capacity utilization above 80-90% can easily result in waiting times longer than the actual charging time. Therefore, it is necessary to incorporate this effect to ensure that non-productive times are reasonable. A number of recent studies contemplate different aspects of the utilization/waiting time relationship. Kim et al. (2017) use a stochastic method to derive steady-state performance measures for charging stations under first-in, first-out (FIFO) and processor sharing (PS) scheduling methods. They find that the optimal scheduling method depends on characteristics of the problem setting, such as the available charging capacity and the behavior of arrivals. Ghamami et al. (2020) and Kavianipour et al. (2021) consider the problem of planning the refueling infrastructure for intercity e-vehicle travel, they take waiting times into account through a deterministic queue assumption, where vehicles only wait if the (deterministic) arrival rate is larger than the service rate; Chen et al. (2020) consider stochastic $M(t)/M/n$ queues by allowing potential charging stations within defined graphs. These studies

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remark on the importance of modeling waiting times – however, in contrast with our study, they treat the fleet size as exogenous.

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 time-frame 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). Kuppusamy et al. (2017) study the technology overhaul of a taxicab service provider. In this setting, the decision is whether to continue with ICVs or to fully switch to an EV fleet with a corresponding battery swap station. They find that the fleet technology

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decision depends on the expected number of miles driven and its variability, and that the structure of the solution allows for switching (i.e., there are optimality ranges for EV adoption). They observe a similar result when limited heterogeneity (where different vehicle types are allowed for short/long haul). Feng and Figliozzi (2013) and Davis and Figliozzi (2013) evaluate the cost competitiveness of a series of e-trucks against their diesel counterparts. They embed their analyses within an optimal fleet replacement framework to analyze the key economic and technological factors driving the cost competitiveness of an eventual transition to AFVs. They found that, given the high acquisition and battery costs, e-trucks required a combination of favorable factors to become competitive; high utilization being a key driver. The authors note, however, that a reduction in costs could favor AFVs in the future. Battery costs, in particular, have fallen threefold since the publication of these articles.

Wang et al. (2013) and Patricksson et al. (2015) are closest in spirit to our paper. The former presents 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. Islam and Lownes (2019) analyse the joint fleet and infrastructure investment problem from the perspective of an American department of transportation, considering, in particular, the opportunities for technology replacement in a passenger bus fleet. In contrast to our work, the authors do not consider the infrastructure location as a decision variable (due to the assumption of a central bus depot), nor do they consider congestion-related queueing issues. Hu et al. (2018) deal with an integrated planning of fleet size, hub locations, and hub capacities for a transportation firm by explicitly considering road congestion. In contrast, we explicitly model the congestion at the charging stations while planning for fleet size and mix, and charging infrastructure capacities. In a recent study, Pelletier et al. (2019)

Journal Pre-proof

examined the optimal transition strategy for a bus fleet. Similar to our study, they consider the effect of charging speed and evaluate the sensitivity of their solution to the future evolution of external parameters such as energy/fuel costs. Due to the difference in setting, however, their approach differs from ours in that they assume depot (or bus-stop) charging, without the consideration of queuing effects.

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 year 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 Model

We consider a freight-moving firm operating within a given geographical region. Similar to Pelletier et al. (2019), we define the fleet composition of the firm using the set of truck types $K = \{1, \ldots, n\}$ where $K_e \subseteq K$ denotes the subset of truck types that are e-trucks and $K_d \subseteq K$ denotes the subset of truck types that are d-trucks. The firm aims to minimize the investment and operational costs associated with its fleet composition over a certain planning horizon $T = \{1, \ldots, t_F\}$ of t_F years. Let V_{tk} denote the number of trucks of type k operated by the firm in year t. We quantify the 'sustainability' of the fleet composition through the Green Ratio (GR), which we define as the fraction of total demand carried by e-trucks; formally, the green ratio in year t is given by $GR_t = \sum_{k \in Ke} V_{tk} / \sum_{k \in K} V_{tk}$. We assume that the firm initially operates with a fleet composed entirely of d-trucks ($GR_0 = 0$).

The firm might reduce the carbon footprint (and associated emission costs) 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

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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 plug-in charging infrastructure.

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 locations 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 dense and origins and destinations can be anywhere due to a large and dispersed population, as well as highly populated areas such as Northeast of the US, North American coasts, and Asian, Latin American, and African metropolitan areas. The problem under consideration applies to any firm that owns and operates a fleet of trucks, whether in-house or for-hire.

We define a "charging facility" as a charging station that contains one or more charging outlets, which we refer to as "charging instruments". We treat the number of facilities and instruments installed as design variables to be optimized. We assume that a firm adopts a single charging technology throughout its infrastructure, which we model by parameterizing the charging times and acquisition costs on the chosen technology. In terms of charging policies, we assume deterministic charging in our numerical experimentation, and investigate the effect of non-linear charging by modeling a scenario where batteries are only charged up to 80% in a shorter time frame. 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. Because we do not model specific routes, we do not distinguish between depots and en-route charging stations; we consider a uniform distribution of equally-spaced charging stations over the service area and include a "detour" parameter to model the average (back and forth) deviation of a truck from its route to a charging station. In contrast, we assume that d-trucks can find a refueling station along their main route whenever necessary

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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/recharging times. We assume that loading and unloading operations are independent of the drivetrain technology of a truck, and thus do not explicitly model them. Technology choice (and the associated infrastructure), however, have a significant effect on the non-productive element associated with the refueling/recharging of a truck. For e-trucks, this 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. For d-trucks, we assume that –given the high density and capacity of gas stations– the only relevant non-productive element is the refueling time at the gas station.

We denote the total working time of a truck, excluding the aforementioned non-productive work elements, as the "productive driving time". For a truck of type $k \in K$, the total productive driving time per day, D_k^p, is estimated by

$$D_k^p = \frac{R_k/v_k}{R_k/v_k + \tau_k} H_k, \tag{1}$$

where v_k is the average speed of a truck of type k, R_k is the driving range of a type k truck, H_k is the total operating hours of a type k truck per day, and τ_k denotes the non-productive work element due to recharging/refueling of a truck of type k, which is dependent on the design of the refueling infrastructure, and is calculated as per Equation (2).

3.2 Charging Infrastructure Design

Transitioning to a greener fleet can be viable only if the operations are backed up with sufficient charging capacity within the geographical service area that the freight-moving firm operates in. At any given year $t \in T$, this capacity is fully determined by F_t, the number of charging facilities installed in the service area in year t, and γ_t, the number of charging instruments installed

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within each facility. Recall that we consider the demand to be homogeneous across the service area, meaning that the charging facilities are spread uniformly within that region with identical capacities. For the operation of an e-truck fleet, the firm must trade-off between installing more charging capacity, which will decrease the non-productive driving at the cost of increasing the 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 design variables δ, the distance between any two charging stations, and ω, the average waiting time at a charging facility due to congestion. In this section we present an estimation of the required charging capacity based on the given values of these design variables. Table 1 shows a summary of all relevant notation for charging capacity estimation.

Table 1: *Summary of parameters for the charging infrastructure design.*

D_k^p:	Productive driving hours of type k vehicle in one day
$\overline{F}$:	Minimum number of charging facilities required to have an access within δ kilometers from anywhere on the road network
F_t:	Number of charging facilities in year t
H_k:	Number of operating hours of a type k vehicle per day
l_k:	Payload efficiency of a type k truck
R_k:	Range of a type k vehicle in kilometers, with a full tank or battery
V_{tk}:	Number of type k trucks operated in period t
W_t:	Daily productive driving hours necessary to satisfy the annual demand in year t
γ_t:	Number of charging instruments kept in each charging facility in year t
δ:	Distance between charging facilities
η_k:	Number of times that a type $k \in K_e$ truck must visit a charging facility per day
θ:	Average detour length coefficient
λ_t^k:	Arrival rate of type $k \in K_e$ trucks per hour to a charging facility in year t
μ_k:	Average recharging or refueling time for a type k truck
ν_k:	Average speed of a type k truck
τ_k:	Total time spent for refueling/recharging including the back-and-forth access time to the charging facility for a truck of type k
ω_k:	Average waiting time in the queue allowed at the charging facility for a type $k \in K_e$ truck

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 of type $k \in K_e$, denoted by μ_k. The design parameters (δ, ω) will dictate the arrival rate and the required γ_t value.

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Estimating the Number of Facilities: Let G be the total area (in km^2) of the region served by the firm. Assuming that the charging stations are installed at the centers of $\delta \times \delta$ grids that span the entire service areas on a continuous scale, $\overline{F}$, the number of charging facilities required to ensure at most δ kilometers between any two charging stations can be estimated by $\overline{F} = G/\delta^2$. The maximum detour length to access a charging station and return to the main route, using a Euclidean metric, is thus $\sqrt{2}\delta$ kilometers from anywhere on the road. Note that this estimation is an upper bound, as it ignores the topology of the network. To account for more realistic values, we include a coefficient, θ, to adjust for the maximum detour length. ($\theta = 1$ represents the most conservative scenario, where an e-truck is always at the farthest point to the nearest charging facility when it needs to be charged and returns to the same point.) Given the ubiquity of gas stations, we assume that d-trucks can always charge on-route, with negligible waiting time.

Under these constructs, the total non-productive time for recharging/refueling a truck, τ_k is given by

$$\tau_k = \begin{cases} \theta\sqrt{2}\delta/v_k + \omega_k + \mu_k & \text{for } k \in K_e, \\ \mu_k & \text{for } k \in K_d \end{cases} \tag{2}$$

where μ_k is the recharging/refueling time of a truck of type k.

If the firm operates with a mixed fleet of d- and e-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 and the charging facilities do not need to be located over the entire service area at once, allocating the 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, the number of charging facilities required in year t, can be estimated by

$$F_t = \frac{l_k V_{tk} D_k^p}{W_t} \overline{F} \text{ for } k \in K_e, \tag{3}$$

where l_k is the payload efficiency of a truck of type k to account for an eventual reduction of the maximum load due to size/weight of the battery packs, and W_t is the total productive driving time

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required to satisfy the demand for the trucking operations in year t. (The latter depends on the number and locations of the destinations to be visited in a given time period.)

Estimating the Arrival Rate: Under the settings described above, the number of charging facilities is proportional to the number of electric trucks. The intuition behind this is that as the electric fleet increases, the demand area covered by electric trucks increases proportionally, enabling us to develop an efficient solution approach. In particular, the proportional increase of identically-spaced facilities allows us to formulate the problem as an integer linear optimization problem, as explained in the next section. We formalize this with the following proposition.

Proposition: The arrival rate of e-trucks of type k in year t to a charging facility is independent of the size of the e-truck fleet, V_{tk} with $k \in K_e$, and is given by

$$\lambda_t^k = \frac{v_k W_t}{R_k l_k D_k^p \overline{F}} \text{ for } k \in K_e$$

Proof:

$$\lambda_t^k = \frac{\eta_k V_{tk}}{F_t} = \frac{\eta_k V_{tk}}{\frac{l_k V_{tk} D_k^p}{W_t} \overline{F}} = \frac{\eta_k W_t}{l_k D_k^p \overline{F}},$$

where $\eta_k = v_k / R_k$. □

Estimating the Number of Instruments: For any $G/D/\gamma_t$ queue with an arrival rate of λ_t^k and service time of μ_k for e-trucks of type $k \in K_e$, 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:

$$\gamma_t = \min_{k \in K_e} \left\{ m : \omega_k \leq \frac{C_a^2}{2} \frac{(\lambda_t^k \mu_k / m)^{\sqrt{2(m+1)}-1}}{m - \lambda_t^k \mu_k} \mu_k \right\} \qquad \text{for } t \in T, \tag{4}$$

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 Sustainable Fleet Management Problem, SFMP. Let $J_k^v = \{0, 1, \ldots, L^k\}$ denote the set of possible ages for truck of type k, with $j \in J_k^v$ representing an age of j years, and L^k being the maximum useful lifespan of a truck of type k. Similarly, let $J^i = \{0, 1, \ldots, L^i\}$ be the set of possible ages for a charging instrument,

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with $j \in J^i$ representing an age of j years, and L^i being the maximum useful lifespan of a charging instrument. Then, we define the non-negative decision-variables used in SFMP as follows: P^v_{tk} indicates the number of type k trucks purchased at the beginning of year t; P^i_t indicates the number of charging instruments purchased at the beginning of year t; Q^v_{jtk} denote the number of type k trucks of age j owned at the beginning of year t; Q^i_{jt} indicates the number of charging instruments of age j owned at the beginning of year t, S^v_{jtk} denotes the number of type k trucks of age j salvaged at the beginning of year t; and S^i_{jt} denotes the number of charging instruments of age j salvaged at the beginning of year t.

Table 2 shows all the set, parameters, and decision variables used in the formulation of the Sustainable Fleet Management Problem, SFMP, which for any given service level target pair (δ, ω), can be formulated as a function of $\overline{F}$ and γ_t as follows:

Journal Pre-proof

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

$$\text{Minimize} \quad \sum_{t\in T}\sum_{k\in K}\beta_t c^v_{tk}P^v_{tk} - \sum_{t\in T}\sum_{k\in K}\sum_{j\in J^v_k}\beta_t s^v_{jtk}S^v_{jtk} + \sum_{t\in T}\sum_{k\in K}\sum_{j\in J^v_k}\beta_t Y(f_{jtk}+m^v_{jtk})D_k Q^v_{jtk}$$
$$+ \sum_{t\in T}\sum_{k\in K}\sum_{j\in J^v_k}\beta_t Y\epsilon_t e^d_{jtk}D_k Q^v_{jtk} + \sum_{t\in T}\sum_{k\in K}\sum_{j\in J^v_k}\beta_t u_t Y H_k Q^v_{jtk}$$
$$+ \sum_{t\in T}\beta_t(A+m^f_t)F_t + \sum_{t\in T}\beta_t c^i_t P^i_t - \sum_{t\in T}\sum_{j\in J^i}\beta_t s^i_{jt}S^i_{jt}$$

subject to

$$Q^v_{0tk} = P^v_{tk} \qquad t\in T, k\in K \tag{5}$$
$$Q^v_{jtk} = Q^v_{j-1,t-1,k} - S^v_{jtk} \qquad t\in T, k\in K, j\in J^v_k\backslash\{0\} \tag{6}$$
$$S^v_{jtk} \le Q^v_{j-1,t-1,k} \qquad t\in T, k\in K, j\in J^v_k\backslash\{0\} \tag{7}$$
$$Q^i_{0t} = P^i_t \qquad t\in T \tag{8}$$
$$Q^i_{jt} = Q^i_{j-1,t-1} - S^i_{jt} \qquad t\in T, j\in J^i\backslash\{0\} \tag{9}$$
$$S^i_{jt} \le Q^i_{j-1,t-1} \qquad t\in T, j\in J^i\backslash\{0\} \tag{10}$$
$$W_t \le \sum_{j\in J^v_k}\sum_{k\in K} l_k D^p_k Q^v_{jtk} \qquad t\in T \tag{11}$$
$$\frac{\sum_{k\in K_e}\sum_{j\in J^v_k} l_k D^p_k Q^v_{jtk}\overline{F}}{W_t} \le F_t \qquad t\in T \tag{12}$$
$$\gamma_t F_t \le \sum_{j\in J^i} Q^i_{jt} \qquad t\in T \tag{13}$$
$$F_t, P^v_{tk}, Q^v_{jtk}, S^v_{jtk} \in \mathbb{Z}_{\ge 0} \qquad t\in T, k\in K, j\in J^v_k \tag{14}$$
$$P^i_t, Q^i_{jt}, S^i_{jt} \in \mathbb{Z}_{\ge 0} \qquad t\in T, k\in K, j\in J^i. \tag{15}$$

Journal Pre-proof

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Table 2: *Set, parameter, and variable definitions for the SFMP model.*

Sets	
T:	Set of t_F years in the planning horizon.
K:	Set of truck types.
J^k:	Set of possible ages for a truck of type k.
J^i:	Set of possible ages for a charging instrument.
Parameters	
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 truck in year t
D_k:	Driving hours of type k truck in one day
e^d_{jtk}:	CO_2 emissions in kg per hour of driving by a type k truck of age j in year t
f_{jtk}:	Fuel/electricity cost of a type k truck of age j in year t for one hour of driving
m^f_t:	Annual maintenance cost required in a charging facility per year
m^v_{jtk}:	Maintenance cost of a type k truck of age j for one hour of driving in year t
Q^v_{j0k}:	Number of trucks of type k of age j owned at the beginning of the planning horizon
Q^i_{j0}:	Number of charging instruments of age j owned at the beginning of the planning horizon
s^v_{jtk}:	Salvage value of a type k truck of age j in year t
s^i_{jt}:	Salvage value of one charging instrument of age j in year t
u_t:	Driver cost per hour in year t
Y:	Number of working days in a year
β_t:	Discount factor for year t
ϵ_t:	Cost of emissions in year t per kilogram of CO_2 emissions
Decision Variables	
P^i_t:	Number of charging instruments purchased at the beginning of year t
P^v_{tk}:	Number of type k trucks purchased at the beginning of year t
Q^i_{jt}:	Number of charging instruments of age j owned at the beginning of year t
Q^v_{jtk}:	Number of type k trucks of age j owned at the beginning of year t
S^i_{jt}:	Number of charging instruments of age j salvaged at the beginning of year t
S^v_{jtk}:	Number of type k trucks of age j salvaged at the beginning of year t.

The objective function calculates the present value of all operational costs and benefits using a discount factor β_t, which include the purchasing cost of trucks (c^v_{tk}); salvage value of trucks (s^v_{jtk}); fuel and electricity costs (f_{jtk}); maintenance costs of trucks (m^v_{jtk}); carbon emission costs (ϵ_t) due to transportation operations based on well-to-wheel emissions (e^d_{jtk}); hourly cost of the driver (u_t); fixed cost of installing charging facilities (A); maintenance costs of charging facilities (m^f_t), and purchasing cost (c^i_t) and salvage value (s^i_{jt}) of the charging instruments. Additionally, the parameter Y in the objective function denotes the number of working days per year.

Given initial fleet and infrastructure compositions, Q^v_{j0k} and Q^t_{j0}, constraint sets (5) – (7) are the balance equations for each type of truck through acquisition and salvaging. Constraint sets (8) – (10) are similar balance constraints for the charging instruments. Constraint set (11) ensures that

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the size of the fleet is adequate to satisfy the demand, considering the available working time of each truck. Constraint set (12) defines the auxiliary decision variable, F_t, which is the required number of charging facilities in year t to serve the e-truck fleet in that year. In this constraint, D_k^p, productive driving time of truck type k, is a parameter given by (1). Constraint set (13) 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 (4). Constraint set (14) and (15) are the non-negativity 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:

$$\sum_{k\in K} c_{tk}^v P_{tk}^v + \sum_{t\in T} AF_t + \sum c_t^i P_t^i \leq B_t^a \qquad \forall t \qquad \text{(OC.1)}$$

$$\sum_{j\in J_k^v}\sum_{k\in K}(f_{jtk} + m_{jtk}^v)YD_kQ_{jtk}^v + \sum_{j\in J_k^v}\sum_{k\in K}\epsilon_t e_{jtk}^d YD_kQ_{jtk}^v + \sum_{t\in T} m_t^f F_t \leq B_t^o \qquad \forall t. \qquad \text{(OC.2)}$$

Green Ratio. An internal constraint can be imposed to achieve a (potentially progressive) target level of "green ratio" in year t, defined as the ratio of demand satisfied by e-trucks. Let GR_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:

$$GR_t \leq \frac{\sum_{j\in J_k^v}\sum_{k\in K_e}\left(l_k D_k^p Q_{jtk}^v\right)}{\sum_{j\in J_k^v}\sum_{k\in K}\left(l_k D_k^p Q_{jtk}^v\right)} \qquad \forall t. \qquad \text{(OC.3)}$$

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

Journal Pre-proof

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:

$$\sum_{j\in J^v_k}\sum_{k\in K} e^d_{j\tau k} YD_k Q^v_{j\tau k} \leq E^a_\tau \tag{OC.4}$$

$$\sum_{j\in J^v_k}\sum_{k\in K} e^d_{jtk} YD_k Q^v_{jtk} \leq \sum_{j,k} e^d_{j,t-1,k} YD_k Q_{j,t-1,k} \qquad \forall t \geq \tau + 1. \tag{OC.5}$$

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

$$\sum_{j\in J^v_k}\sum_{k\in K} e^d_{jtk} YD_k Q^v_{jtk} \leq \left(\frac{100 - E^p}{100}\right)\sum_{j\in J^v_k}\sum_{k\in K} e_{j,t-1,k} YD_k Q^v_{j,t-1,k}. \tag{OC.6}$$

3.5 Shared Infrastructure Investments

So far we have considered a focal firm that invests in its own charging infrastructure, either due to lack of existing charging facilities or for strategic reasons aimed at ensuring high productive driving times. Nevertheless, the focal firm might not have to bear all of the charging infrastructure investment costs. We envision three possibilities to that end:

- The investment might be (partially) subsidized by the governmental bodies in an effort to incentivize firms in their transition to renewable energy use. This could be, for example, by designating places 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 its own charging network at these locations—in order not to risk longer waiting times. Such an initiative taken by public authorities will eliminate the charging facility installation and maintenance costs for the firms. 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 the SFMP by setting $A = 0$ and $m^f_t = 0\ \forall t$. 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.

Journal Pre-proof

- The focal firm might want to make use of the already available public charging facilities that are also open to personal vehicles -in addition to its own charging stations-, possibly covering only a fraction of the area that the firm serves, e.g., in the urban areas only. In order to avoid long non-productive driving times due to congestion in those public charging facilities, it could be in the focal firm's interest to invest in increasing the charging capacity of these public charging facilities so that it can meet the average waiting time target ω. In this way, the focal firm engages in a public-private partnership (PPP) with the government, creating a triple win situation (for the focal firm, government, and the public users as they will also enjoy shorter waiting times). While this will eliminate the charging facility installation and maintenance costs for the focal firm as in the previous case, the firm will be bearing investment costs of some charging instruments that will also serve public users. In Appendix C we present how the SFMP can be modified to address such a PPP mechanism. Furthermore, in Section 4.9 we analyze this option numerically and discuss the conditions that lead to a profitable PPP.

- The focal firm might want to collaborate with a potential partner (or partners) who will co-invest and co-use the charging infrastructure with the focal firm. This is a typical application of resource pooling and it will result in decreased (shared) charging infrastructure investment costs, but the capacity should be carefully decided in order not to jeopardize the productive driving time requirements of the focal firm. To facilitate the analysis with our model, we let $W_{partner} = \phi W$ and assume a proportional share of the facility and instruments costs among partners, such that the focal firm's share is $1/(1 + \phi)$. Observations that we make through our numerical analysis are presented in Section 4.9.

Journal Pre-proof

4 Numerical Study

In this section, we present a numerical study (i) to demonstrate how our model can help practitioners in making strategic decisions for transitioning to sustainable transportation and (ii) to generate insights into identifying the key technological, economical, and political factors that influence this transition, which can be valuable for the practitioners and governing bodies.

Journal Pre-proof

4.1 The Data Set

As is expected for a product category in its introductory phase, the technical specifications and costs of e-trucks and the related ecosystem are constantly evolving. Furthermore, the need to transition to a more sustainable economy implies shifts in the energy market that are expected to affect fuel and electricity prices as well as the energy mix. Given that our goal is to provide a strategic transition plan, we are interested in the medium to long term evolution of said technologies and costs. We surveyed the state of the art of the competing vehicle technologies (diesel and electric), the related costs, and their expected evolution to come up with a realistic data set to use in our numerical analysis. We use sources from the literature, governmental agencies, and personal interviews with two North American large-sized carriers, an in-house and a for-hire fleet operator. Details of the collected data are given in Appendix A and the specific values of the parameters are summarized in Table 3.

Naturally, our numerical results predicate on the curated data set, therefore, they should not be considered as a plug-and-play solution; however, we expect all the high-level insights that we generate to prevail in relative terms under different problem parameters. In addition to the parameters given in Table 3 (see Appendix A for details), 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[1] 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%. The inflation and the discount rates are set to 2% and 10%, respectively. Hourly wage of a driver is set to \$20. 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. We do not implement any of the operational constraints defined in Section 3.4 to focus on the behavior of the unconstrained model, but they can easily be incorporated by a decision maker. We solved the linear relaxation of the model[2] using Gurobi Optimizer with a 3.2 Ghz Intel i5 CPU and 12 GB RAM. We set the planning horizon to $t_F = 22$ years and report the results of the first 15 years to

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

[2]This solution is obtained within a second and deviates from the integer optimal solution by a fractional percentage.

Journal Pre-proof

Table 3: *Summary of parameters for base run of computational experiments.*

Parameter	Diesel Trucks	Electric	Reference
Vehicles			
Type	Class 8 d-truck	Class 8 e-truck	Coppola and Kharif (2018)
Purchase cost	$ 118,000	$ 118,000 (without battery)	Statista (2019)
Δ purchase cost	0.8 %/year	0.8 %/year	Statista (2019)
Maintenance costs	$0.13/km	$0.09/km	Danielis et al. (2018); Weldon et al. (2018); Interviews
Δ maintenance costs	20 %/year	20 %/year	Martin (2016)
Salvage period	7 Years	7 Years	Danielis et al. (2018)
Fuel economy	2.98 km/liter	0.8-1.15 km/kWh	
Refueling time	15 min	30 min (80% charge) 60 min (100% charge)	EVConnextions (2019)
Range	800 km	350 km (300 kWh Battery) 800 km (1000 kWh Battery)	Lambert (2020) Teslarati (2018b)
Payload efficiency	1	1	Saarinen (2020)
Emissions			
Carbon emissions (use)	3.3 kg CO2e/liter	0.456 kg CO2e/kWh	Sen et al. (2017); Zhou et al. (2017)
Carbon emissions (manufacture)	350 kg CO2e	350 kg CO2e (truck) 100 kg/kWh (battery)	Sen et al. (2017) Hao et al. (2017)
Carbon tax	$20 /Ton	$20 /Ton	Plumer and Popovich (2019)
Δ Carbon tax	20% /year	20% /year	
Batteries			
Cost	-	$ 200/kWh	Li et al. (2020)
Δ battery cost	-	−8 % year	
Salvage period	-	7 Years	Danielis et al. (2018)
Charging Stations			
Charging station cost	-	$15,000 /year	Smith and Gonzales (2014)
Charging instrument cost	-	$15,000 /year	SCA (2019)
Charging station maintenance	-	$10,000 /year	
Target service level (ω)	-	15 min	
Energy			
Energy cost	$0.66 /liter	$0.1 /kWh	EIA (2020)
Δ energy cost	3.2 % /year	2 % /year	DoE (2019)
Electricity mix	-	67% fossil/biomass 20% nuclear 14% renewables	EPA (2018b)

avoid any end-of-horizon effects. We parameterize one truck type per technology for each run, ie. K = {electric, diesel}, and use sensitivity analysis to understand the effect of each parameter on the

Journal Pre-proof

model's results.

4.2 Impact of Battery Capacity and Price

Figure 1 shows the total costs, emissions, and average green ratio over 15 years 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 [3](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 battery option "1000 kWh @ \$60/kWh".

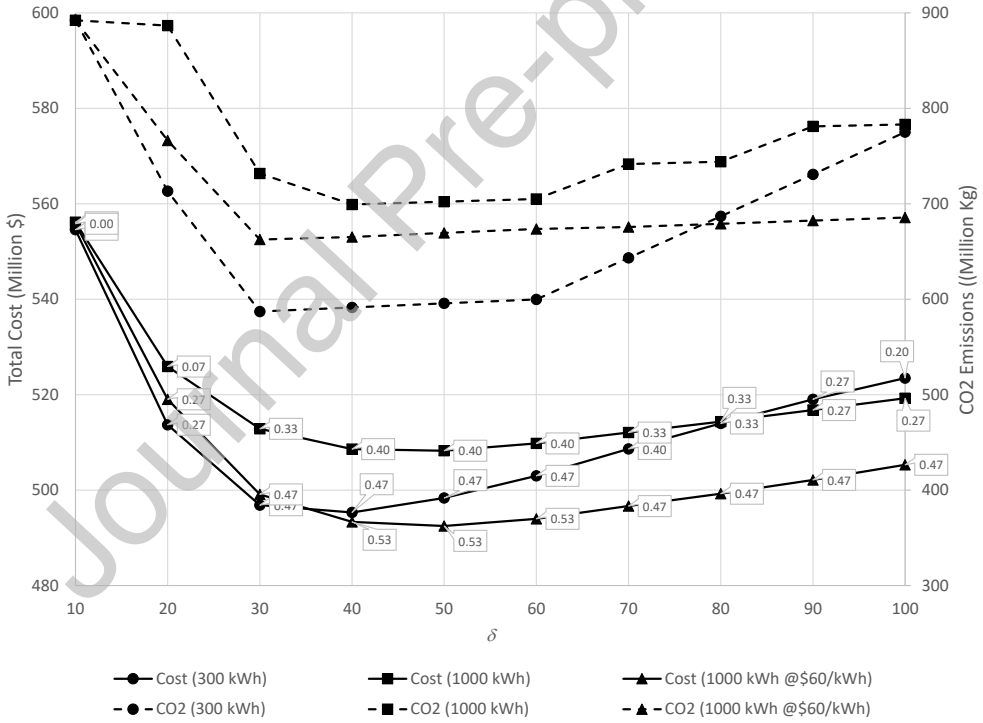


Figure 1: *Total Cost and Total CO_2 Emissions for Varying δ values for 300 and 1000 kWh batteries in Dense Demand Scenario. The labels accompanying each of the cost-values indicate the average green ratio (GR) over 15 years.*

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

[3]As of May 2020, the reservation price for a base-model 500-mile range Tesla semi is \$180,000, see https://www.tesla.com/semi.

Journal Pre-proof

detouring to recharge the e-trucks becomes excessive in the latter case (which also results in a lower green ratio in the optimal solution). This is counter to the general expectation of the practitioners, who might think that the e-trucks would only be feasible with a ubiquitous charging network similar to diesel refueling stations or that the creation of a private recharging network would bring excessive costs. For the parameter set that we consider, the optimal δ is 40 or 50 kilometers, depending on the cost of the battery. Another counter intuitive result is about the battery size. 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 higher green ratio, i.e., 0.53 instead of 0.47. It is interesting to observe that smaller batteries typically result in lower total emissions because of the lower manufacturing emissions associated with smaller batteries and earlier adoption associated with lower capital costs, as reflected by higher green ratios.

4.3 Impact of Charging Choices

Table 4 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). The results show that the optimal infrastructure investment depends strongly on the demand density, with higher demand density associated with higher infrastructure density. The trade-off is such that the infrastructure cost limits the density of the charging infrastructure, which, in turn, limits the adoption of e-vehicles. This effect is also visible in all other tables that we present, i.e., the optimal green ratio is higher for dense demand. Furthermore, the optimal solution involves quickly charging batteries to "almost full" status (cf. rapid charging to 80%), rather than waiting for a full charge. Charging choice is particularly crucial in making electric truck investment decisions. The optimal green ratio is significantly affected by that choice and under some parameter values not shown here, the effect can go inasmuch as no investment in electric trucks being made if the

Journal Pre-proof

charging policy is to fully charge the batteries.

Table 4: *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**	**495**	**591**	**0.47**
	60 Min/100%	40	511	636	0.40
Sparse	30 Min/80%	60	516	723	0.27
	60 Min/100%	60	526	860	0.07

4.4 Comparison of Alternative Fleet Strategies

Table 5 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. 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, the additional emission savings can be achieved at a moderate cost penalty (or even with cost savings for some parameter values that are not shown here). However, 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.

Table 5: *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 δ = 10
Dense	Cost	-59 (11%)	+32 (6%)	+351 (63%)
	CO2	-301 (34%)	-563 (63%)	-593 (66%)
Sparse	Cost	-40 (7%)	+19 (3%)	+1723 (310%)
	CO2	-169 (19%)	-543 (61%)	-593 (66%)

Increasing the green ratio has a large direct effect on emissions and a relatively minor effect

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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-trucks. Fleet composition decisions, however, cannot be dissociated from infrastructure decisions; optimizing both fleet size and charging infrastructure appears critical for the success of e-truck adoption.

4.5 Effect of Carbon Cost

Table 6 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 ratio.

Table 6: *Effect of carbon cost on the optimal solution (base scenario in boldface).*

	Dense Demand				Sparse Demand			
ϵ_1 ($/Ton CO_2)	δ^* (km)	Cost ($)	CO_2 (Ton)	GR	δ^* (km)	Cost ($)	CO_2 (Ton)	GR
10	40	480	592	0.47	–	496	892	0.00
20	40	**495**	**591**	**0.47**	60	**516**	**723**	**0.27**
40	40	524	562	0.53	60	549	599	0.47
100	40	601	416	0.80	60	638	535	0.60

This is consistent with prior research, which suggests that increasing emission costs incentivizes 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 choice, our results show that a significant effect on the green ratio can be observed within the order of magnitude of the current carbon price (the carbon allowance price of the EU emission trading scheme, EUA, has been within 20-30 Euros/ton in 2019). Accordingly, carbon taxes can be effectively used to steer existing truck fleets towards electric alternatives. These results also indicate that carbon tax achieves the desired effect typically through increasing the attractiveness of converting additional vehicles to electric; as the infrastructure intensity decision remains robust in our scenarios, as long as the green ratio is positive.

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4.6 Effect of Energy Mix

Table 7 shows the effect of the assumptions behind the adoption rate of renewable electricity generation and the initial proportion of renewable content in the energy mix. The base scenario is derived from the average energy mix in the USA, as discussed in Section 5, 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.

Table 7: *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	**495**	**591**	**0.47**	60	**516**	**723**	**0.27**
	10%	40	486 (2%)	536 (9%)	0.47	60	507 (2%)	636 (12%)	0.33
	25%	40	479 (3%)	476 (20%)	0.47	60	500 (3%)	534 (26%)	0.40
0.228	5%	40	487 (2%)	528 (11%)	0.47	60	508 (2%)	634 (12%)	0.33
0	–	40	478 (3%)	465 (21%)	0.47	60	499 (3%)	526 (27%)	0.40

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 less emissions. We observe that the energy mix also shows a second order effect: the greener the power source, the larger the average green ratio becomes (in the weak sense), because the energy mix plays an important role in the dynamics of e-truck adoption. For the parameter set that resulted in Table 7, the increase in green ratio is observed only for the sparse demand case, but in the extended numerical experiments we conducted, we observe that for the dense demand case, as well. Renewable energy generation offsets the (relatively high) emissions related to the production of e-trucks—a large proportion of renewables speeds up the adoption of e-trucks.

4.7 Impact of Diesel Engine Efficiency

Table 8 shows the effect of technological advances in diesel engines. Observe that if the diesel efficiency increases significantly, its environmental benefits can even surpass the benefits of e-truck adoption (under the sparse demand case here). Thus, when diesel engines become "good

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enough", it is optimal not to invest in any charging/e-truck infrastructure, potentially resulting in lower total emissions. The side effect is that in some cases the optimal solution with higher diesel efficiency is environmentally outperformed by the optimal solution with lower diesel efficiency (e.g., under dense demand here, but also for sparse demand in some other numerical experiments we have run). 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 d-trucks become good enough to postpone investments in e-trucks, but not good enough to bring about a substantial decrease in emissions. In such cases, policy-makers may have to intervene (see Table 6) to ensure the transition to green technologies.

Table 8: *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	**495**	**591**	**0.47**	60	**516**	**723**	**0.27**
2.50%	40	493	575	0.47	60	510	806	0.07
5.00%	–	481	705	0.00	–	490	705	0.00

4.8 Fleet Transition over Time

In our numerical setup, e-trucks become cheaper in time with advancements in technology. In the scenarios that a transition to e-trucks is observed, there is a time period in which investing in e-trucks (together with the charging infrastructure at a corresponding density) becomes cheaper than operating with brand new d-trucks. Starting from that period and on, it is optimal to invest in e-trucks only. However, based on the cost factors, there can be a transition period during which the d-trucks of older ages are kept for a while until their end of life or until they become relatively costly to operate. The salvage value, useful life of the trucks, and the increasing cost of maintenance by age are among the factors that determine the length of this transition. Figure 2 depicts a problem instance of such a transition period with a hybrid fleet composition.

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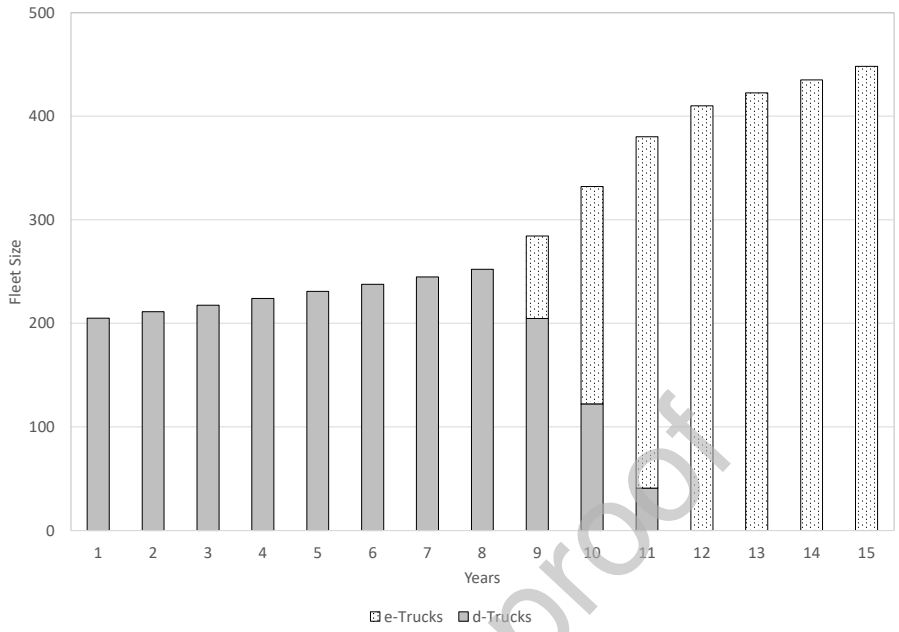


Figure 2: *Fleet Composition over 15 years under Dense Demand and Base Scenario with annual maintenance cost increase equals 3%*

4.9 Analysis of Shared Infrastructure Investments

In this section, we experiment with the shared investment models presented in Section 3.5. First, we consider the case of governmental subsidy. Figure 3 depicts the trade-off between emission savings obtained and the corresponding cost for the public with this initiative, considering a single 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 3 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. The "biggest bang for the buck" depends on the network density (at $\delta = 70$ for sparse demand and $\delta = 30$ for dense demand), but comparable savings can be materialized both in sparse and dense demand cases.

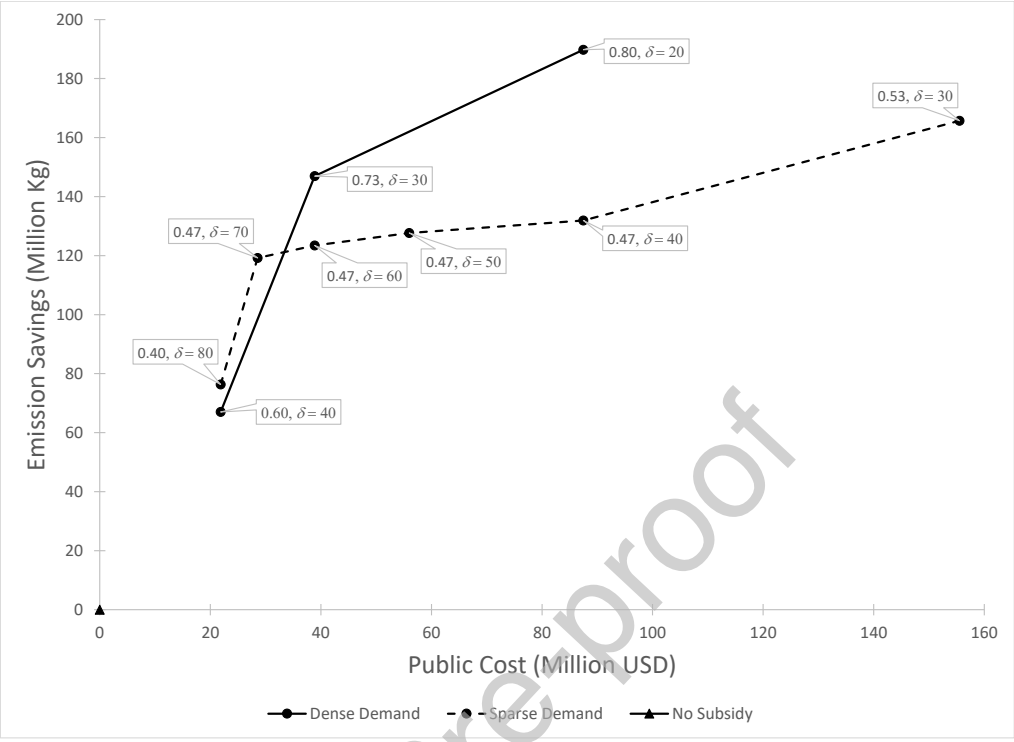


Figure 3: *Efficient Frontier for Emission Savings versus Public Cost. First numbers in the boxes indicate the Green Ratio at that efficient solution.*

Next, we analyze the PPP model. We first consider a base scenario in which there exist public charging facilities in 10% of the service region with an average of 10 km distance between them (i.e., $\delta^P = 10$, see Appendix C for notation and formulation). In this scenario, if the traffic ratio at the public facilities is 0.95 then PPP brings 0.65% reduction to total system costs (i.e., not just the charging infrastructure costs, but all costs as given in the objective function of SFMP) for the focal firm, corresponding to $3.6 Million. PPP stays to be the preferred option under the same setting for all $\delta^P < 60$ km. In these cases, the density of the private network δ^V is 40 km. When $\delta^P = 60$ km, then the best PPP alternative starts becoming more costly than the status quo because of the elevated unproductive driving times at the public charging space caused by long detours. Another scenario in which PPP is not desirable is when the public charging network is denser with $\delta^P = 5$ km under a higher traffic ratio of 0.989. This time, the extensive charging instrument requirement to reduce the waiting times to acceptable levels and excessive number of facilities to be invested

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become too costly to make it a viable option. Nevertheless, we observe several cases for which PPP is desirable in our numerical tests.

Finally, regarding the private partnership model, we present an illustration in Table 9. This table presents the cost and CO2 emission savings as well as improvement in green ratio for different values of ϕ where the partner's demand is equal to ϕ times the company's demand. These results indicate that the biggest benefit is obtained for the smaller company in this partnership. We also observe that as the size of the partnership increases, the charging network becomes denser and the green truck adoption starts earlier.

Table 9: *Savings Under Private Partnerships - Dense Demand Scenario*

ϕ	δ^*	Cost	CO2	GR
0	40	495	591	0.47
0.25	30	493 (0.5%)	587 (0.7%)	0.47
1	30	487 (1.7%)	558 (5.7%)	0.53
4	20	476 (3.9%)	475 (19.8%)	0.67

4.10 Sensitivity to Other Parameters

In addition to the above, we also analyzed the sensitivity of the results to a number of parameters: ratio of e-truck/d-truck price, rate of price increases, payload efficiency, detour length coefficient, cost of the charging facility, and the charging level on the adoption decisions. The insights discussed thus far are generally robust. Lower values of the e-truck to d-truck price ratio predictably favor higher e-truck adoption: the GR drops to a minimum of 0.4 when $c^v_{0e}/c^v_{0d} = 2$ under dense demand. (Here the sub-indices e and d denote, respectively, the electric and diesel truck types.) Under sparse demand, $c^v_{0e}/c^v_{0d} = 1.25$ is required to achieve the same GR. The GR is well above 0.27 for $l_e \geq 0.9$ and $\theta \leq 1$ for both dense and sparse demand. We observe that the optimal solution is not sensitive to the choice of charging facility costs; GR does not change even if the annual investment cost is increased to $20,000$. Finally, we observe that the transition to sustainable transportation is only possible using Level 3 chargers.

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5 Conclusions

In this study, we model the adoption of electric trucks in the context of an existing fleet of commercial d-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 e-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 parameter configurations, 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

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the trucks. In particular, we see that 300 kWh batteries with charging stations spaced 40 km 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. If there is no or scarce charging infrastructure that a firm can utilize for their operations, then transitioning to greener fleets can become economical only if the firm optimizes these two decisions simultaneously. Because otherwise, existing infrastructure may lead to excessive unproductive driving times or the firm may presume that the only feasible path for the transition is to invest in an infrastructure that will maximize the utilization of the e-trucks. In both cases, the firm will be mistaken to identify the e-truck transition as non-economical. Moreover, 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 trucks 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. The question remains, though, what the effect of a substantial increase in energy demand would be on the energy mix. While we assumed those two to be independent in our study, the results could shift in either direction, depending on whether the demand could only be met by heavier utilization of fossil fuels, or expedite an overall transition to renewable energy.

Our results also show that the optimal policy may be a gradual shift towards e-trucks resulting in a mixed fleet during the transition to a greener fleet. Moreover, the timing of said transition is dependent on firm-level parameters in addition to global, technology-dependent parameters. 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", and certainly not "every firm at once".

Our model is useful when a firm makes strategic analysis of if and when they should start the transition process and in what type of e-trucks that they should invest in. When the firm decides to initiate this process based on this strategic analysis, they should resort to custom-design models that pertain to the specifics of their operating characteristics to make operational decisions.

Journal Pre-proof

It may be possible for the focal firm to alleviate the burden of undertaking the whole charging infrastructure investment on its own by engaging in a shared investment model. We considered three possibilities in this article. 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. Concerning PPP, we demonstrate that it is generally beneficial for the focal firm to engage in such a partnership, unless the public charging network is too sparse or too dense, the former resulting in high unproductive driving times and the latter resulting in too high investment costs. Finally, the private partnership model benefits the parties due to resource pooling, particularly favoring the smaller company. Furthermore, larger partnerships speed up green truck adoption.

Our motivation to study e-trucks as the contending green technology stems from the current technological developments. However, there are many uncertainties as to which will be widely adopted. For example, in this article, we have considered plug-in charging as it seems to be obtaining wider acceptance than the battery-swapping technology. We refer the reader to Avci et al. (2015), Sun et al. (2019a), and Sun et al. (2019b), for analyses of adopting battery-swapping technology and Appendix B for a sketch of how our model could be adjusted to incorporate battery-swapping. Similarly, we have not considered other AFVs such as fuel cell electric vehicles powered by hydrogen. Furthermore, there are other green technologies in preparation, lab, or idea phase making the future of e-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.

Acknowledgement

We thank the anonymous reviewers and the associate editor for their valuable suggestions, which helped us improve the content and the presentation of the study.

Journal Pre-proof

References

Adkins, R., D. Paxson. 2011. Renewing assets with uncertain revenues and operating costs. *Journal of Financial and Quantitative Analysis* **46**(3) 785–813.

Adkins, R., D. Paxson. 2017. Replacement decisions with multiple stochastic values and depreciation. *European Journal of Operational Research* **257**(1) 174–184.

Aflaki, S., S. Netessine. 2017. Strategic investment in renewable energy sources: The effect of supply intermittency. *Manufacturing & Service Operations Management* **19**(3) 489–507.

Afroditi, A., M. Boile, S. Theofanis, E. Sdoukopoulos, D. Margaritis. 2014. Electric vehicle routing problem with industry constraints: Trends and insights for future research. *Transportation Research Procedia* **3** 452–459.

Ansaripoor, A. H., F. S. Oliveira, A. Liret. 2016. Recursive expected conditional value at risk in the fleet renewal problem with alternative fuel vehicles. *Transportation Research Part C: Emerging Technologies* **65** 156–171.

Avci, B., K. Girotra, S. Netessine. 2015. Electric vehicles with a battery switching station: Adoption and environmental impact. *Management Science* **61**(4) 772–794.

Bohn, T., H. Chaudhry. 2012. Overview of sae standards for plug-in electric vehicle. *2012 IEEE PES Innovative Smart Grid Technologies (ISGT)*. IEEE, 1–7.

Brandstätter, G., M. Leitner, I. Ljubić. 2020. Location of charging stations in electric car sharing systems. *Transportation Science* **54**(5) 1408–1438.

BusinessInsider. 2019. CO2 European emission allowances. https://markets.businessinsider.com/commodities/co2-european-emission-allowances. Accessed: 2022-01-06.

Carbonfund. 2019. How we calculate? https://carbonfund.org/how-we-calculate/. Carbonfund.org Foundation. Accessed: 2022-01-06.

Chen, R., X. Qian, L. Miao, S. V. Ukkusuri. 2020. Optimal charging facility location and capacity for electric vehicles considering route choice and charging time equilibrium. *Computers & Operations Research* **113** 104776.

Chocteau, V., D. Drake, P. R. Kleindorfer, R. Orsato. 2011. Collaborative innovation for sustainable fleet operations: The electric vehicle adoption decision. INSEAD Working Paper No. 2011/52/TOM/INSEAD Social Innovation Centre. https://ssrn.com/abstract=1791623.

Cleantechnica. 2018. Innogy to supply deutsche post dhl with ev charging stations. https://cleantechnica.com/2018/02/07/innogy-supply-deutsche-post-dhl-ev-charging-stations/. Accessed: 2022-01-06.

CommercialFleet. 2020. Renault master ze gains 3.5t variants: pricing and specs revealed. https://bit.ly/2Zl1ri1. Accessed: 2022-01-06.

Coppola, G., O. Kharif. 2018. Daimler adds two electric trucks in race against Tesla, VW. https://www.bloomberg.com/news/articles/2018-06-06/daimler-adds-two-electric-trucks-in-race-against-tesla-vw. Accessed: 2022-01-06.

Cortés-Murcia, D. L., H. M. Afsar, C. Prodhon. 2019. Recharge at lunch, an alternative to handle the range issues of electric vehicles. Université de Technologie de Troyes. Working Paper.

Courtney, H., J. Kirkland, P. Viguerie. 1997. Strategy under uncertainty. *Harvard Business Review* **75**(6) 67–79.

Daimler. 2020. Electrified on the highway. https://bit.ly/336HnVk. Accessed: 2022-01-06.

Danielis, R., M. Giansoldati, L. Rotaris. 2018. A probabilistic total cost of ownership model to evaluate the current and future prospects of electric cars uptake in Italy. *Energy Policy* **119** 268–281.

Das, H., M. Rahman, S. Li, C. Tan. 2020. Electric vehicles standards, charging infrastructure, and impact on grid integration: A technological review. *Renewable and Sustainable Energy Reviews* **120** 109618.

Journal Pre-proof

Davis, B. A., M. Figliozzi. 2013. A methodology to evaluate the competitiveness of electric delivery trucks. *Transportation Research Part E: Logistics and Transportation Review* **49**(1) 8–23.

Deloitte. 2019. New market. New entrants. New challenges. Battery electric vehicles. https://bit.ly/3G2Wn58. Accessed: 2022-01-06.

DoE. 2019. Annual energy outlook 2019 with projections to 2050. https://bit.ly/3eXyMak. Department of Energy. Accessed: 2022-01-06.

DoE. 2020. Annual energy outlook 2020 with projections to 2050. https://bit.ly/3n3DVSq. Department of Energy. Accessed: 2022-01-06.

Drake, D. F., P. R. Kleindorfer, L. N. Van Wassenhove. 2016. Technology choice and capacity portfolios under emissions regulation. *Production and Operations Management* **25**(6) 1006–1025.

Drake, D. F., S. Spinler. 2013. OM forum—sustainable operations management: An enduring stream or a passing fancy? *Manufacturing & Service Operations Management* **15**(4) 689–700.

Ecoscore. 2019. How to calculate the co2 emission from the fuel consumption? https://ecoscore.be/en/info/ecoscore/co2. Accessed: 2022-01-06.

EDF. 2019. The true cost of carbon pollution. https://www.edf.org/true-cost-carbon-pollution. Environmental Defense Fund. Accessed: 2022-01-06.

EEA. 2019. Trends and projections in europe 2019. Tech. Rep. EEA Report 15/2019. DOI: 10.2800/51114, European Environmental Agency.

EIA. 2020. Gasoline and diesel fuel update. https://www.eia.gov/petroleum/gasdiesel/. U.S Energy Information Administration. Accessed: 2022-01-06.

EPA. 2018a. eGRID Summary Tables 2018. https://bit.ly/2R486IL. Environmental Protection Agency. Accessed: 2022-01-06.

EPA. 2018b. Us transportation sector greenhouse gas emissions: 1990–2016. Tech. Rep. EPA-420-F-18-013, Office of Transportation and Air Quality.

EPA. 2019. Sources of greenhouse gas emissions. https://bit.ly/32NGfX5. Environmental Protection Agency. Accessed: 2022-01-06.

Erdoğan, S., E. Miller-Hooks. 2012. A green vehicle routing problem. *Transportation Research Part E: Logistics and Transportation Review* **48**(1) 100–114.

Evarts, E. 2019. Nikola releases semi-trucks two and tre, maps out hydrogen network. https://bit.ly/3JHNPmJ. Accessed: 2022-01-06.

EVConnextions. 2019. How long does it take to charge an electric car? https://bit.ly/3pWSSYw. Accessed: 2022-01-06.

Extremetech. 2019. Volvo plans big electric trucks for local, regional hauls. https://www.extremetech.com/extreme/298830-volvo-plans-big-electric-trucks-for-local-regional-hauls. Accessed: 2022-01-06.

Felipe, Á., M. T. Ortuño, G. Righini, G. Tirado. 2014. A heuristic approach for the green vehicle routing problem with multiple technologies and partial recharges. *Transportation Research Part E: Logistics and Transportation Review* **71** 111–128.

Feng, W., M. Figliozzi. 2013. An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the usa market. *Transportation Research Part C: Emerging Technologies* **26** 135–145.

Figliozzi, M. 2010. Vehicle routing problem for emissions minimization. *Transportation Research Record* **2197**(1) 1–7.

Finesso, R., E. Spessa, M. Venditti. 2016. Cost-optimized design of a dual-mode diesel parallel hybrid electric vehicle for several driving missions and market scenarios. *Applied Energy* **177**(C) 366–383.

Journal Pre-proof

Ghamami, M., M. Kavianipour, A. Zockaie, L. R. Hohnstadt, Y. Ouyang. 2020. Refueling infrastructure planning in intercity networks considering route choice and travel time delay for mixed fleet of electric and conventional vehicles. *Transportation Research Part C: Emerging Technologies* **120** 102802.

Girod, B., D. P. van Vuuren, S. Deetman. 2012. Global travel within the 2C climate target. *Energy Policy* **45**(C) 152–166.

GreenCarReports. 2020. Ev battery pack prices fell 13% in 2020. https://bit.ly/3JJnC73. Accessed: 2022-01-06.

Hagman, J., S. Ritzén, J. J. Stier, Y. Susilo. 2016. Total cost of ownership and its potential implications for battery electric vehicle diffusion. *Research in Transportation Business & Management* **18**(C) 11–17.

Hao, H., X. Cheng, Z. Liu, F. Zhao. 2017. Electric vehicles for greenhouse gas reduction in china: A cost-effectiveness analysis. *Transportation Research Part D: Transport and Environment* **56** 68–84.

Hartman, J. C., C. H. Tan. 2014. Equipment replacement analysis: a literature review and directions for future research. *The Engineering Economist* **59**(2) 136–153.

Hoen, K. M., T. Tan, J. C. Fransoo, G.-J. van Houtum. 2013. Switching transport modes to meet voluntary carbon emission targets. *Transportation Science* **48**(4) 592–608.

Hopp, W. J., M. L. Spearman. 2011. *Factory Physics*. Waveland Press, Long Grove, Illinois.

Howe, K. M., G. M. McCabe. 1983. On optimal asset abandonment and replacement. *Journal of Financial and Quantitative Analysis* **18**(3) 295–305.

Hu, L., J. X. Zhu, Y. Wang, L. H. Lee. 2018. Joint design of fleet size, hub locations, and hub capacities for third-party logistics networks with road congestion constraints. *Transportation Research Part E: Logistics and Transportation Review* **118** 568–588.

IEA. 2016. *World Energy Outlook*. International Energy Agency.

IEA. 2017a. *CO2 Emissions from Fuel Consumption*. International Energy Agency.

IEA. 2017b. *The future of trucks*. International Energy Agency.

IEA. 2019. *Global EV Outlook 2019*. International Energy Agency.

Islam, A., N. Lownes. 2019. When to go electric? A parallel bus fleet replacement study. *Transportation Research Part D - Transport and Environment* **72** 299–311.

Jaffe, A. B., R. G. Newell, R. N. Stavins. 2003. *Technological change and the Environment*, vol. 1. Elsevier Masson SAS.

Kane, M. 2020. Scania introduces its first commercial plug-in electric truck range. https://bit.ly/3i6rn7O. Accessed: 2022-01-06.

Karaca-Mandic, P. 2011. Role of complementarities in technology adoption: The case of DVD players. *Quantitative Marketing and Economics* **9**(2) 179–210.

Kavianipour, M., F. Fakhrmoosavi, H. Singh, M. Ghamami, A. Zockaie, Y. Ouyang, R. Jackson. 2021. Electric vehicle fast charging infrastructure planning in urban networks considering daily travel and charging behavior. *Transportation Research Part D: Transport and Environment* **93** 102769.

Keskin, M., B. Çatay, G. Laporte. 2021. A simulation-based heuristic for the electric vehicle routing problem with time windows and stochastic waiting times at recharging stations. *Computers & Operations Research* **125** 105060.

Keskin, M., G. Laporte, B. Çatay. 2019. Electric vehicle routing problem with time-dependent waiting times at recharging stations. *Computers & Operations Research* **107** 77–94.

Kim, J., S.-Y. Son, J.-M. Lee, H.-T. Ha. 2017. Scheduling and performance analysis under a stochastic model for electric vehicle charging stations. *Omega* **66** 278–289.

Kleindorfer, P. R., A. Neboian, A. Roset, S. Spinler. 2012. Fleet renewal with electric vehicles at La Poste. *Interfaces* **42**(5) 465–477.

Journal Pre-proof

Koç, Ç., O. Jabali, J. E. Mendoza, G. Laporte. 2018. The electric vehicle routing problem with shared charging stations. *International Transactions in Operational Research* **26**(4) 1211–1243.

Kucukoglu, I., S. Ene, A. Aksoy, N. Ozturk. 2013. Green capacitated vehicle routing problem fuel consumption optimization model. *Computational Engineering Research* **3** 16–23.

Kullman, N. D., J. C. Goodson, J. E. Mendoza. 2021. Electric vehicle routing with public charging stations. *Transportation Science* **55**(3) 637–659.

Kuppusamy, S., M. J. Magazine, U. Rao. 2017. Electric vehicle adoption decisions in a fleet environment. *European Journal of Operational Research* **262**(1) 123–135.

Lambert, F. 2017. Tesla releases 'expected price' of semi electric truck: $150,000 to $200,000. https://bit.ly/2GA9gtC. Accessed: 2022-01-06.

Lambert, F. 2018. DAF delivers its first all-electric truck. https://bit.ly/2Zi5JH2. Accessed: 2022-01-06.

Lambert, F. 2020. Daimler delivers more electric freightliner ecascadia semi-trucks. https://bit.ly/3zwSlj9. Accessed: 2022-01-06.

Letmathe, P., M. Suares. 2017. A consumer-oriented total cost of ownership model for different vehicle types in Germany. *Transportation Research Part D: Transport and Environment* **57** 314–335.

Lévay, P. Z., Y. Drossinos, C. Thiel. 2017. The effect of fiscal incentives on market penetration of electric vehicles a pairwise comparison of total cost of ownership. *Energy Policy* **105** 524–533.

Li, X., Y. Tan, X. Liu, Q. Liao, B. Sun, G. Cao, C. Li, X. Yang, Z. Wang. 2020. A cost-benefit analysis of v2g electric vehicles supporting peak shaving in shanghai. *Electric Power Systems Research* **179** 106058.

Liu, L., G. A. Keoleian, K. Saitou. 2017. Replacement policy of residential lighting optimized for cost, energy, and greenhouse gas emissions. *Environmental Research Letters* **12**(11) 114034–11.

Macrina, G., L. D. P. Pugliese, F. Guerriero, G. Laporte. 2019. The green mixed fleet vehicle routing problem with partial battery recharging and time windows. *Computers & Operations Research* **101** 183–199.

Mak, H.-Y., Y. Rong, Z.-J. M. Shen. 2013. Infrastructure planning for electric vehicles with battery swapping. *Management Science* **59**(7) 1557–1575.

Martin, M. 2016. The most and least expensive cars to maintain. https://bit.ly/336osdt. Accessed: 2022-01-06.

Mitropoulos, L. K., P. D. Prevedouros, P. Kopelias. 2017. Total cost of ownership and externalities of conventional, hybrid and electric vehicle. *Transportation Research Procedia* **24**(2004) 267–274.

Montoya, A., C. Gueret, J. E. Mendoza, J. G. Villegas. 2017. The electric vehicle routing problem with nonlinear charging function. *Transportation Research Part B: Methodological* **103** 87–110.

Morris, D. 2015. Tesla veteran explains how electric motors crush gas engines. https://bit.ly/3n0O9mR. Accessed: 2022-01-06.

NTM. 2019. Network for transport measures. https://bit.ly/3ztBugY. Accessed: 2022-01-06.

Patricksson, Ø. S., K. Fagerholt, J. G. Rakke. 2015. The fleet renewal problem with regional emission limitations: Case study from roll-on/roll-off shipping. *Transportation Research Part C: Emerging Technologies* **56** 346–358.

Pelletier, S., O. Jabali, G. Laporte. 2016. 50th anniversary invited article—goods distribution with electric vehicles: Review and research perspectives. *Transportation Science* **50**(1) 3–22.

Pelletier, S., O. Jabali, J. E. Mendoza, G. Laporte. 2019. The electric bus fleet transition problem. *Transportation Research Part C: Emerging Technologies* **109** 174–193.

Pereirinha, P. G., J. P. Trovão. 2011. Standardization in electric vehicles. *12th Portuguese-Spanish Conference on Electrical Engineering, XIICLEEE*.

Journal Pre-proof

Plumer, B., N. Popovich. 2019. These countries have prices on carbon. Are they working? https://www.nytimes.com/interactive/2019/04/02/climate/pricing-carbon-emissions.html. Accessed: 2022-01-06.

PodPoint. 2019. How long does it take to charge an electric car? https://bit.ly/3HCer6A. Accessed: 2022-01-06.

Propfe, B., M. Redelbach, D. J. Santini, H. Friedrich. 2012. Cost analysis of plug-in hybrid electric vehicles including maintenance & repair costs and resale values. *World Electric Vehicle Journal* **5**(4) 886–895.

Quddus, M. A., M. Kabli, M. Marufuzzaman. 2019. Modeling electric vehicle charging station expansion with an integration of renewable energy and vehicle-to-grid sources. *Transportation Research Part E: Logistics and Transportation Review* **128** 251–279.

Reindorp, M. J., M. C. Fu. 2011. Capital renewal as a real option. *European Journal of Operational Research* **214**(1) 109–117.

Rinaldi, M., E. Picarelli, A. D'Ariano, F. Viti. 2020. Mixed-fleet single-terminal bus scheduling problem: Modelling, solution scheme and potential applications. *Omega* **96** 102070.

Saarinen, M. 2020. Electric van payloads explained. https://bit.ly/34gyRnc. Accessed: 2022-01-06.

Sari, T. 2017. The strategy to increase the adoption rate of electric vehicle. Master's thesis, Eindhoven University of Technology.

SCA. 2019. Smart Charge America EV Stations - Commercial. https://smartchargeamerica.com/electric-car-chargers/commercial/. Smart Charge America. Accessed: 2022-01-06.

Scania. 2020. Scania battery electric truck. https://bit.ly/3G2Z5Yj. Accessed: 2022-01-06.

Schiffer, M., G. Walther. 2017. The electric location routing problem with time windows and partial recharging. *European Journal of Operational Research* **260**(3) 995–1013.

Schiffer, M., G. Walther. 2018. Strategic planning of electric logistics fleet networks: A robust location-routing approach. *Omega* **80** 31–42.

Schneider, M., A. Stenger, D. Goeke. 2014. The electric vehicle-routing problem with time windows and recharging stations. *Transportation Science* **48**(4) 500–520.

Sen, B., T. Ercan, O. Tatari. 2017. Does a battery-electric truck make a difference?–life cycle emissions, costs, and externality analysis of alternative fuel-powered class 8 heavy-duty trucks in the united states. *Journal of Cleaner Production* **141** 110–121.

Smith, M., J. Gonzales. 2014. Costs associated with compressed natural gas vehicle fueling infrastructure. https://doi.org/10.2172/1156975. U.S. Department of Energy, Office of Scientific and Technical Information. Accessed: 2022-01-06.

Statista. 2019. Average price of new class 8 trucks in the United States from 2010 to 2017. https://www.statista.com/statistics/937418/new-truck-average-price-in-the-united-states/. Accessed: 2022-01-06.

Sternad, M. 2019. Cost calculation in road freight transport. *Business Logistics in Modern Management* .

Stone, D. 2016. Proposed standards for medium- and heavy-duty vehicles would reduce diesel consumption. https://www.eia.gov/todayinenergy/detail.php?id=26832. Accessed: 2022-01-06.

Stutzman, S., B. Weiland, P. Preckel, M. Wetzstein. 2017. Optimal replacement policies for an uncertain rejuvenated asset. *International Journal of Production Economics* **185**(C) 21–33.

Sun, B., X. Sun, D. H. Tsang, W. Whitt. 2019a. Optimal battery purchasing and charging strategy at electric vehicle battery swap stations. *European Journal of Operational Research* **279**(2) 524–539.

Sun, H., J. Yang, C. Yang. 2019b. A robust optimization approach to multi-interval location-inventory and recharging planning for electric vehicles. *Omega* **86** 59–75.

Sun, Y., J. Ogden, M. Delucchi. 2010. Societal lifetime cost of hydrogen fuel cell vehicles. *International Journal of Hydrogen Energy* **35**(21) 11932–11946.

Journal Pre-proof

SuproÅ, B. 2018. Analysis of cost structure of international road transport operators in west pomeranian voivodship in the years 2008-2014. *The Central European Review of Economics and Management (CEREM)* **2**(2) 61–86.

Teslarati. 2018a. Tesla semi trucks battery pack and overall weight explored. https://bit.ly/35j0F9c. Accessed: 2022-01-06.

Teslarati. 2018b. Tesla semi's temporary 'megacharger' system glimpsed in madonna inn sighting. https://bit.ly/35i7dVm. Accessed: 2022-01-06.

UCSUSA. 2018. Electric vehicle battery: Materials, cost, lifespan. https://www.ucsusa.org/clean-vehicles/electric-vehicles/electric-cars-battery-life-materials-cost#.W8eP4PlRdhE. Union of Concerned Scientists. Accessed: 2022-01-06.

UNFCCC. 2010. Decision 1/cp.16 the cancun agreements outcome of the work of the ad hoc working group on long term cooperative action under the convention. Framework Convention on Climate Change, United Nations. https://unfccc.int/resource/docs/2010/cop16/eng/07a01.pdf.

Wang, W., M. E. Ferguson, S. Hu, G. C. Souza. 2013. Dynamic capacity investment with two competing technologies. *Manufacturing and Service Operations Management* **15**(4) 616–629.

Wang, Y.-W. 2007. An optimal location choice model for recreation-oriented scooter recharge stations. *Transportation Research Part D: Transport and Environment* **12**(3) 231–237.

Weldon, P., P. Morrissey, M. O'Mahony. 2018. Long-term cost of ownership comparative analysis between electric vehicles and internal combustion engine vehicles. *Sustainable Cities and Society* **39** 578–591.

Whitt, W. 1983. The queueing network analyzer. *Bell System Technical Journal* **62**(9) 2779–2815.

WorldBank. 2019. Carbon pricing dashboard. https://carbonpricingdashboard.worldbank.org/map_data. Accessed: 2022-01-06.

Wu, G., A. Inderbitzin, C. Bening. 2015. Total cost of ownership of electric vehicles compared to conventional vehicles: A probabilistic analysis and projection across market segments. *Energy Policy* **80** 196–214.

Xie, F., C. Liu, S. Li, Z. Lin, Y. Huang. 2018. Long-term strategic planning of inter-city fast charging infrastructure for battery electric vehicles. *Transportation Research Part E - Logistics and Transportation Review* **109** 261–276.

Yatsenko, Y., N. Hritonenko. 2015. Algorithms for asset replacement under limited technological forecast. *International Journal of Production Economics* 160(C) 26–33.

Yatsenko, Y., N. Hritonenko. 2017. Machine replacement under evolving deterministic and stochastic costs. *International Journal of Production Economics* **193** 491–501.

Zhang, A., J. E. Kang, C. Kwon. 2017. Incorporating demand dynamics in multi-period capacitated fast-charging location planning for electric vehicles. *Transportation Research Part B: Methodological* **103** 5–29.

Zhou, T., M. J. Roorda, H. L. MacLean, J. Luk. 2017. Life cycle GHG emissions and lifetime costs of medium-duty diesel and battery electric trucks in toronto, canada. *Transportation Research Part D: Transport and Environment* **55** 91–98.

Zhu, Z.-H., Z.-Y. Gao, J.-F. Zheng, H.-M. Du. 2016. Charging station location problem of plug-in electric vehicles. *Journal of Transport Geography* **52** 11–22.

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Appendix A. Technological State of the Art and Operational Costs

We group the relevant parameters into four categories: Vehicle technology, battery technology, charging infrastructure, and energy and regulatory considerations.

Vehicle technology

Purchasing Costs: In this paper, we consider heavy duty Class 8 trucks that can accommodate about 15 tons. The average price of a Class 8 d-truck in 2017 was $118,000 (USD), and the average price increase since 2011 was 5% (Statista, 2019). There are no e-trucks available in the market as of 2020, but several manufacturers such as Daimler, Scania, and Tesla have announced plans to produce and sell functionally comparable e-trucks with varying prices and technological characteristics in the near future (Lambert, 2018, 2020; Coppola and Kharif, 2018; Kane, 2020). Because these announcements are in the form of marketing initiatives to create public interest, the announced price information is speculative. In the consumer e-vehicles market, however, we observe that the price differential between an e-vehicle and a comparable IC-vehicle is mostly explained by the battery price (IEA, 2017b). Based on this assumption, the potential price of an e-truck with a 300 km-800 km autonomy is in the range of $180,000-320,000 (USD). (See below for battery price information.)

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 consumer EVs retain 10% of their value after 6 years).

Maintenance Costs: Both firms interviewed reported that their maintenance and repair costs are approximately $0.2 per mile. 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; Mitropoulos et al., 2017). Such potential savings reported in literature vary between 18 – 45% (Danielis et al., 2018; Letmathe and Suares, 2017; Weldon et al., 2018). Regarding the evolution of maintenance costs along the lifetime of a vehicle, it's intuitive to infer that such costs increase with age and cumulative usage (Martin, 2016). There is, however, to the best of our knowledge no consensus estimate in the literature to quantify said costs; studies typically assume maintenance costs to be fixed throughout the lifetime of a vehicle (Danielis et al., 2018) or a function of a mean

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time between failures assumed to be identically distributed over the lifetime of a vehicle (Propfe et al., 2012).

Consumption Rates: The U.S. 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 2019 is 6 miles per gallon (mpg) for diesel Class 7-8 trucks and is expected to rise to 7.8 mpg by the year 2050 (DoE, 2020). Interviews with our contact carrier firms are in line with this data: they reported their current consumption rate to be around 7 mpg, with the help of their recent sustainability initiatives. The electricity consumption rate for consumer EVs is heavily dependent on the make and model and ranges (according to EPA fuel economy tests) between 4.6 km per kWh (2019 Tesla model S P100D) and 6.4 km per kWh (2019 Hyundai Ionic). For e-trucks, standardized tests are not available but manufacturer claims suggest a much higher consumption rate; Daimler's eCascadia is expected to incorporate a 550 kWh battery for a range of 400 km (1.38 km per kWh) and their Freighliner eM2, a 325 kWh battery and a 370 km range (1.15 km per kWh; Daimler, 2020). Tesla has not announced the size of the battery for their Semi e-truck, but sources suggest 1000 kWh are needed to achieve the announced 800 km range (0.80 km per kWh – Teslarati, 2018a). The most recently announced e-truck fleet, from Scania, present similar estimates: up to 250 km range on 300 kWh batteries (0.83 km per kWh; Scania, 2020).

Payload Efficiency: All else equal, electric vehicles tend to hold less payload than their diesel counterparts due to the excessive weight of the battery (Saarinen, 2020). Technical data is not available at the time of writing regarding the announced Class 8 trucks from, e.g., Daimler and Tesla. However, the payload efficiency of existing electric light delivery vehicles (e.g., Renault Master Z.E) is in the order of 0.85-0.95 (CommercialFleet, 2020).

Carbon Emissions: The carbon emissions associated with trucks comprise the the usage of the trucks and the emissions related to manufacturing and transporting the fuel. 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 (Zhou et al., 2017). Sen et al. (2017) report the total GHG emissions due to the manufacturing of a 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 tons CO_2e per kWh of capacity.

Journal Pre-proof

The emissions associated to the combustion of one liter of diesel fuel (i.e., tank-to-wheel) is 2.64 kg of CO_2 (Ecoscore, 2019). Reasonable estimates inflate this value by 25% to adjust for fuel production and transport (i.e., well-to-wheel) emissions (NTM, 2019). For electric vehicles, "well-to-wheel" emissions are entirely attributed to the production phase of the electricity, the value of which depends on the energy mix of a particular grid. Based on the latest figures reported by the EPA, the average mix in the USA corresponds to approximately 65% fossil and biomass, 20% nuclear, and 15% renewables (see EPA, 2018a, for detailed data). Such an energy mix emits 0.456 kilograms of CO_2 per 1 kWh of electricity (Carbonfund, 2019). The DoE (2019) projects, in their reference scenario, that the percentage of renewable energy in the total electricity generation capacity will increase up to around 25% in 2030. Therefore the GHG emissions related to electric vehicle usage are expected to decrease as a function of the shift in energy sources.

Battery technology *Battery Size:* The range of currently pre-announced Class 8 e-trucks is between 370 km (e.g., Daimler Freighliner eM2) and 800 km (e.g., Tesla Semi) (Lambert, 2020). Such an autonomy implies battery sizes between 300-1000 kWh.

Battery price: The current industry-standard battery pricing is in the order of $200 per kWh (Li et al., 2020; GreenCarReports, 2020), with a projected 8% rate of decrease per year (Letmathe and Suares, 2017; UCSUSA, 2018). However, the pre-announced expected price of Tesla's "Semi" e-truck implies a battery price in the order of $60 per kWh. (The feasibility of this pricing is disputed as of this writing, see Teslarati, 2018b.)

Charging Times: Battery charging times rely on the battery capacity, charging voltage, and power of the charger. There is a vast array of different EV chargers; some use 120/240 V single-phase AC, others use triple-phase 400 V connections, and yet others feed DC voltage directly to the battery. In addition to the input voltage, the current (and thus power) can also vary dramatically. The power of the charger, expressed in kilowatts (kW), directly determines the speed at which a battery can charge. A general rule of thumb is that the approximate time–in hours–required to charge a battery is equal to the battery capacity in kilowatt hours (kWh) divided by the charger power in kW. Even though charging speed is non-linear, the first 80% of the capacity charges at an approximately linear rate (Montoya et al., 2017). The goal set by manufacturers is for almost-full ($\sim$ 80%) charging in 30 minutes, as an industry standard (EVConnextions, 2019; PodPoint, 2019; Kane, 2020).

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Charging technology

Charging Facilities: 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. Smith and Gonzales (2014) estimate installation costs between $50,000 (e.g., modifications required at an existing facility) and $350,000 (maximum installation

Charging Instruments There exist a number of different standards for electric chargers. Most well known are the American SAE standard, which defines charging technology as Level 1 (AC up to 1.92kW), Level 2 (AC up to 19.2kW), and Level 3 (DC up to 400kW) and the IEC, which defines Mode 1 (slow AC), Mode 2 (slow AC with protection), Mode 3 (fast AC), and Mode 4 (fast DC) (Bohn and Chaudhry, 2012; Pereirinha and Trovão, 2011). In addition, firms also develop and trademark their own charging technology (e.g., Tesla "superchargers", which are 150Kw DC chargers). The expected battery sizes of e-trucks will require the deployment of high-end Level 3 charges to achieve reasonable charging speeds. These DC chargers require an elevated upfront cost of procurement and installation compared to Level 1 and 2 counterparts. 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).

Energy and regulatory considerations

Energy 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 U.S. Department of Energy (DoE, 2019) projects, in their reference scenario, that retail prices of diesel oil will increase in 2018 dollars by 13% from 2020 to 2030 and that electricity prices will remain stable during the same period. Current energy prices in the USA are in the order of $2.5 per gallon for diesel and $0.1 per kWh for electricity.

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

Journal Pre-proof

$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.

Appendix B. Battery Swapping

In order to incorporate battery swapping instead of plug-in charging in our approach, one needs to make some basic changes in the model to reflect the characteristics associated with battery swapping operations. A battery swapping system works as follows: The battery of an arriving vehicle is taken out by some swapping machinery and possibly operator(s) -when its turn comes-, and replaced by a charged spare battery whenever available. The removed battery is brought to an available charging instrument to recharge it immediately. If no charging instrument is available, then this battery joins a queue to be charged later whenever there is availability. The charged battery joins the spare battery pool.

While the plug-in charging system can be described by the number of charging stations, the number of charging instruments in those stations, and the vehicle arrival pattern, modeling the battery swapping alternative requires taking the following additional factors into account: 1) the battery inventory at a charging station to be used for swapping, 2) the swapping machinery and the operator(s) to be deployed, and 3) choice of charging technology (level 1, 2, or 3) for each of the charging instruments. Consequently, the battery swapping system can no longer be modeled as an $M/D/c$ queuing system unlike the plug-in charging model. Rather, it resembles an $M/G/c$ queue in which the service time is generated by a two-echelon (spare parts) inventory system. In specific, the process of removing the depleted battery by machinery/operators generates a demand for a charged battery from the lower echelon of the inventory system (cf. retailer) which is operated

Journal Pre-proof

with a base stock policy and each such order triggers a recharging request to the upper echelon operated with limited number of charging instruments (cf. a capacitated warehouse at the upper echelon).

If this system is to be adopted to our approach, then the decision maker should first find the minimum costly combinations of the (i) number of swapping machinery/operator used, (ii) number of spare batteries to operate with, (iii) number of charging instruments, and (iv) charging level used that satisfy the design parameter ω_k for every year in the planning horizon. A parameter similar to γ_t should be defined for each of the first three factors mentioned here and decision variables similar to Q^i_{jt} and P^i_t should be defined accordingly.

Appendix C. Implementation of Public Private Partnership Model

In what follows, we modify the SFMP to incorporate the option of PPP for demonstrative purposes. We do not attempt to engineer the full-fetched system, but lay out a simple approach that is sufficient to capture the main dynamics of such partnerships.

Let

- ψ: Fraction of the service region G that accommodates the public charging network
- δ^P: Average distance between two public charging facilities
- λ^P: Average arrival rate of e-vehicles to the public charging facilities
- γ^P: Number of public charging instruments installed in each public facility

define the characteristics of the public charging network. Then, the number of public charging facilities in region ψG and the expected waiting time at the public charging stations can be estimated by $\overline{F_P} = \frac{\psi G}{(\delta^P)^2}$ and $\omega^P_k = \frac{C_a^2}{2} \frac{(\lambda^P_k \mu_k/\gamma^p)^{\sqrt{2(\gamma^P+1)}-1}}{\gamma^P - \lambda^P_k \mu_k}$ respectively, with $k \in K_e$ (because only e-trucks use charging stations). If $\omega^P_k \leq \omega_k$ then the public charging network aligns with the company's service level target and hence PPP model will be beneficial for the company. Otherwise, the company will investigate the viability of installing γ'^P_t charging instruments in each public facility in each year t so that the expected waiting time at these facilities can be lowered to an acceptable level. In such a case, the productive driving time of the e-trucks in the public region and the rate of arrivals in

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year t to the public charging facilities by the company's e-trucks can be approximated by

$$D_k^{pP} = \frac{R_k/v_k}{R_k/v_k + \theta\sqrt{2}\delta^P/v_k + \omega_k + \mu_k} \text{ and } \lambda_{tk}'^P = \frac{v_k W_t}{R_k l_k D_k^{pP} \overline{F_P}}$$

respectively, with $k \in K_e$. Let δ^V be the design parameter for the private charging network that the company establishes in the remaining service area, $(1-\psi)G$ and $\overline{F}_V = \frac{(1-\psi)G}{(\delta^v)^2}$ be the number of private charging facilities installed. Similarly, the productive driving time and the arrival rate of the e-trucks to the private facilities in each year t can be approximated by

$$D_k^{pV} = \frac{R_k/v_k}{R_k/v_k + \theta\sqrt{2}\delta^V/v_k + \omega_k + \mu_k} \text{ and } \lambda_{tk}^V = \frac{v_k W_t}{R_k l_k D_k^{pV}((1-\psi)G/(\delta^V)^2)}$$

respectively in the private region. The weighted average productive driving time under the PPP model can then be estimated as $\overline{D}_e^p = \psi D_e^{pP} + (1-\psi)D_e^{pV}$. Let γ_t^V be the charging instruments installed in each private facility. Then, the company can identify all $(\gamma_t'^P, \gamma_t^V)$ pairs for all t that make

$$\overline{\omega_k} = \psi\omega_{tk}'^P + (1-\psi)\omega_{tk}^V \leq \omega$$

where

$$\omega_{tk}'^P = \frac{C_a^2}{2}\frac{((\lambda_{tk}^P + \lambda_{tk}'^P)\mu_k/(\gamma'^P + \gamma_t'^P))^{\sqrt{2((\gamma'^P+\gamma_t'^P)+1)}-1}}{(\gamma'^P + \gamma_t'^P) - (\lambda'^P + \lambda_t'^P)\mu_k} \text{ and } \omega_{tk}^V = \frac{C_a^2}{2}\frac{(\lambda_{tk}^V\mu_k/\gamma_t^V)^{\sqrt{2(\gamma_t^V+1)}-1}}{\gamma_t^V - \lambda_{tk}^V\mu_k},$$

where $k \in K_e$. For each possible $(\gamma_t'^P, \gamma_t^V)$ vector pairs, the following optimization model can be solved to find out the least costly PPP model. If this minimum cost is less than the optimal cost of operating with private network only, then PPP model is not a viable option. Otherwise, the company can choose to get engaged in a PPP model and make use of the already available public charging network. Given this set-up, the decision maker needs to solve the following optimization problem:

SFMP-PPP$(\overline{F_P}, \overline{F_V}, \gamma_t'^P, \gamma_t^V | \delta^P, \delta^v, \overline{\omega_k})$:

Minimize $\sum_{t\in T}\sum_{k\in K}\beta_t c_{tk}^v P_{tk}^v + \cdots + \sum_{t\in T}\beta_t(A + m_t^f)F_t^V + \cdots - \sum_{j\in J^i}\sum_{t\in T}\beta_t s_{jt}^i S_{jt}^i$

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subject to: (5) – (12)

$$W_t \leq \sum_{j \in J_k^v} \sum_{k \in K} l_k \overline{D}_k^p Q_{jtk}^v \qquad t \in T \tag{A.1}$$

$$\frac{\sum_{j \in J_k^v} \sum_{k \in K_e} l_k \overline{D}_k^p Q_{jtk}^v}{W_t} - \psi \geq -X_t^P \qquad t \in T \tag{A.2}$$

$$\frac{\sum_{j \in J_k^v} \sum_{k \in K_e} l_k \overline{D}_k^p Q_{jtk}^v}{W_t} - \psi \leq 1 - X_t^P \qquad t \in T \tag{A.3}$$

$$Z_t^P - \frac{\sum_{j \in J_k^v} \sum_{k \in K_e} l_k \overline{D}_k^p Q_{jtk}^v}{W_t} \geq -(1 - X_t^P) \qquad t \in T \tag{A.4}$$

$$Z_t^P \geq \psi(1 - X_t^P) \qquad t \in T \tag{A.5}$$

$$\frac{Z_t^P}{\psi} \overline{F_P} \leq F_t^P \qquad t \in T \tag{A.6}$$

$$\frac{\frac{\sum_{j \in J_k^v} \sum_{k \in K_e} l_k \overline{D}_k^p Q_{jtk}^v}{W_t} - \psi}{1 - \psi} \overline{F}_V \leq F_t^V \qquad t \in T \tag{A.7}$$

$$\gamma_t^V F_t^V + \gamma_t^P F_t^P \leq \sum_{j \in j^i} Q_{jt}^i \qquad t \in T \tag{A.8}$$

$$F_t^P, F_t^V, P_{tk}^v, P_t^i, Q_{jtk}^v, Q_{jt}^i, S_{jtk}^v, S_{jt}^i \in \mathbb{Z}_{\geq 0}; Z_t^P, X_t^P \in \{0, 1\} \tag{A.9}$$

In this formulation, the original objective function is updated with the number of charging facilities in the private domain. Constraint set (A.1) assures that the total driving demand is satisfied with the weighted average productive driving times under the PPP model. Constraint sets (A.2) – (A.5) are a series of logical constraints which ensures that the auxiliary decision variable Z_t^P, the proportion of the demand satisfied within the public charging service area, is less than or equal to ψ. Another auxiliary binary variable X_t^P is used in these constraints to setup the logic. Note that $\sum_{j \in J_k^v} \sum_{k \in K_e} l_k \overline{D}_k^p Q_{jtk}^v / W_t$ is the proportion of the whole demand satisfied with e-trucks and at most ψ of this proportion can be satisfied within the public service area. We assume that the company deploys their e-truck fleet starting from the area served by the public charging stations. Constraint sets (A.6) and (A.7) ensures that sufficient charging facilities are opened in the public and private service areas. Constraint set (A.8) relates the required number of charging instruments to the number of instruments owned. In the numerical results presented in Section 4.9, we simplify the above model by assuming that the switch to e-trucks materialize all at once.

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