Data needs and challenges for planning electric charging infrastructure for road freight

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SHORT SUMMARY

To reduce the dependency on fossil fuels in the on-road freight sector, adopting vehicles utilizing alternative fuels, including electricity, requires large investments in infrastructure and distribution of fuels for refueling/charging facilities. Unique to the electric vehicles, journey length and charging time impose important constraints in the placement of charging stations. 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 road freight. Our review shows that estimating energy demand using vehicle-based measurements of highly detailed operational conditions of the vehicles is particularly important for modeling electrified freight. We conclude with major research gaps and future data needs in modeling of electric freight transport.

Keywords: Alternative fuel vehicles, freight transport, energy modelling, transport modelling, charging infrastructure.

1. INTRODUCTION

Freight transportation is the most energy-intensive transport mode (Çabukoglu et al., 2018) and runs almost exclusively on fossil fuels (Fridell et al., 2019). To reduce the dependence on fossil fuels there is an increased interest in shifting to alternative fueled vehicles (AFV) fueled by hydrogen, biofuels or electricity (Ko et al., 2017). The development of a sufficiently ubiquitous refueling infrastructure is the most commonly cited barrier to AFV adoption in the freight sector (Sathaye and Kelley, 2013). New data collection and modelling is needed to better address this.

Recently, vehicle-based measurement systems, such as portable measurement systems and onboard-diagnostic (OBD) data have become a preferred option for acquiring information in real conditions, including the vehicle's energy consumption, GPS position and road and route condition. These measurement systems fill reported gaps between real-world and simulated data (Cicconi et al., 2016; Rosero et al., 2021).

This paper provides 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, with a special focus on electrification of on road freight. The review is based on a SCOPUS search for the combination of the terms: "freight", "infrastructure", and "energy modelling", with related alternative fuels: "biofuel", "hydrogen", "battery electric vehicle", and "electric road". After considering only relevant publications, through screening the abstract then the whole paper, about 100 publications were considered as the basis for the presented review. This short paper focuses on the needs for freight electrification.

2. Planning for charging infrastructure

Planning charging infrastructure includes calculating the energy consumption per vehicle and charging demand of the fleet to provide suitable charging facilities (Kavianipour et al., 2021). Compared to other AFVs, Battery Electric Trucks (BET) have special challenges related to longer charging time and limited range. Building new stationary or dynamic charging (i.e., charging on roads while driving) facilities at depos and/or along traveled routes require special planning due to the potentially large impacts on the costs and infrastructure of local power grid that need to be evaluated as well (Kavianipour et al., 2021). A summary of BET challenges in energy consumption and charging demand models are shown below in **Error! Reference source not found.**.

Table 1 Planning Infrastructure challenges for BET with stationary and dynamic charging

Data sources	Challenges for energy/infrastructure modelling	Derived information with portable measurements
• Vehicle flow data • Representative surveys • Vehicle tracking systems and performance monitoring systems • Vehicle simulation • Point of interests (e.g., depos, parking lots) and land use. •	• 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 the real energy consumption • Power grid use is 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	Stop/start driving patterns, validation, 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 stops

3. Modelling vehicle energy consumption

Energy consumption of the vehicle can differ according to vehicle type and several operational conditions such as travel and road conditions (Rosero et al., 2021). The operating conditions that can influence energy consumption can be categorized based on (i) the vehicle design (e.g., type of vehicle, driveline configuration, power train technology, fuel type, and aftertreatment system technology); (ii) driver characteristic (e.g., driver behaviour); (iii) travel conditions (e.g., passenger load and auxiliary power demands); (iv) traffic flow conditions (e.g., congestion); (v) road
As found in the in the literature, vehicle-based data could be used to acquire real-world accurate measurements of such important information to calculate the energy consumption of the vehicles. For instance, using only GPS measurements, Rosero et al., (2021) were able to model consumed energy for each vehicle as a function of some operating conditions (e.g., travel conditions and driver characteristic) to account for local conditions. Furthermore, Chan et al., (2013) used simple GPS data to obtain vehicles travel patterns as inputs in their energy model, while Pang and Rasdorf, (2009) used portable emissions/energy measurement system to identify real-world on-road energy use. Others used the portable measurement from a prototype vehicle to validate their simulated/virtual model (Lewis et al., 2020).

4. Modelling charging demand challenges

Many approaches are used to allocate charging facilities for charging demand with the use of different tools, such as optimization, to fulfill a target, e.g., minimizing cost. Most approaches split the main BET charging demand challenges into two: 1) charging infrastructure locations on routes and 2) charging infrastructure facility characteristics. For the first step, calculating the energy demand from the fleet is based on flow data from passages to express demand in tour-based freight models. In these models a tour is specified by a predetermined route among customers and vehicles. Tour-based models are suitable when considering intermediate stops and the effect that these stops have on vehicle traveled distance (Moore, 2019). The energy demand is calculated by splitting the routes into smaller route segments and adding up the consumption of every segment for each passed vehicle (Kretzschmar et al., 2016). Probable charging stations are allocated along split routes. The next step is defining charging facility characteristics at each charging point, i.e., determining power level and charging capacity, which can be determined considering vehicle type and trip and tour characteristics. Thus, a major issue is the setting of charging capacity, ensuring an adequate level of charging service in terms of charging time and waiting time in queue (Ko et al., 2017).
Utilizing vehicle-based measurements, grouping trip ends into destinations allows the GPS 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 (Kavianipour et al., 2021). Most studies focus on GPS data to derive travel patterns, the most important stop locations and probable charging events to allocate vehicle energy demand (Limb et al., 2019). Others utilize vehicle-based measurements for both identifying the vehicle based demand and the charging facility characteristics via deriving vehicle operational data. This determines the number and location of charging points required within the area of service, the charging point's power transfer rates, the capacity of the on-board battery for each charging option (Nicolaides et al., 2019), the impact on the grid, and the change in loads in high resolution (Shepero and Munkhammar, 2018).

5. Conclusion

Allocating charging infrastructure for alternative fuel vehicles (AFVs) in the freight sector faces different challenges in estimating energy demand and planning of 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 models results. Data collected at 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 system. Future research should consider focusing more on utilizing such data to plan the role out more purposefully of charging infrastructure for on road freight.

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