CHARGING AND TRAFFIC CONSTRAINTS IN ELECTRIC ROAD FREIGHT JOURNEYS

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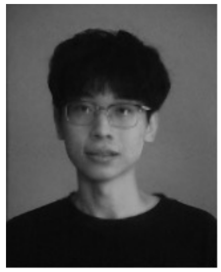

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Abstract
Electrification has been shown to be one of the most promising solutions for decarbonizing HGVs. However, it comes at a cost – mainly, increased journey time and cost due to charging, and limited range. In this paper, we present simple models to analyze the effect of charging on journey time, and the effect of traffic on energy consumption and hence range. First, we discuss our work on extracting traffic data from various sources in the UK and logging it. This data is used to correlate vehicle start-stop conditions with an increase in vehicle energy consumption. Second, we present an 'optimal charging diagram' that shows the least possible increase in journey time for a certain battery size and charging configuration. This diagram can be used to compare different charging strategies to pick one that can optimize between battery size and charging time requirements. The results from these two models can be used to plan electric HGV journeys and reduce their operating cost penalties.

Keywords: Electric Heavy Goods Vehicles; Sustainable Road Freight; Traffic Flow; Vehicle Energy Consumption; Electric Vehicle Charging

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1. Introduction

Heavy Goods Vehicles (HGVs) account for 22% of the UK's road transport carbon emissions despite being small in population (Department for Transport, 2023). They are crucial for most industries, businesses, and the functioning of society. Electrification is the most promising way to decarbonize long-haul road freight (de Saxe et al., 2023). However, it is unclear how the price-sensitive logistics industry would transition from exclusively using diesel HGVs worldwide to operating battery electric HGVs which comes with additional operating costs that depend on the nature of the logistics task.

The journey of a battery electric vehicle (BEV) is strongly affected by two factors: (i) the need to stop for charging, and (ii) uncertainty in journey duration due to traffic congestion. In congested traffic conditions, it is expected that vehicles would encounter frequent start-stop situations, resulting in delays and additional energy consumption due to frequent acceleration after braking. This additional energy consumption is uncertain and depends on the traffic state, and can reduce the range of the vehicle requiring additional charging stops. Adding unscheduled charging stops to a journey also presents direct operational challenges due to increased journey time. This includes missing delivery time windows or exceeding driver shift hours, resulting in increased logistics costs.

There exist many models to estimate vehicle energy consumption, from crude estimates of energy consumption per km to high-resolution drive cycle modeling (Das et al., 2021; Wang et al., 2018). Modeling and optimizing large fleets of HGVs in a complex journey network requires simplified models that can correlate traffic state with energy consumption. The main challenge here is extracting, generalizing, and utilizing good-quality traffic data, along with having high-resolution vehicle data for the same location and time. Important use cases include range and journey time prediction and optimizing charging strategies.

In this paper, we aim to analyze the effect of traffic state on energy consumption of the vehicle, and the effect of additional charging stops on travel time. The objectives are (i) to identify the relationship between macroscopic traffic state and individual vehicle energy consumption, and (ii) to find the lowest possible increase in journey time for a given vehicle and charger configuration. The following section describes the methodology used for both models, followed by a section with the results and some preliminary conclusions.

2. Methodology

The first part of this section summarises how traffic data was extracted and processed to obtain the traffic state on a road at a given location and time. The traffic data is represented using 'fundamental diagrams' (FDs) of traffic that correlate the three key macroscopic traffic parameters – flow rate, average speed, and traffic density. We define a methodology to calculate the additional energy consumed by the vehicle at any given traffic state based on these fundamental diagrams.

Following this, we present a technique to define the optimal charging strategy for a journey that would result in the lowest possible increase in total travel time. This is used to plot optimal charging diagrams, which are further used to compare charging strategies.

2.1. Traffic Data Processing

A previous study by Chai et al. (2024) detailed various sources of traffic data available in the UK, along with a methodology to extract and clean the data, which is utilized in this paper. Traffic flow and time-averaged speed with a time resolution of 15 minutes were extracted from the National Highways database (National Highways, 2024). This data was combined with road data from 19,000 counting stations across England. Space-mean traffic speed data from HERE Maps (HERE Maps, 2021) was extracted in real-time during journeys by vehicles fitted with SRF Loggers (Na and Cebon, 2022). HERE Maps algorithms were also used to classify the counting stations by road type, based on the speed limit and number of lanes. After data filtration and segmentation, representative roads were selected, and FDs were constructed for each type of road, with speed limits ranging from 30 mph to 70 mph and number of lanes varying from 1 to 5.

As HGVs in the UK are speed-limited to 56 miles per hour, the FDs for HGVs were constrained to this speed limit. The fitted FDs were tested against random samples of roads of the corresponding type and high-resolution vehicle speed data from SRF Loggers and were found to accurately represent the traffic state at that time and location. An example of extracted and filtered data for a three-lane road in the UK from a location on the M60 motorway is shown in Figure 1. The data from several such locations with the same speed limits was combined to form an FD equation for that class of road.

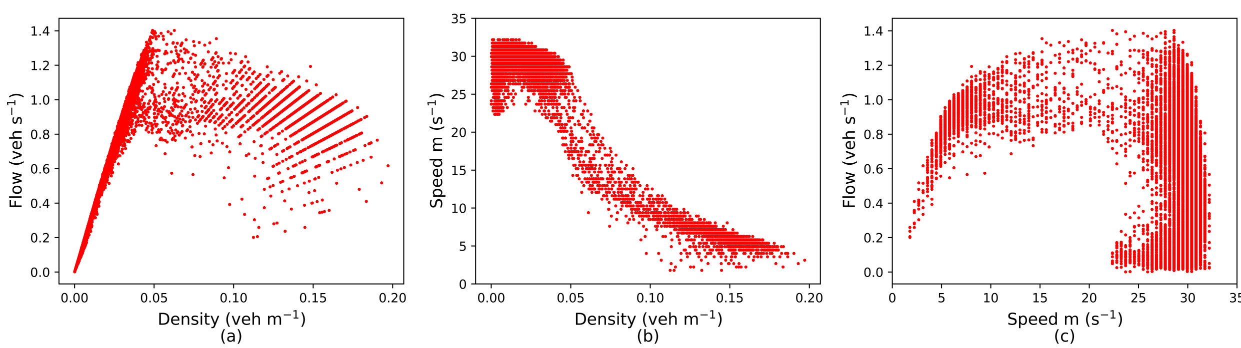

Figure 1 – Filtered traffic data for fundamental diagrams at a site on a three-lane motorway (Chai et al., 2024)

2.2. Energy Consumption Modelling

While the traffic FDs represent the macroscopic traffic state of a road, they do not consider vehicle-level impacts such as energy consumption. One of the methods of estimating energy consumption is using high-resolution vehicle speed profiles. Together with the road gradient, the speed profile can be used to estimate energy consumption by considering vehicle acceleration, aerodynamic drag, and rolling friction (Hunt et al., 2011; Madhusudhanan and Na, 2020). In congested traffic conditions, rapid fluctuations in vehicle speed lead to additional energy consumption due to kinetic energy being lost when braking and needing to be added back when accelerating. In this model, we estimate this additional kinetic energy using vehicle speed data and correlate it with the traffic state at that point in time using the fundamental diagram.

The vehicle's high-resolution speed profile is obtained from SRF Loggers and is divided into 5-minute segments. The additional kinetic energy per unit mass (ke) required for each segment is calculated as:

$$\text{ke} = \sum_{i=1}^{n-1} \frac{\Delta_i W_i}{2}, \tag{1}$$

where,

$$\Delta_i = \frac{1}{2}(v_{i+1}^2 - v_i^2), \tag{2}$$

$$W_i = \begin{cases} 0 & \text{if } \Delta_i \leq 0, \\ 1 & \text{if } \Delta_i > 0. \end{cases} \tag{3}$$

Here, v_i is the speed of the vehicle at time i, and n is the total number of timestamps in the 5-minute interval. It is assumed that energy used during acceleration entirely comes from the powertrain and that there is no kinetic energy recovery when braking (Madhusudhanan et al., 2021). However, BEVs have a significant advantage over diesel HGVs in congested traffic conditions due to the presence of regenerative braking (Midgley and Cebon, 2012). To account for this, the factor W_i in equation (3) is modified as follows:

$$W_i = \begin{cases} \eta & \text{if } \Delta_i \leq 0, \\ 1 & \text{if } \Delta_i > 0, \end{cases} \tag{4}$$

where η is the efficiency of the regenerative braking system.

2.3. Optimal Charging Strategy

One of the major barriers to adopting electric HGVs in current logistics is the extra time required for charging. This is especially evident with current battery sizes in electric HGVs, where the range is insufficient to perform many operations in the same way as a diesel HGV. There is also a trade-off between battery size and charging time, as a larger battery can be more expensive to purchase and reduce payload capacity, while a smaller battery would result in increased charging time, increasing logistical costs.

To determine whether a particular charging strategy is optimal, the correlation between journey time and battery size needs to be modeled. Figure 2 shows a simple journey from the origin 'O' to the destination 'D' with a total journey length 'L'. This journey could include several charging stops 'C_i' depending on the battery size. Each charging stop has a charging time t_i and the charger power provided is P. Given such a scenario, to complete this journey with the smallest battery size possible, the lowest 'battery dip' (drop in battery state of charge) has to be minimized. For this, it is assumed that all charging stops have the same duration, charger type, and overhead time, and the battery dip value before each charging stop is the same and matches the battery dip at the end of the journey.

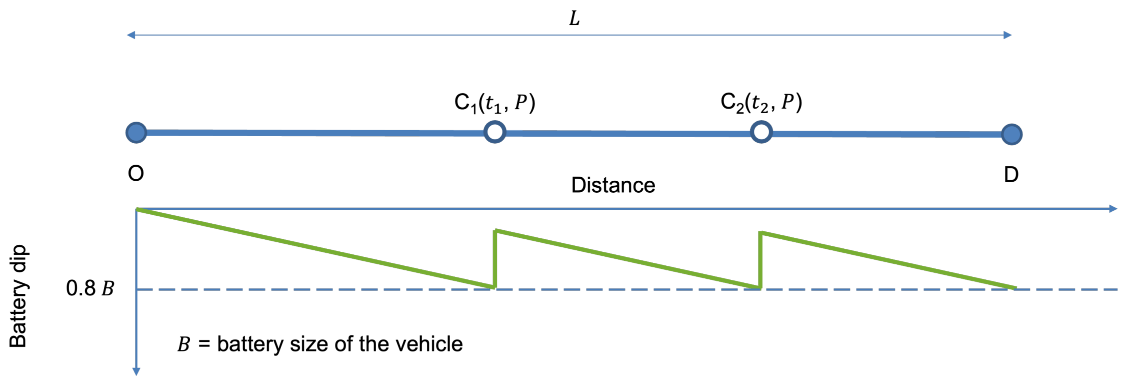

Figure 2 – Optimal charging stop placement for a single journey

The exact methodology to obtain the battery size based on such a charging configuration is shown in the flow diagram in Figure 3. The algorithm starts with no charging, adds charging stops, and increases their duration in the inside loop. The battery dip is limited to 80% of the battery size to comply with manufacturer instructions and limit battery health degradation. The time factor is calculated as the increase in journey time divided by the base journey time.

3. Results

The results from the traffic energy consumption model and optimal charging model are presented below.

3.1. Energy Consumption in Traffic

A dataset of 6,618 five-minute segments was extracted from journeys measured by the SRF Logger – some overlapping in time – and the corresponding traffic speeds at that time and location were obtained from the National Highways WebTRIS database. The data extracted was from 38 sites on the M25 motorway, with 4 lanes and a speed limit of 70 mph. The additional kinetic energy per unit mass was calculated for each journey using the methodology discussed in Section 2.2. The journeys were binned into 30 equal intervals according to traffic speed, and the median of the additional kinetic energy was calculated for each bin. The median kinetic energies were plotted against traffic speed, and a second-order polynomial was fitted. For BEVs, the efficiency of regenerative braking, η, is assumed to be 80%. The results are shown in Figure 4.

When the traffic speed ranges from 25 mph to 50 mph, the energy consumption is the highest, with a peak at around 40 mph. In this region, the traffic flow is unstable and the formation of backward-moving traffic waves results in frequent acceleration and deceleration of vehicles (Coifman, 2015). The additional kinetic energy at the peak is around 1.4 times the average additional energy consumption in the high-speed free-flow region. At high traffic speeds, the traffic is in a free-flow state and speed fluctuations are low. This is consistent with the results reported by Fotouhi et al. (2014). At low traffic speeds, the traffic is congested and vehicles cannot accelerate to high speeds, resulting in lower additional kinetic energy.

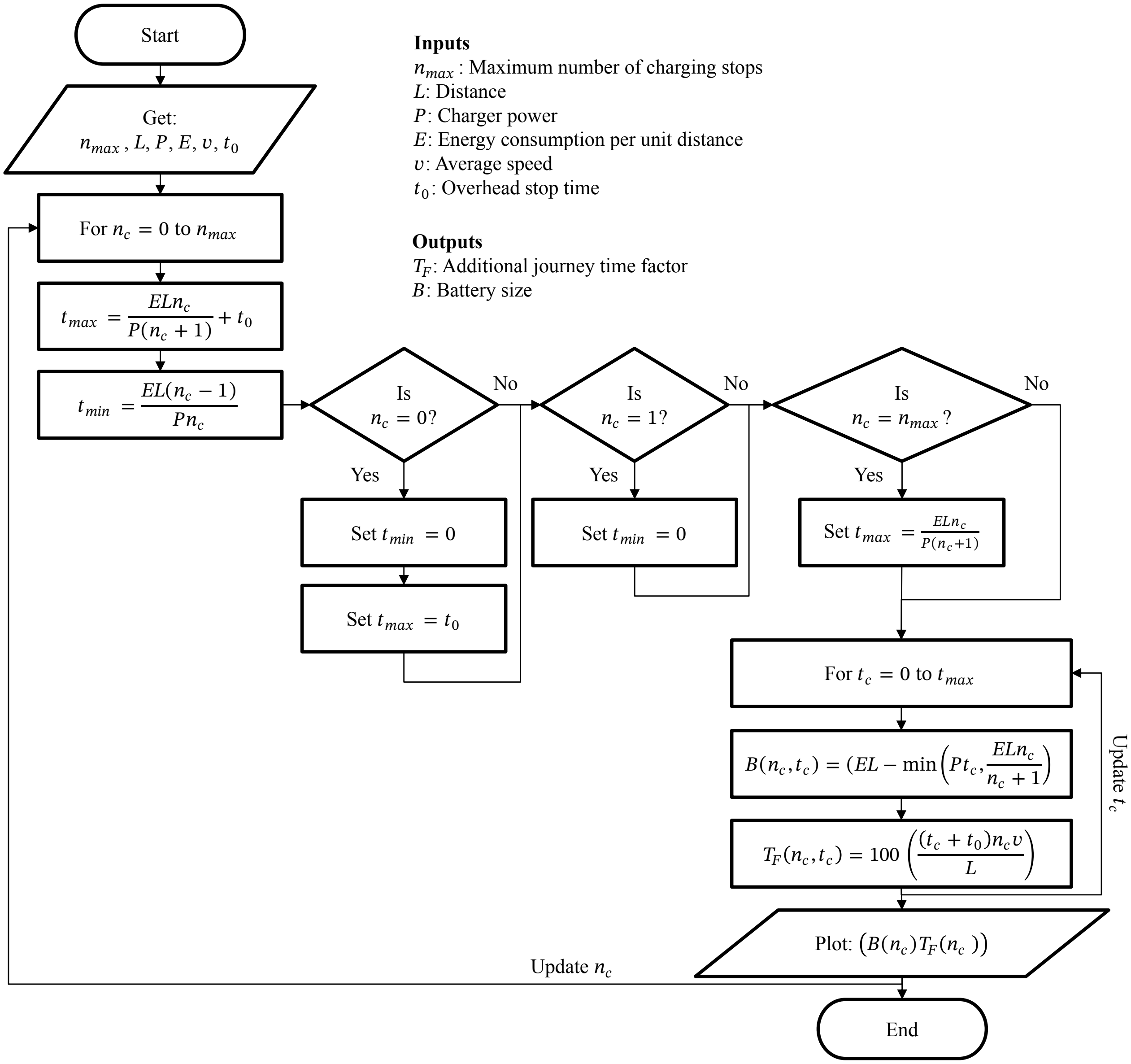

Figure 3 – Flowchart for finding optimal charging stops

The patterns observed are similar for diesel vehicles and BEVs, but the additional kinetic energy required is significantly lower for BEVs due to the presence of regenerative braking. The plot for BEVs is approximately a 20% scale-down of the diesel one at all speeds, but not exactly due to slightly different braking and accelerating profiles.

3.2. Optimal Charging Curves

Based on the methodology described for obtaining the optimal charging strategy, the following results were generated (Deshpande et al., 2023b).

Figure 5 shows the direct output of the flowchart shown in Figure 3 for a journey of length 400 km

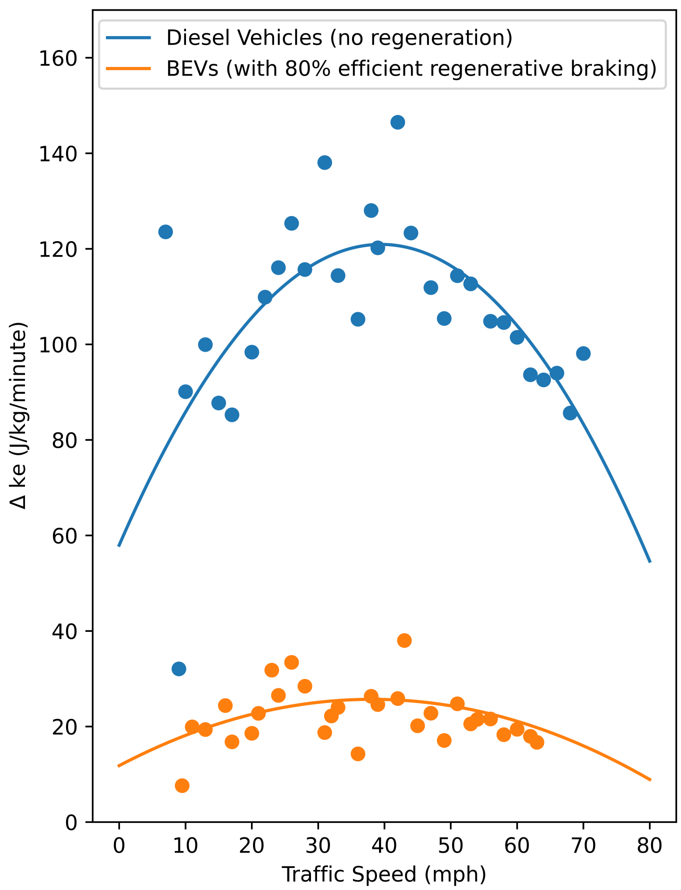

Figure 4 – Increase in ke by traffic speed for diesel and electric vehicles

with 300 kW chargers and a maximum of 10 charging stops. The average speed is set to 90 km/h, the average energy consumption (for a 42-tonne electric HGV) is 1.7 kWh/km, and the 'overhead time' per charging stop is assumed to be 10 minutes (time spent at each stop not charging). On the extreme right, the plot shows the largest battery size required for the journey without any en-route charging. When the battery size gets down to about 430 kWh, one charging stop has to be added. As it goes to the left, further charging stops are added with increasing charging stop duration and hence an increase in journey time. This continues to the left until the defined maximum number of charging stops is reached.

This curve represents the lowest possible increase in journey time for a given battery size, which means that any other charging strategy should automatically be placed above the curve. This is called the Pareto optimal charging curve. This curve can be used to compare various charging strategies given their placement on the diagram relative to it. Thus, the diagram could be considered to be the 'fundamental diagram' for electric HGV charging, similar to traffic fundamental diagrams used in the previous sections.

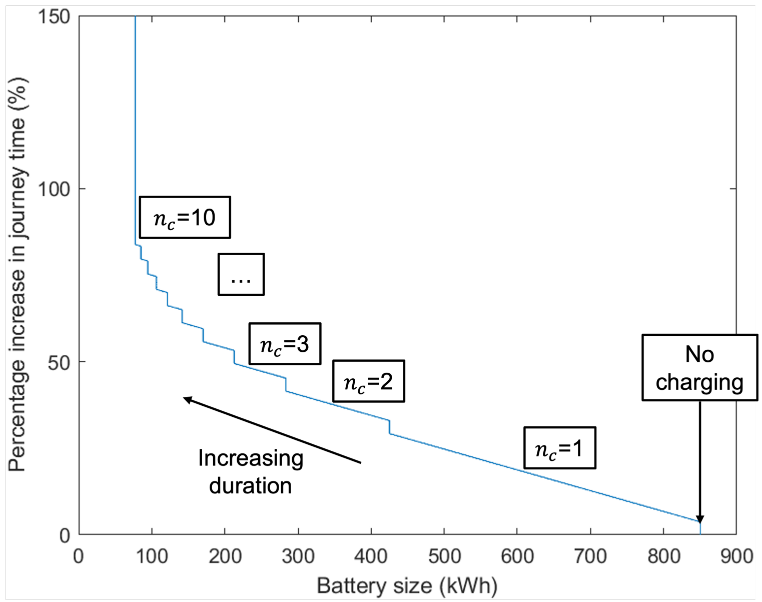

Figure 5 – Optimal charging curve for 400 km with 300 kW chargers

Figure 6 shows multiple such curves, each for different journey lengths from 100 km to 800 km. While the largest battery size for each corresponds directly to the battery size required for that journey with no charging, there is significant overlap between around 300 kWh and 600 kWh, suggesting that this range of battery sizes is suitable for a range of longer journey lengths with multiple charging stops. However, this depends on the cost of batteries and logistics, which is a topic that needs to be explored in more detail. These diagrams do not include compulsory rest-stop charging. However, they can also be used to compare various rest-stop policies, which will be discussed in the next section.

Figure 7 shows results for a 400 km journey with varying charger powers from 100 kW to 1.1 MW. It is seen that lower-powered chargers such as 100 kW and 300 kW result in significantly higher journey times. However, there is not much difference between journey times for 500 or 700 kW chargers than 1.1 MW chargers, primarily because of the 10 min 'overhead time' for each charging stop.

An important consideration when using fast chargers is a limit on the charging rate (C-rate), which is measured as 1C = charging a battery from 0-100% in 1 hour. Most large batteries can currently support a maximum charging rate of 2C, which is highlighted by the grey area in Figure 7. The charging curves that fall in the grey area are not feasible with current battery chemistries. This is a major portion of the fastest charging curves (e.g., the megawatt chargers).

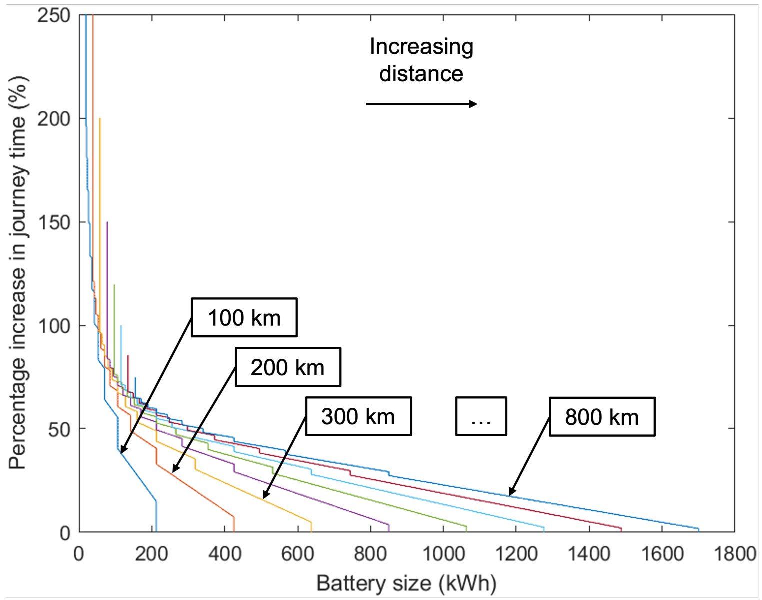

Figure 6 – Optimal charging curves for varying distances with 300 kW chargers

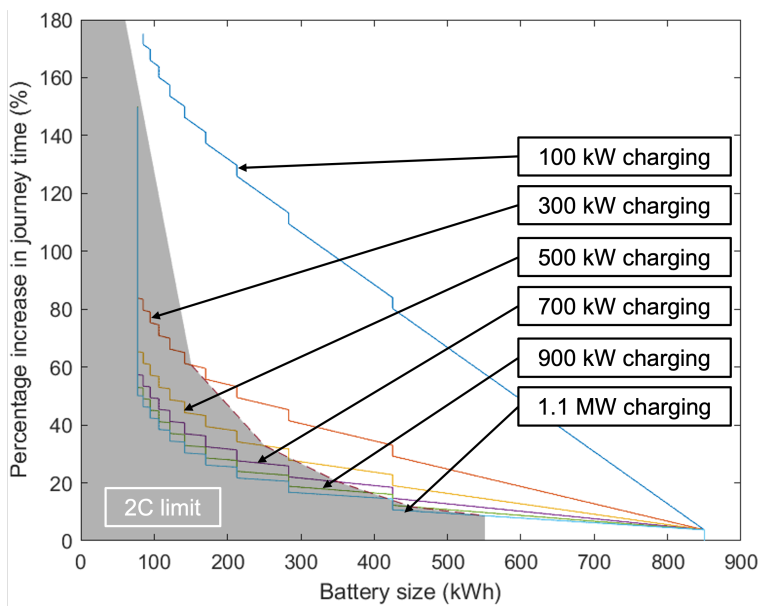

Figure 7 – Optimal charging curves for 400 km with varying charger powers and C-rate

3.3. Rest Stop Strategy Comparison

The optimal charging curves from the previous section can be used to compare various charging strategies. One such example is rest-stop regulations. Regulatory rest stops can be used to add some charge without adding extra journey time over diesel HGVs. Current rest stop strategies in the UK are based on regulations requiring a 45-minute stop after 4.5 hours of driving. While drivers are allowed to split the rest stop so that the first stop is of at least 15 minutes and the second stop is of at least 30 minutes, this is done rarely. A 15-minute stop is also too short for any purpose.

An alternative rest stop regulation is to stop for 30 minutes after 2h 15m of driving (Deshpande et al., 2023a). Figure 8 shows how this results in smaller battery sizes than the current rest-stop strategy at various charger powers, for a journey of 810 km. This is because it reduces the magnitude of the lowest 'battery dip' by having an early charging stop. This can be understood in more detail by plotting the optimal charging curve for 300 kW chargers, as shown in Figure 9. It is seen that the additional time factor required for this journey is around 12%, but it results in a significant reduction of 280 kWh in the battery size required.

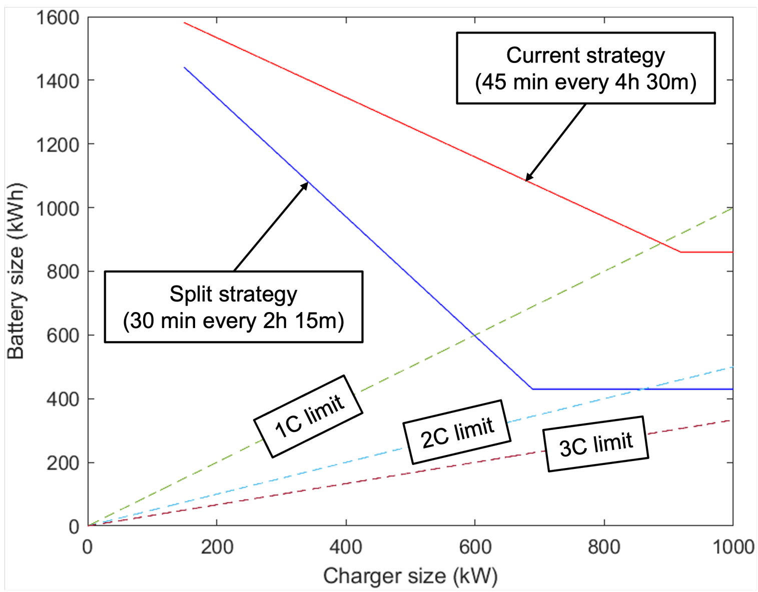

Figure 8 – Battery size reduction with varied rest stop strategies with charger power for a journey of 810 km

4. Conclusions

In this paper, we first analyzed the effect of traffic congestion on energy consumption of HGVs. Traffic data from sources in the UK such as National Highways and HERE Maps was used to develop traffic fundamental diagrams. Then, the additional energy consumption of HGVs in a specific traffic state was calculated. This showed that the highest energy consumption is at intermediate traffic speeds, due to starting and stopping in congested traffic. At low traffic speeds, vehicles are stationary most of the time or in a 'creeping' state, while at high traffic speeds, vehicles are not significantly affected by traffic. This also gives us a way to estimate additional vehicle energy consumption in traffic given any one of the macroscopic traffic parameters defining traffic state - flow, speed, or density.

In the next part, we analyzed a simple journey model to develop an 'optimal' charging curve for a journey to minimize the increase in journey time. This helped compare various charging stop strategies for a specific vehicle-charger configuration and analyze the increase in journey time for each strategy. For example, an alternative rest stop strategy of stopping for 30 minutes after 2h 15m

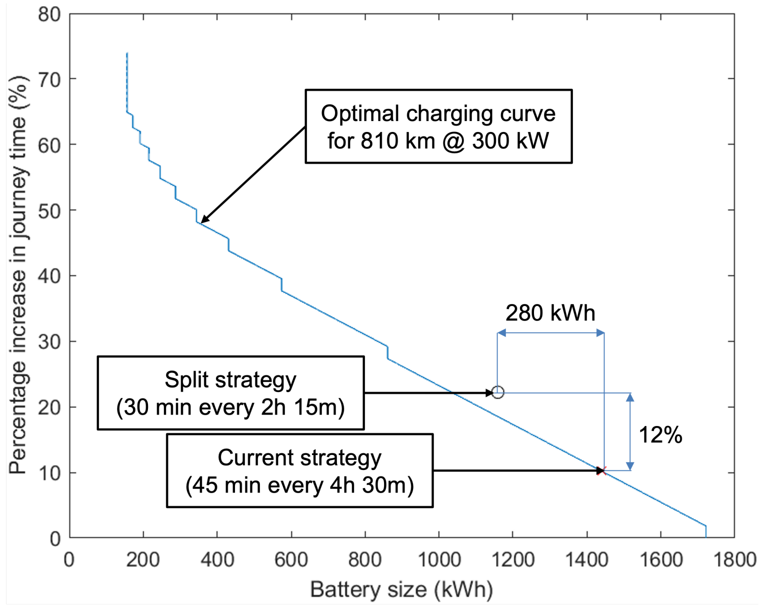

Figure 9 – Optimal charging curve for 810 km with varied rest stop strategies

of driving instead of 45 minutes after 4h 30m of driving resulted in a battery size reduction of 280 kWh with an increase of only 12% in journey time.

These models form the basis for understanding how electric HGV journeys would differ from diesel HGV journeys. This is particularly important during the transition to electric HGVs, as it helps quantify the range and journey time limitations. It also enables analysis of whether electric HGVs can be compatible with current logistics or if the industry needs to change to adapt operating procedures to the new vehicles. In the future, we aim to implement the range and time models discussed in this paper for specific operator journeys and to quantify the cost and carbon emissions alongside the range and time variables.

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