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Data needs and modeling challenges for planning charging infrastructure of on-road electric freight

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Summary

To reduce fossil-fuel dependency in the on-road freight sector, adopting vehicles utilizing alternative fuels requires large investments in infrastructure including the production and distribution of fuels and refueling/charging facilities. Unique to the electric vehicles, journey length and charging time impose important constraints in the battery size requirement and the placement and characteristics of charging infrastructures. This research reviews the data needs and challenges in modeling infrastructure requirements, and the role of vehicle-based measurements in alleviating these obstacles, with a special focus on electrification of on-road freight. Our review shows that vehicle-based measurements of detailed driving operational conditions, including the truck's energy consumption and spatial position, are particularly important for better planning for electric charging infrastructure due to capturing electric vehicle's significant distinctions and limitations.

Keywords: electric vehicles, electric trucks, charging infrastructure, road freight transport, decarbonized transport.

1 Introduction

Freight vehicles account for up to 50% of road transport pollutant emissions, despite being on average a small share of vehicles in urban networks [1]. Freight transportation is also the most energy-intensive transport mode [2] and runs almost exclusively on fossil fuels [3]. To reduce the dependence on fossil fuels there is an increased need to shift to alternative fueled vehicles (AFV) fueled by hydrogen, biofuels, natural gas (NG) or electricity [4]. The development of a sufficiently ubiquitous refueling infrastructure is the most commonly cited barrier to AFV adoption in the freight sector [5]. Many issues hinder AFV's infrastructure allocations including 1) uncertainty regarding the estimation of demand for alternative fuel refilling, due to a lack of available information on alternative fuel's driver behavior, 2) shipment drivers have time restrictions when their vehicle could potentially be charging, and technology differs across vehicles and is continually changing, 3) the design of new industrial facility locations should simultaneously account for the major impacts of freight shipment distribution on the existing infrastructure networks (including traffic congestion and pavement deterioration) [6].

In order to understand charging needs, more information is needed than for other alternative fuels for trucks since developing infrastructure for hydrogen, biofuels and NG differs from the case of electricity. Biofuels and NG can be handled by converting already existing diesel stations, while hydrogen will require building new fueling stations and distribution. The refueling time of biofuels, NG and hydrogen is relatively fast and similar to diesel thus, the key issue for these fuels is the supply and distribution of fuels to stations. On the other hand, battery electric trucks (BET) have significant distinctions and limitations in terms of, among others, charging time and range since charging power and battery storage onboard are limited compared with other alternative fuels. One solution is to carry big batteries that need more frequent and/or longer charging, either at stationary charging stations or dynamically on electric road systems (ERS). For instance, fully charging a BET with 800 km battery range requires 60 minutes–8 hours, depending on the stationary charging power, compared to 10-20 minutes for a fuel cell electric truck with 1200 km range [7].

Traditional data (e.g., traffic count) used in traditional transport models (e.g., trip-based four step transport models) cannot assess many BET's electrification issues due to limitations in modeling BET characteristics and real driving conditions. Electrifying trucks requires constructing new charging facilities and developing the power grid in addition to properly equip the BET with enough battery size. Charging stations and power grids need to, among others, account for truck capacity and permitted charging periods due to driving patterns.

Proper planning and development of electric charging facilities require details about probable energy demand from BETs at such facilities. Recently, vehicle-based measurement systems, such as portable measurement systems and onboard-diagnostic (OBD) data [8], [9], have become a preferred option for acquiring information in real conditions, including the vehicle's energy consumption, spatial position, road condition and slope. This data is not collected through active solicitation; rather generated for other purposes [10]such as telemetry data generated by vehicle operators for vehicle tracking, but can be potentially used for research. This data also comes from different sensors and devices, such as GPS and motor energy consumption sensors integrated into the vehicle.

In this article, we lay out data requirements needed to study BETs and their charging needs. We do this through a literature review of data used for AFV's freight infrastructure allocation and planning, data needs and challenges as well the role that vehicle-based measurements could have in solving the challenges. The review is based on a SCOPUS search for the combination of the terms: "freight", "infrastructure", and "energy modeling", with related alternative fuels: "biofuel", "hydrogen", "battery electric truck", and "electric road". After considering only relevant publications, through screening the abstract then the whole paper, about 40 publications are considered.

The remainder of this paper is constructed as follows. The next section presents some infrastructure planning challenges that vehicle-based data can solve compared to traditional data sources. Section 3 and 4 describe the two steps needed to plan charging infrastructure for BETs with vehicle-based data, i.e., vehicle energy consumption and charging demand allocation. Section 5 presents the challenges in acquiring such data. Finally, we present conclusions in section 6.

2 The need for vehicle-based data in planning for charging infrastructure

Planning charging infrastructure includes calculating first the energy consumption per vehicle and then the charging demand of the fleet to provide suitable charging facilities [11]. Both steps are discussed in later sections. Compared to other AFVs, battery electric trucks (BET) have special challenges related to longer charging time and limited range. Building new dynamic (i.e., charging on roads while driving) or stationary charging facilities at depos and/or along traveled routes [11] requires special planning to account for the needed energy for the BETs [12]. Traditional data sources and models fail to capture important features and characteristics of the BET, as shown in Table 1. Vehicle-based data captures important details relevant to BET charging infrastructure planning, see Table 1, which could solve the challenges related to traditional data.

Table 1 Examples of traditional data sources and their challenges for BET infrastructure allocation as well as derived information from vehicle-based data that can solve these challenges.

Aspect	Examples
Sources of traditional/conventional data	• Vehicle flow • Representative surveys • Vehicle tracking systems and performance monitoring systems • Vehicle simulation • Point of interests (e.g., parking lots) and land use
Challenges for energy/infrastructure modeling with traditional data sources	• Uncertainties in models due to insufficient temporal and spatial resolution • Laboratory-based engine dynamometer tests are not representative of those obtained under real-world conditions • Aggregated data reports in grams per brake-horsepower (bhp)-hour, which are not directly relevant to in-use emissions/energy estimation • Power demand on engines does not accurately describe real energy consumption • Power grid use and impact are not easy to identify • Trip-based models fail to include complexities and details, especially prevalent trip-chaining behavior • Not all urban trips can begin with fully charged batteries
Sources of vehicle-based measurements	Different portable on-vehicle sensors that measure different parameters coupled with GPS/spatial measurements.
Derived/acquired information with vehicle-based measurements that can solve the aforementioned challenges	Stop/start driving patterns, tour/trip chains, accurate drive cycles, accelerator, braking, battery state of charge, cargo weight, vehicle speed, atmospheric pressure, topography, weight of the vehicle, characteristics of a vehicle, temperature, number and type of previous charging cycles, trip purpose, and land use characteristics at the start/stops.

3 Vehicle energy consumption

Energy consumption per vehicle could be measured with different tools. The majority of existing (i.e., traditional) energy consumption data uses laboratory-based engine dynamometer tests which are based on steady-state modal tests [13], [14]. The results of such tests may not be representative of real-world duty cycles and conditions, especially when driving in urban areas [13], [15]. Studies that use constant consumption rates in their energy modeling provide insufficient temporal and spatial resolution, e.g., for urban scale studies due to different delivery patterns, which contribute to the uncertainties in the modeled benefits [16]. Some studies implement a vehicle energy simulator to estimate the consumed fuel [17]. However, the use of such simulators is time-consuming given that users have to construct numerous input profiles through a graphical user interface every time they use it [17].

Energy consumption can differ according to several operational conditions [14] that are missed with traditional energy consumption measurements. To put things into context, for example, [18], [19] find that there is up to a 28% difference between the total energy consumption for individual trucks from vehicle-based measured and different simulation results. Overall, the operating conditions can be categorized based on (i) the vehicle design (e.g., type of vehicle, driveline configuration, power train technology, fuel type, materials of tires, and after treatment system technology); (ii) driver characteristic (e.g., driver behaviour); (iii) travel conditions (e.g., load factor); (iv) traffic flow conditions (e.g., congestion); (v) road conditions (e.g., road grade and pavement structure); (vi) ambient conditions (e. g., temperature); (vii) geographic conditions (e.g., atmospheric pressure) and (viii) regenerative braking [13]–[16], [18], [20], [21]. These operational conditions become even more significant when considering an electrified freight fleet at a high geographical scale, such as the whole EU. [15] find that 55–60% of the variance in energy consumption can be explained by vehicle speed, pavement structure, temperature, vehicle load and road grade.

With vehicle-based measurements, many of the aforementioned challenges with energy consumption modeling could be solved. For instance, using only GPS measurements, [10], [14], [22], [23] model consumed energy for each vehicle as a function of certain operating conditions (e.g., travel conditions and driver characteristics). This approach allows for customized assessments that account for local conditions for different operation conditions. Furthermore, [15], [17], [24]–[27] use only GPS data to obtain vehicles travel patterns (e.g., speeds, acceleration, and deceleration) as inputs in their energy consumption model, while [13], [18], [19], [28]–[30] use the portable energy measurement system, that includes GPS and energy consumption measurements, to identify real-world, in-use, on-road energy use for vehicles fuelled either with fossil fuel or AFV. Others use the portable measurement from a prototype vehicle to validate their simulated/virtual model [1], [10], [12], [18], [27]. In all studies, important relations between changing operating conditions and energy consumption are noted.

4 Charging demand

Current approaches split the main BET charging demand challenge into two sub-challenges: 1) charging infrastructure locations on routes and 2) charging infrastructure facility characteristics. In this section, we describe both sub-challenges and the role vehicle-based data plays to solve them.

For the first sub-challenge, calculating the energy demand for the fleet is based on flow data from passages to express demand either in a trip or tour-based freight models. Traditional trip-based models rely on trip data, which can be defined as the movement between two consecutive stops [31]. These models fail to include complexities and details, especially prevalent behavior found within tour/trip-chains [11]. A tour or trip chain is a journey between ‘significant’ locations (e.g. depos or warehouses) that show how drivers link segments into journeys [31], [32]. Although the traditional four-step travel demand model has typically been used to model trip-based passenger movements, it fails to capture information regarding the interdependency of multiple trips within tours, e.g., it may not capture charging battery events at stops, and thus, it is not necessarily suitable for modeling freight tours of BET. Trip-based models also fail to enable linking multiple trips to a single vehicle. The results are also accounted into specified zones which hinders the identification of depot locations, stop/break locations and roads used during trips. Another drawback is that the modeling does not take into account what type of vehicles are used thus, evaluation of the representativeness of the results is hard to perform [33]. Further, the number and the frequency of deliveries are undoubtedly growing, together with a decrease in shipment volumes, triggering the use of smaller vehicles performing multiple stops. These changes will affect charging demand at specific charging stations [1] and road segments in the case of ERS [34]. Therefore more disaggregate demand analysis derived from vehicle level data is required [35].

Tour-based models are more suitable for considering intermediate stops and the effect that these stops have on vehicle traveled distance [36] compared to trip-based models because they more specifically follow the vehicle. The tour is specified by a predetermined route between customers and the vehicle characteristics and status, especially the current charge status. The energy consumption is calculated by splitting the route into segments and adding up the consumption for every segment for each vehicle. The underlying idea is to segment in a way, which ensures that every parameter such as speed, acceleration and gradient is picked up [23]. The distances of a single urban trip are generally much shorter than the range of typical BETs in the market, but vehicles are supposed to serve a daily chain of trips instead of a single trip. Also, not all urban trips can begin with fully charged batteries due to various reasons such as different charging powers at charging stations or ERS road segments or lack of charging time. This calls for a comprehensive data set that includes daily chains of trips for all vehicles [11].

The second sub-challenge, to BET charging demand, is identifying charging facility characteristics at each charging point, e.g., determining the needed power level of chargers and charging capacity. These characteristics can be determined considering vehicle type, trip and tour characteristics of the vehicles stopping to charge at the facilities. Thus, a major issue is setting the charging capacity and ensuring an adequate level of charging service in terms of charging time and waiting time in queue [4].

Massive freight GPS trip data in the form of origins and destinations can help to identify optimum locations for charging infrastructure facilities for BET with stationary chargers [33]. Also, grouping trip ends into destinations allows vehicle-based data to be used for modeling and analyzing the repetitiveness of commercial vehicle tours, and for combined models of visited locations, stop frequency, and stop duration to simulate charging behavior based on various trip attributes and charger types [11], [37], [38]. Most studies focus on GPS data to derive travel patterns, most importantly stop locations and probable charging events to allocate vehicle energy demand [34]. Others utilize other vehicle-based measurements to derive vehicle's operational conditions to identify both the vehicle-based demand and the charging facility characteristics. Using vehicle-based measurements helps determine the number and location of charging points required within an area of service, the charging points' power transfer rates, the capacity of the on-board battery for each charging option [18], the impact on the grid, and the change in loads in high resolution [38].

5 Challenges with vehicle-based data

The challenge of acquiring high-resolution vehicle-based data is significant due to its commercial sensitivity [33], which hinders many logistics companies from sharing it. Moreover, due to uncertainties with GPS accuracy and collection, significant post-processing of GPS data is required to obtain route data that is suitable for vehicle route modeling [26]. Such data is not easy to handle and requires experts to collect, share and analyze. Companies might result to sharing aggregated datasets of the vehicle-based data (e.g., vehicles grouped at zone level) which makes it less suitable for charging demand-related applications. Adequate cooperation between freight operators is a necessity to collect datasets that are helpful for charging infrastructure allocation.

6 Conclusion

Allocating charging infrastructure for alternative fuel vehicles (AFVs) in the freight sector faces different challenges in estimating energy demand and planning charging infrastructure. Vehicle-based measurements provide high detailed insights that could be used to calculate energy consumption, relate it to real-world operational conditions or validate simulator and model results. Data collected at the vehicle level could also be used to analyze travel patterns and visited locations, both needed in the planning of stationary charging infrastructure and electric road systems. Future research should consider focusing more on utilizing such data to plan the rollout more purposefully of charging infrastructure for on-road freight.

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