38th International Electric Vehicle Symposium and Exhibition (EVS38) Göteborg, Sweden, June 15-18, 2025

Assessment of the European Long-Haul Truck Transport System Incorporating Data Interoperability

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Executive Summary

Long-haul trucks are major contributors to carbon emissions in road transport, and electrifying truck fleets is essential for reducing emissions in the transport sector. This transition requires not only adequate charging infrastructure along highway corridors but also advanced software and information systems that seamlessly connect charger operators and vehicles. Data interoperability offers a promising means to enhance data sharing between operators and trucks, yet its effect on charging supply–demand efficiency remains unclear. In this study, we quantify the performance of long-haul truck networks under data interoperability. We develop an assessment framework to estimate and assign charging demand across the given charging infrastructure. A case study on European highway networks demonstrates that implementing data interoperability can reduce daily delayed charging time by 19%. We also find that marginal benefits are larger at lower penetration rates of data interoperability, which encourages early-stage implementation of data interoperability.

Keywords: Heavy Duty Electric Vehicles, Intelligent Transportation System for EVs, V2I Communication

1 Introduction

The transport sector contributes over 20 % of global carbon emissions [1], with road transport alone responsible for 71 % of that share [2]. Although heavy-duty vehicles represent 8 % of the total fleet, they account for more than 35 % of road transport emissions [3]. To achieve the net-zero carbon emission target by 2050, electrifying heavy-duty vehicles has been considered to be a promising and feasible pathway worldwide. The European Union has responded with ambitious CO_2 standards for new heavy-duty vehicles in 2024, identifying long-haul truck electrification as a critical milestone [4]. In 2025, the Chinese Ministry of Transport launched a policy to promote the large-scale deployment of zero-emission heavy-duty trucks according to local conditions [5]. In the US, under the Advanced Clean Fleets regulation, truck manufacturers must ensure 100% of market share for zero-emission vehicles by 2036 [6].

Smooth and successful vehicle electrification requires sufficient charging infrastructure to alleviate range anxiety. This is especially critical for long-haul electric trucks, which typically cover long distances. At the policy level, the European Union requires heavy-duty electric vehicle charging stations along the trans-European transport core network at intervals not exceeding 60 kilometers by 2030 [7]. At the research level, a growing number of studies focus on the deployment and siting of charging infrastructure specifically for long-haul electric trucks [8-10].

Besides the charging infrastructure requirements, advanced software and information sharing systems that serve and seamlessly connect charger operators and vehicles are also necessary. Data interoperability, which allows multiple systems to exchange and effectively use shared charging information, offers a promising way to enhance interactive data sharing between charging operators and vehicles [11]. Such data interoperability systems facilitate charging convenience for drivers. In addition, by leveraging information on charging demands and time windows (i.e., arrival and departure time) of vehicles, smart charging strategies that incorporate dynamic charging power rates have proven effective in mitigating peak loads within depot aggregate load profiles [12].

Quantifying the impact of data interoperability on long-haul electric truck drivers' experience is essential for decision-making and implementation, especially given limited financial resources and high upfront costs. To date, no studies have examined this issue. To fill this gap, we measure the effect of data interoperability by defining delayed charging time at charging points as the key metric. We then develop an assessment framework to estimate charging demand and distribute it across the given infrastructure. Finally, we conduct a case study on the entire European core road network using a synthetic road freight transport flow dataset [13].

This study makes two aspects of contributions. First, we present an assessment framework that estimates spatiotemporal charging demand for long-haul electric trucks and assigns this demand using three approaches: uniform allocation, user equilibrium, and system optimization. Uniform allocation represents a business-as-usual scenario, while user equilibrium and system optimization capture the effects of data sharing under data interoperability. Second, we conduct a large-scale case study to analyze simulation outcomes and derive practical insights for relevant stakeholders. The remainder of this paper is structured as follows. Section 2 describes the methods developed in this study. Section 3 presents the simulation results. Section 4 offers discussion, conclusions, and limitations.

2 Method

This section begins by describing the problem setting within the context of data interoperability. Next, we introduce two key datasets used in this study. Then, we outline our method for estimating spatiotemporal charging demand for long-haul electric trucks in 2030. Finally, we present three approaches to simulate charging demand assignment across charging points under three scenarios.

2.1 Problem setting

First, we define the following three simulation scenarios. a) Business as usual (BAU): No data interoperability exists between trucks and charging points. Truck drivers select charging locations uniformly along their route, subject only to standard break rules; b) Data interoperability with user equilibrium (DI-UE): Real-time charging information is shared between trucks and charging points. Drivers choose charging points according to the user equilibrium principle; c) Data interoperability with system optimization (DI-SO): Real-time charging information is shared between trucks and charging points. Charging point operators centrally schedule driver demand to maximize system efficiency. Drivers should follow the assigned schedules. Next, we present the fundamental assumptions in this study, aside from the scenario definitions above:

Assumption 1. Drivers can only recharge their trucks during scheduled breaks at charging points. According to the European Commission's regulation [14], we assume that after every 4.5 hours of driving, a driver must take a 45-minute break. This break is divided into two segments: a 15-minute segment and a 30-minute segment, designed to maximize charging opportunities in an electrification context. In addition, after nine hours of work, a driver must take a nine-hour rest. We also assume that during the 15-minute or 30-minute breaks, trucks use megawatt chargers with a power of 1000 kW, whereas during the nine-hour rest period, they charge using fast chargers at 100 kW.

Assumption 2. Drivers are restricted to charging points along their predetermined routes, so rerouting to find charging points is not considered in this study. Battery state of charge (SoC) is constrained between 20 % and 100 %.

Assumption 3. Under the DI-UE scenario, drivers select charging points to minimize their delayed charging time. Under the DI-SO scenario, the charging point operator assigns charging demands among charging points to minimize the total delayed charging time of drivers. Delayed charging time is defined as the extra waiting time incurred before charging due to limited charging resources. We assume both drivers and charging point operators can access updated information one hour in advance with data interoperability.

Assumption 4. We assume that, before reaching their scheduled break or rest period, drivers have two additional opportunities at road nodes to exit and locate charging points.

2.2 Datasets

This study used two primary public datasets: synthetic European road freight transport flow data [13] and European truck parking locations data [15]. From the synthetic European road freight transport flow dataset, we extract origin–destination (OD) pairs and road network details. Each OD pair includes origin and destination locations, the corresponding road route, and the projected annual freight volume in tons for 2030. The road network dataset includes information on road nodes and edges. The European truck parking locations data mainly includes the locations of current truck parking points, which are selected as the charging points in this study.

2.3 Charging demand estimation

Using the OD pair data and origin departure times (generated from the assumed distribution), we could determine when and how much electricity each truck is recharged. First, we use the following equations to calculate the truck's electricity consumption (*TEC* in kWh) [16].

$$TEC = 0.212 \cdot W^{0.6672} \cdot Advanced\_Factor \tag{1}$$

Here, we use *W* to denote the total weight of the truck in tons. Let *Advanced_Factor* denote the adjustment factor reflecting battery technology advancements in 2030, and we set *Advanced_Factor* to be 0.73. To determine the total truck weight per OD pair, we assume that 30 % of freight flows use trucks with an 8-ton tare weight (excluding battery weight), and 70 % use trucks with an 11-ton tare weight (excluding battery weight). Given a battery energy density of 260 Wh/kg [17], we define seven battery capacities ranging from 600 kWh to 1000 kWh and assign each OD truck's battery capacity according to its OD pair's total distance. Based on the Eurostat database [18], we assume an average payload of 13.4 tons for domestic transport and 15.7 tons for international transport.

Given the origin departure time, we could determine the break and rest timetable for each OD according to the European Commission's regulation and OD route information. During the break and rest time, the truck is recharged according to the following equation.

$$RechargedEnergy = \min\{(1 - SoCPresent) \cdot Capcacity, Power \cdot AvailableTime\} \tag{2}$$

Here, let *RechargedEnergy* denote the amount of recharged electricity in kWh. Let *SoCPresent* denote the current SoC of the battery. Let *Capacity* denote the vehicle battery capacity in kWh. We use *Power* to denote the charging power in kW of chargers. *AvailableTime* represents the available charging time during the break or rest. We assume that upon arriving at a charging point, each truck requires a five-minute charging preparation period.

Then, we calculate the hourly charging demand at each road node daily. First, we calculate the annual electric truck flows (*AnnualElectricFlow*) for each OD as below.

$$AnnualElectricFlow = \frac{AnnualVolume}{AverageLoad} \cdot ElectricShare \tag{3}$$

Here, *AnnualVolume* represents the projected annual freight volume in tons for 2030 for an OD pair. *AverageLoad* means the average payload in tons of trucks for an OD pair. *ElectricShare* represents the share of electric trucks for an OD in 2030, which can be estimated by the following equation.

$$ElectricShare = \frac{ElectricShareO \cdot AnnualVolumeO + ElectricShareD \cdot AnnualVolumeD}{AnnualVolumeO + AnnualVolumeD} \tag{4}$$

Here, *ElectricShareO* denotes the share of electric trucks in 2030 for the country containing the origin, and

ElectricShareD denotes the share for the country containing the destination. *AnnualVolumeO* is the 2030 annual freight volume from origin to destination, while *AnnualVolumeD* is the volume from destination to origin. Then, the daily electric truck flows for each OD (*DailyElectricFlow*) could be obtained via *AnnualElectricFlow/*365. For each OD, given *DailyElectricFlow* and *RechargedEnergy*, we then calculate the hourly charging demand at road nodes, which corresponds to the OD pair's break and rest periods.

Based on the estimated hourly charging demand at each road node, we determine the required number of megawatt chargers at each charging point as input for the three simulation scenarios. In this study, we focus exclusively on megawatt chargers and their charging demand, since delayed charging time is relevant during 15- or 30-minute breaks rather than the nine-hour rest period. We divide the entire region covered by the road network dataset into 50 km × 50 km zones. Within each zone, we identify the peak-hour charging demand at each road node and determine the minimum number of megawatt chargers required at each node from that demand. Next, we sum the total number of megawatt chargers required for each zone and uniformly allocate 70 % of these chargers among all charging points within that zone to simulate a scenario where charging demand exceeds supply.

2.4 Charging demand assignment under three scenarios

Up to this point, charging demand has not been allocated to specific charging points, as we have only calculated the recharged electricity for each OD pair during its break and rest periods. As Figure 1 shows, we have assumed that, before reaching their scheduled break or rest period, drivers have two additional opportunities to locate charging points. Therefore, drivers generally have three road nodes where they can exit the highway to find a charging point before their break or rest period.

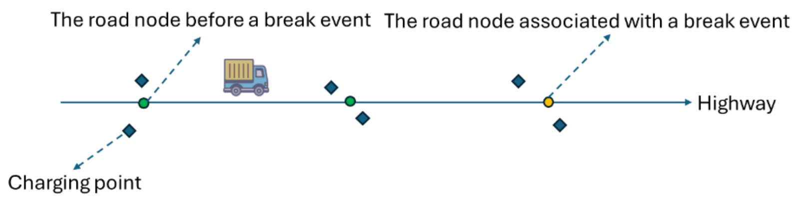

Figure 1: The illustration of charging point selection

Under the BAU scenario, the charging demand assignment is simulated for each divided zone based on Algorithm 1. The hourly charging demand for each OD pair in each zone is uniformly assigned to accessible charging points of the corresponding OD pairs. The cumulative delayed charging time at the current hour equals the previous hour's cumulative delayed time plus the delayed time incurred in the current hour.

Algorithm 1. Charging demand assignment under the BAU scenario.

for each zone:
  Set the current unmet charging demand to be zero for each charging point.
  Set the current total accumulated delayed charging time in this zone to be zero.
  for *t* from 1 to 24:
    for each OD via this zone:
      Uniformly assign the charging demand among accessible charging points.
      Update the current unmet charging demand for each charging point in this zone.
      Update the current total accumulated delayed charging time in this zone.
    end
  end
end

Under the DI-UE scenario, charging demand is allocated within each zone using Algorithm 2. We employ the Method of Successive Averages (MSA), a widely used iterative algorithm for traffic assignment, to approximate the user equilibrium solution [19]. In line 15 of Algorithm 2, we define a termination condition for the MSA iteration. Specifically, we monitor the maximum change in charging demand at any charging point between consecutive iterations. If this change falls below 0.1, the iteration process is terminated.

Algorithm 2. Charging demand assignment under the DI-UE scenario.

```
1   for each zone:
2       Set the current unmet charging demand to be zero for each charging point.
3       Set the current total accumulated delayed charging time in this zone to be zero.
4       for t from 1 to 24:
5           Set demand_x to be a zero vector, and the length of demand_x is the number of charging points.
6           Let n = 0.
7           while True:
8               Let n = n + 1.
9               for each OD via this zone:
10                  Assign the charging demand to the charging point with the least unmet charging demand.
11              end
12              Update the current charging demand assignment solution, and denote it as demand_y.
13              Update demand_x as demand_x = demand_x + (1/n)*(demand_y - demand_x).
14              Update the current unmet charging demand for each charging point.
15              If the termination condition is met, go to line 17; otherwise, return to line 8.
16          end
17          Update the current total accumulated delayed charging time in this zone.
18      end
19  end
```

Under the DI-SO scenario, we develop a linear programming model to minimize the total delayed charging time for each zone at each hour. Let *I* denote the set of charging points in the zone. Let *t* denote the current hour *t*. We use $d_{i,t}^{MCS,cumulated}$ denote a continuous decision variable that represents the cumulated charging demand at charging point *i* and hour *t*. Let $D_{i,t}^{MCS}$ denote the satisfied charging demand at charging point *i* and hour *t*. The objective function (5) is to minimize the total delayed charging time for the zone at hour *t*.

$$min \sum_{i \in I} (d_{i,t}^{MCS,cumulated} - D_{i,t}^{MCS}) \tag{5}$$

Let *J* denote the set of road nodes in the zone. Let *K* denote the OP pair set that passes through the zone. We use $d_{j,k,i,t}^{MCS}$ denote a continuous decision variable, which means the assigned charging demand associated with OD pair *k*, road node *j*, charging point *i*, and hour *t*. Let $D_{j,k,t}^{MCS}$ denote the input information that represents the charging demand associated with OD pair *k*, road node *j*, and hour *t*. Constraint (6) ensures that the total charging demand allocated across all charging points equals the charging demand at the road node.

$$\sum_{i \in I} d_{j,k,i,t}^{MCS} \quad - D_{j,k,t}^{MCS} \quad = 0, \forall j \in J, k \in K \tag{6}$$

Let $\delta_{j,k,i}$ be a binary indicator parameter equal to 1 if the charging demand of OD pair *k* at road node *j* can be assigned to charging point *i*, and 0 otherwise. Constraint (7) restricts the assignment of charging demand to only those charging points that are accessible for the given OD pair.

$$d_{j,k,i,t}^{MCS} - \delta_{j,k,i} D_{j,k,t}^{MCS} \leq 0, \forall j \in J, k \in K, i \in I \tag{7}$$

Let $d_{i,t}^{MCS}$ denote the total charging demand at charging point *i* and hour *t*. It is also a continuous decision variable, and it can be calculated as Constraint (8) shows.

$$\sum_{j \in J} \sum_{k \in K} d_{j,k,i,t}^{MCS} = d_{i,t}^{MCS} \quad , \forall i \in I \tag{8}$$

Constraint (9) gives the relationship between the cumulated charging demands at hour *t* - 1 and *t*.

$$d_{i,t}^{MCS,cumulated} = d_{i,t}^{MCS} + d_{i,t-1}^{MCS,cumulated} - D_{i,t-1}^{MCS}, \forall i \in I \tag{9}$$

Let N_i^{MCS} denote the input information that represents the number of megawatt chargers at charging point i. Constraints (9) and (10) ensure that the satisfied charging demand does not exceed the charging supply. All decision variables are non-negative in this linear programming model.

$$D_{i,t}^{MCS} - d_{i,t}^{MCS,cumulated} \leq 0, \forall i \in I \tag{10}$$

$$D_{i,t}^{MCS} - 1000 \cdot N_i^{MCS} \leq 0, \forall i \in I \tag{11}$$

We solve the proposed linear programming model independently for each zone and sequentially for each hour from 1 to 24. For hour *t*, we regard $d_{i,t-1}^{MCS,cumulated}$ and $D_{i,t-1}^{MCS}$ as model inputs, and all linear programming models are solved by Gurobi solver.

3 Results

3.1 Charging demand distribution in 2030

In this study, we focus on the charging demand distribution for megawatt chargers, covering 39 countries in Europe. On an average day, total charging demand during the 15- and 30-minute break periods exceeds 17 million kWh. Figure 2 illustrates the cumulative probability curve of the daily total charging demand of road network nodes before charging demand assignment under the three scenarios. We find that 90 % of road nodes have a daily charging demand of less than 10,000 kWh.

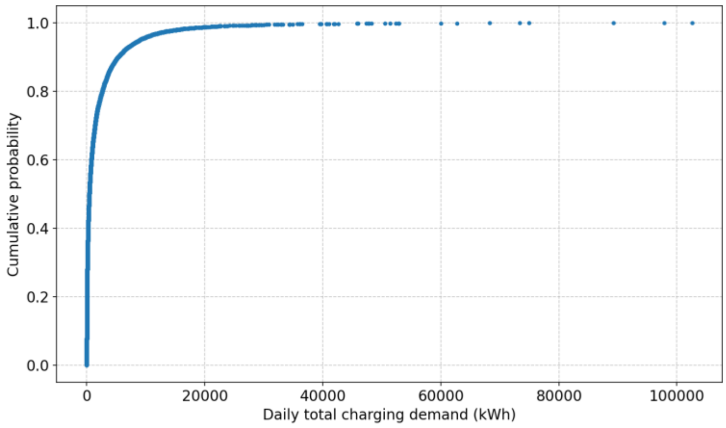

Figure 2: Cumulative probability curve of the daily total charging demand of road network nodes

To identify daily charging demand patterns, we normalized each node's hourly charging demand by its total daily demand and then applied K-means clustering. Figure 3 presents six distinct patterns; five of these exhibit pronounced peaks in charging demand at specific times of day. In patterns 1, 5, and 6, the peak hour accounts for more than 40 % of the total daily charging demand. In this situation, charging infrastructure experiences highly uneven demand: drivers arriving outside this window contend with minimal waiting, whereas those arriving during the peak face substantial queuing delays. Identifying and quantifying such temporal spikes enables operators to implement targeted congestion-mitigation strategies, such as introducing data interoperability systems.

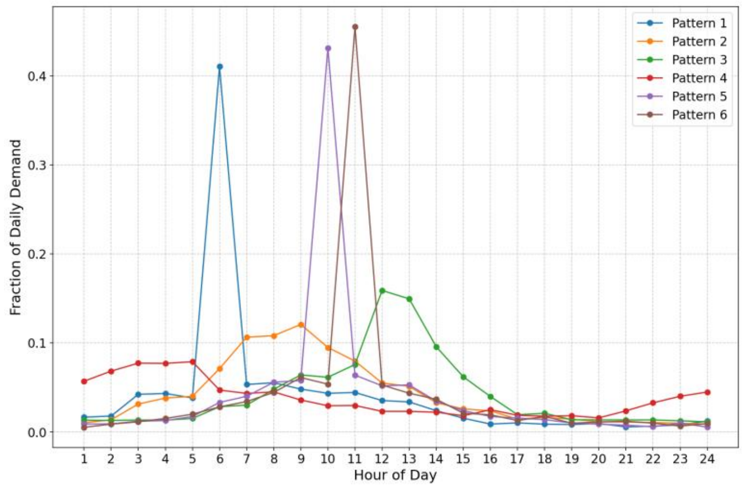

Figure 3: Six daily charging demand distribution patterns

3.2 Impacts of data interoperability on delayed charging time

To assess the impact of data interoperability on delayed charging time, we compare average delayed charging time per zone under BAU and DI-UE scenarios (Figure 4). In this figure, each point represents a zone, with its x-coordinate indicating delayed charging time under DI-UE and its y-coordinate indicating delayed charging time under BAU. The average total delayed charging time per zone is 21.5 hours under BAU and 17.5 hours under DI-UE. The results indicate that the daily delayed charging time under DI-UE is 19 % lower than under BAU. Figure 4 shows that nearly all zones experience improvements after introducing data interoperability.

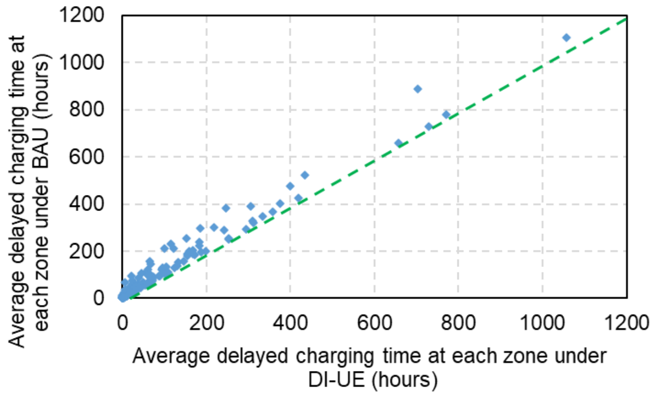

Figure 4: Comparing the average delayed charging time at each zone under the scenarios of BAU and DI-UE

Now, we compare average delayed charging time per zone under DI-UE and DI-SO scenarios (Figure 5). In this figure, each point represents a zone, with its x-coordinate indicating delayed charging time under DI-UE and its y-coordinate indicating delayed charging time under DI-SO. The average total delayed charging time per zone is 17.9 hours under DI-SO and 17.5 hours under DI-UE. The results indicate that the daily delayed charging time under DI-SO could not be improved by system optimization assignment. This is primarily because our optimization is performed on an hourly basis rather than across the entire 24-hour period. Under data interoperability, we have assumed that both drivers and charging point operators can access updated information one hour in advance with data interoperability. It is unrealistic to expect charging point operators to predict demand a full day ahead. Therefore, the solution that is optimal for the current hour does not coincide with the globally optimal solution over the entire day.

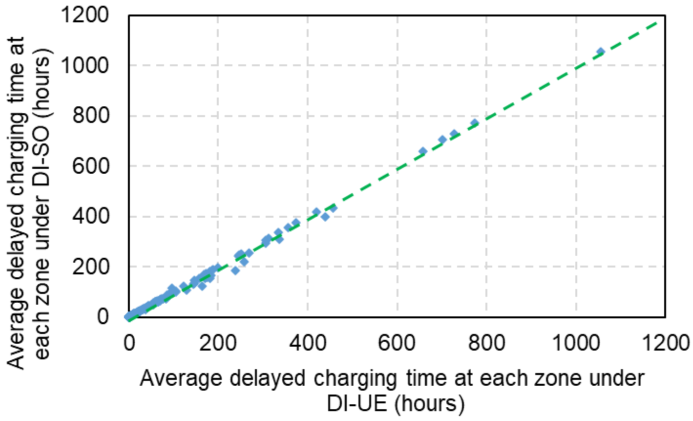

Figure 5: Comparing the average delayed charging time at each zone under the scenarios of DI-SO and DI-UE

Lastly, we examine how varying the penetration rate of trucks participating in data sharing affects the average delayed charging time (Figure 6). For example, at a 20 % penetration rate, we allocate 20 % of the charging demand via Algorithm 2 and the remaining 80 % via Algorithm 1. Figure 6 shows that with just 30 % of drivers participating in data sharing, half of the total reduction achieved at 100 % participation is realized. Notably, the marginal benefit of data interoperability is greater at lower penetration levels than at higher ones. This finding is encouraging for the early-stage implementation of data interoperability.

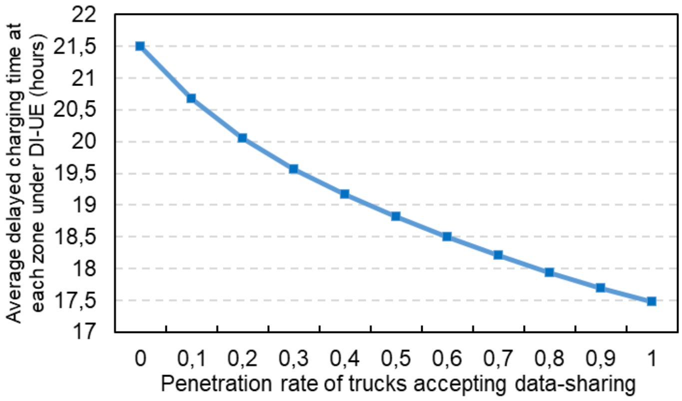

Figure 6: Average delayed charging time with different penetration rates of trucks participating in DI-UE

4 Conclusion

This study demonstrates that data interoperability could alleviate delayed charging time for long-haul electric trucks. Under the DI-UE scenario, average per-zone delayed charging time decreases by 19 % compared to business-as-usual, indicating that real-time information sharing can meaningfully improve queuing issues. The gain achieved by DI-SO suggests that, given the one-hour information horizon, hourly-level optimizations cannot capture inter-hour demand dynamics. In practice, charging operators would require foresight beyond a single hour to approach the global daily optimum; however, such lead times are infeasible in a real-time context.

Clustering of normalized daily demand profiles reveals that five of six patterns exhibit highly concentrated peak hours, with up to 40 % of a road node's daily charging demand occurring in a single hour. These pronounced spikes highlight the importance of mitigating localized congestion. Without data interoperability, drivers arriving during peak hours face disproportionately long waits. The adoption of real-time sharing enables more balanced utilization, reducing the gap between peak and off-peak waiting times.

Analysis of penetration-rate effects indicates that raising data-sharing participation from 0 % to 30 % captures roughly 50 % of the maximum achievable delay reduction. This nonlinear benefit highlights that early-stage implementation yields disproportionately large improvements. Policy initiatives and charging-network providers should therefore prioritize lightweight, interoperable communication protocols even before full ecosystem coverage is attained.

Despite these promising results, several limitations merit consideration. First, our optimization assumes uniform detour opportunity within predefined highway nodes; in reality, geographic constraints and driver preferences may further limit accessible alternatives. Second, the analysis uses synthetic freight-flow data and assumes perfect compliance with break schedules. Therefore, field-level validation is required to quantify behavioral variability.

Acknowledgments

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Presenter Biography

Dr. Xiaohan Liu received a PhD from Beihang University, China, in 2024. At present, He is a postdoc in the Urban Mobility Systems research group. His research focuses on sustainable transportation electrification and renewable energy integration. Special interests are attached to establishing new approaches and data-driven frameworks for electric vehicle charging demand estimation, charging infrastructure planning and management, and coupled transportation and energy systems. The overall goal is to facilitate green, economically sustainable, and resilient electrified transportation systems in the uncertain future against climate change and societal development. Dr. Liu has published 22 peer-reviewed journal papers and 3 peer-reviewed conference papers in the fields of transport and energy, including leading journals of Nature Energy, npj sustainable mobility and transport, Transportation Research Part E/D/F, Computer-Aided Civil and Infrastructure Engineering, Renewable and Sustainable Energy Reviews, and Sustainable Cities and Society.