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Load profiles of charging stations for long-haul electric trucks

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Executive Summary

Electric trucks play a crucial role for achieving a zero-emission future. As battery electric technology advances, electric trucks are expected to become a cost-effective and sustainable alternative to diesel trucks. Despite their potential, the adoption rate for long-haul electric trucks remains low due to challenges like limited range and long charging times.
Research on high-power charging stations for long-haul trucks is limited. Long-haul trucks have unique driving patterns that affect their charging needs, and investigating the load profiles to be expected is fundamental to conduct a proper assessment of the impact of trucks fleet electrification on the charging infrastructure.
This article presents an agent-based modeling approach to estimate high-power charging station load profiles, leveraging open data and behavioral modeling. A case study along a Norwegian highway highlights the framework's applicability for evaluating the grid impact under diverse truck charging behavior and heavy-duty transport electrification scenarios.

Keywords: electric vehicles, modeling & simulation, fast and megawatt charging infrastructure, heavy-duty electric vehicles & buses, consumer demand

1 Introduction

The electrification of transport is a crucial measure for reducing global greenhouse gas emissions, yet progress varies widely across vehicle classes. Norway exemplifies this gap: despite achieving an 85% electric passenger car sales rate in 2024, the electrification of heavy-duty vehicles (HDVs) and trucks lags considerably, with only an 11% sales share for electric trucks and 23% for electric long-distance buses in the same year [1]. Such contrast reveals the complexities of scaling sustainable solutions for commercial transport sectors.

A major barrier to the widespread electrification of commercial HDVs is the current inadequacy of charging infrastructure capable of delivering megawatt-scale power. Establishing such infrastructure necessitates a coordinated effort between charging point operators, distribution system operators, and transport companies to ensure sufficient charging availability and power levels that meet operational requirements. This challenge is amplified by increasing regulatory pressure, particularly from governing bodies like the European Union, aiming to enforce stricter emission standards and potentially mandate minimum charging infrastructure availability for heavy-duty transport [2, 3].

To facilitate the transition towards electric truck transport, it is fundamental to develop smart solutions for planning and operating the future charging infrastructure. In this context, understanding EV charging load profiles is essential for power system operators, infrastructure planners, and policymakers [4]. Accurate characterization of HDEV charging patterns provides valuable insights into peak demand periods, that combined with knowledge of load distribution across the network, and potential grid bottlenecks, plays a central role in developing effective strategies for load management, grid reinforcement, and connection agreements [5].

In the face of these challenges, researchers have employed various methodologies to gain insights into EV charging load profiles. However, as the widespread adoption of EVs, especially HDVs, is relatively recent, the available real-world data for detailed characterization remains limited. Consequently, modeling techniques are essential to bridge these data gaps. A recent review by Amara-Ouali et al. [6] categorizes electric vehicle (EV) load modeling techniques into three main groups: (1) **Statistical characterization:** Approaches based on statistical analysis of input and output variables, often leveraging travel survey data or other exogenous factors to infer charging behavior; (2) **Stochastic processes:** Methods that explicitly represent the probabilistic nature of EV travel and charging, including Markov Chains, Monte Carlo simulations, and Agent-Based Models (ABM); (3) **Machine learning models:** Data-driven techniques such as Artificial Neural Networks (ANN), clustering, and Support Vector Machines (SVM), which uncover charging patterns from large datasets of historical charging events.

Modeling the load demand of electric long-haul trucks presents unique challenges compared to passenger vehicles, due to their distinct driving patterns and operational requirements. The limited adoption of electrified heavy-duty vehicles to date means that comprehensive datasets for statistical or machine learning approaches are not yet widely available. On the other side, stochastic process-based methods offer a flexible framework for capturing the inherent variability in truck operations and charging behavior, even in the absence of extensive empirical data. This makes them especially well-suited for scenario analysis and infrastructure planning for electric long-haul transport. In this contect, ABM has proven valuable for for analysing the dynamic variation of EV traffic [7], and for simulating charging patterns by effectively incorporating the driving behaviors and operational constraints of vehicle users [8, 9]. Unlike passenger vehicles, where charging decisions can be highly variable and influenced by diverse individual needs, heavy-duty vehicle operations often follow more structured and predictable patterns governed by logistical requirements and regulations, such as mandatory driver rest times. ABM allows for a bottom-up simulation where individual truck agents behave according to these defined rules, schedules, and constraints (e.g., route, SOC, regulatory stops, etc.). By simulating the actions and interactions of numerous individual agents, ABM can accurately capture the emergent, system-level charging demand patterns arising from these operations.

In this paper, we propose a methodology employing agent-based modeling to determine the expected load profiles from long-haul electric trucks charging. Using this bottom-up approach, the accuracy of the simulated charging demand relies heavily on a correct representation of individual vehicle charging patterns. Key inputs influencing this representation include national statistics on electric truck adoption rates, regulatory frameworks (e.g., mandatory breaks), vehicle technical specifications, behavioural characterization of heavy-duty vehicles' drivers, and the location of charging infrastructure along major long-haul routes.

To the best of the authors' knowledge, this is one of the first studies to quantify expected charging demand from long-haul heavy-duty transport using a detailed agent-based modeling approach tailored specifically for high-power charging scenarios. The key contributions of this work are threefold: (1) development of a behavioral framework that captures both regulatory-driven and anxiety-based charging decisions in heavy-duty transport; (2) scenario analysis examining the sensitivity of demand patterns to fleet electrification rates, driver behavior and charging infrastructure density; and (3) evaluation of whether planned infrastructure deployment will adequately meet projected demand under various adoption trajectories. This approach provides valuable insights for infrastructure planning, grid capacity requirements, and policy development as heavy-duty transport transitions toward electrification.

The remainder of this paper is structured as follows: Section 2 describes the agent-based modeling methodology and the processing of the input data. Section 3 details the case study design, including the geographical area and scenario definitions. Section 4 presents the simulation results and discusses how charging load demand responds to different modelling assumptions. Finally, Section 5 summarizes the main findings and outlines directions for future research.

2 Model

The method is based on an agent-based modeling approach proposed in our previous work [8], which describes dynamic agent-based interactions for analyzing spatial flexibility in EV charging demand at public fast charging stations. As illustrated in Figure 1, the methodology employs a three-stage process flow: data preparation, agent-based simulation, and load profile generation. In the initial phase, five critical input categories are preprocessed: street topology (geographical network data), truck models (technical specifications including battery capacity, energy consumption rates, and charging power), HDV traffic (temporal vehicles' counting over monitored roads), transport routes (origin-destination matrices), and driving patterns (including mandatory rest periods and driving behaviors).

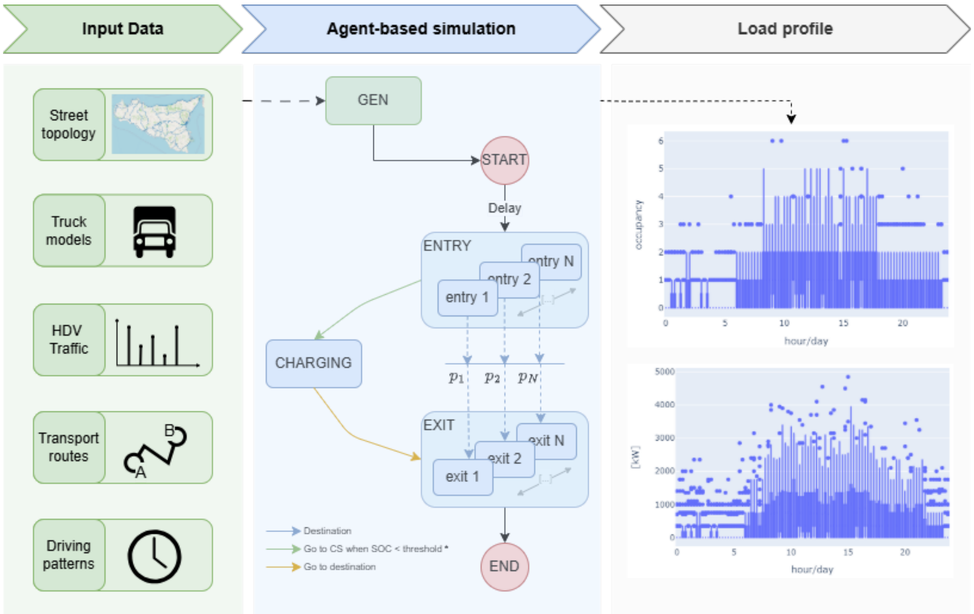

Figure 1: Schematic representation of the methodology proposed

During the simulation phase, individual vehicle agents are stochastically generated and operate as autonomous entities following decision rules formulated over the preprocessed input data. Each vehicle progresses through distinct states: generation (GEN), entry into the simulation area (ENTRY through different p_1, p_2, p_n for different entry points), potential charging events, and exit from the system. The charging decision is triggered when a vehicle's State of Charge (SOC) falls below a predetermined threshold influenced by the vehicle's specific energy requirements.

The charging station agents track vehicle charging sessions in terms of energy delivery and occupancy levels throughout the simulation period. The output of the simulation provides aggregated charging station load profiles, visualized as temporal power demand patterns throughout the day.

In the next subsections, additional details on each step are provided.

2.1 Input data

To establish the conditions for the charging event, each generated vehicle has to be instantiated based on certain input conditions that significantly influence charging behaviors and energy demand profiles.

Street topology The spatial arrangement of charging stations represents a critical constraint for route planning and charging decisions. Research on charging infrastructure optimization demonstrates that strategic placement along major corridors significantly impacts utilization rates and overall system efficiency [10]. The road network represents the observed simulation environment, and is modeled as a directed graph between several entry and exit points. A number of charging stations are considered to be placed along the road network, representing the observed charging infrastructure.

Truck models The technical specifications of heavy-duty electric vehicles represent fundamental parameters that directly influence charging requirements and energy consumption patterns. Modern heavy-duty long-haul electric trucks feature battery capacities ranging from 300 kWh to over 700 kWh, supporting charging rates from 350 kW to 1 MW for the most advanced models, with typical consumptions between 0.7-1.5 kWh/km depending on load conditions and vehicle configuration. These values significantly affect range capabilities and charging frequency requirements. Each vehicle within the simulation is characterized by distinct attributes including battery energy capacity, energy consumption rates and maximum charging power.

HDV traffic Traffic conditions significantly influence both travel times and energy consumption patterns, which directly affect charging behaviors and overall energy demand [11]. This data is often used for modeling of charging stations load profiles, based on assumptions concerning the relationship between traffic on road stretches and the arrival rate to charging stations [12]. High traffic density not only extends travel duration but also increases the probability of charging due to extended idle periods and stop-and-go conditions that deplete battery reserves. The model incorporates traffic temporal variations to simulate realistic fluctuations in charging demand.

Transport routes The operational patterns and mission profiles of heavy-duty vehicles fundamentally determine their energy needs and charging behaviors. Long-haul operations covering hundreds of kilometers before reaching the observed area significantly impact the initial SOC distribution of arriving vehicles. The simulation incorporates origin-destination matrices derived from freight movement data to generate realistic travel patterns and energy demand along major corridors.

Driving patterns Driver preferences regarding minimum acceptable SOC levels, charging location selection, and charging duration significantly influence overall charging patterns. In this context, for example, regulatory requirements for driver rest periods create natural opportunities for charging. The State of Charge (SOC) estimation framework models two distinct driver archetypes. These are described in the Section 2.1.1 below.

2.1.1 SOC estimation

The State of Charge (SOC) estimation framework models two distinct driver archetypes. The Schedule-Compliant Charging (SCC) model reflects regulated fleet operations, where drivers adhere strictly to mandated 4.5-hour driving intervals. This deterministic approach prioritizes operational reliability over energy efficiency. In contrast, the Anxiety-Driven Charging (ADC) model captures individualistic behavior through a stochastic process. Drivers evaluate charging needs at a time interval corresponding to charging infrastructure density, corresponding to the expected distance between charging stations. The overall method for processing the 5 data sources described above is summarized in Algorithm 1.

Algorithm 1 Master Initialization and Charging Workflow

```
function COMPUTESOC(Vehicle V, Network N, Mode M, CS-interdistance D)
    // Initialize driving times and SOC
    T_max ← V.max_driving_time
    d_trip ← SampledDistance(N.OD_matrix)          ▷ From transport routes dataset
    d_cs ← DistanceToNearestCS(N.nodes)            ▷ From street topology dataset
    t_drive ← d_trip/V.v                           ▷ V.v is the driving speed
    V.t_cs ← d_cs/V.v
    V.t_since_break ← t_drive mod T_max
    V.dt ← V.t_since_break + V.t_cs
    V.df ← GetDensity(D)                           ▷ Equation (1)
    // Invoke selected charging model
    if M = SCC then
        V.SOC ← SCC(V)                             ▷ Algorithm 2
    else
        V.SOC ← ADC(V, D)                          ▷ Algorithm 3
    end if
    return V.SOC
end function
```

The algorithm takes as input the vehicle parameters, the road network topology, the selected charging mode and the charging station interdistance. It then calculates the maximum driving time per day (e.g., 8 hours), the distance of the ENTRY node from the travel's origin (input from the Transport route's dataset) and the distance of the ENTRY node to the nearest charging station (input from the street topology). Based on these input datasets, and considering an average driving speed (e.g., 80 km/h) the algorithm computes the time since the last long break, assumed as a charging session at the depot with full SOC, and therefore the time of the current daily shift (V.dt). A density factor is also calculated based on the expected distance between charging stations (1).

$$\mathrm{df} = 1.5 - \frac{D - D_{\text{min}}}{D_{\text{max}} - D_{\text{min}}} \tag{1}$$

where D is the distance between the current position of the vehicle and the nearest charging station, D_{min} is the minimum distance between two charging stations, and D_{max} is the maximum distance between two charging stations. The value of the density factor can assume values from 0.5 (sparse network) to 1.5 (dense network), and is used in the ADC model to determine the probability of charging at a given time. The SOC is then calculated using either the SCC or ADC model, depending on the selected mode.

SSC mode (Algorithm 2) simulates truck charging by enforcing mandatory stops at fixed driving intervals (every 4.5 hours), where the vehicle recharges enough to reach the next station with an added safety buffer (b in line 3, where S_{min} and S_{max} are the minimum and maximum battery capacity). After counting the number of mandatory breaks n in the daily shift $V.\text{dt}$, for each stop i, the truck's battery energy S is reduced by the energy used since the last break, then recharged by an amount sufficient to reach the next station plus the safety buffer. The charging session can eventually be interrupted before if the maximum stop duration (e.g., 45 minutes) is reached (see Line 8). This process repeats for all required breaks, and after the final break, the energy is further reduced by the energy needed to reach the destination station.

ADC mode (Algorithm 3) simulates charging decisions at each station stop based on the driver's state of charge and the density of available stations, with the probability of charging increasing as the battery nears depletion or stations are sparse. For each leg, calculated according to the expected distance between charging stations, upon arriving at a station, the algorithm calculates an anxiety value a based on the current SOC and station density. Anxiety is calculated using a density-modulated sigmoid function as shown in equation (2), where low SOC and sparse stations exponentially increase charging probability. In equation (2), r refers to the SOC in perunit, $V.\theta$ represents the vehicle's threshold below which the anxiety rises rapidly and k is the sigmoid steepness parameter, which represents how quickly the anxiety rises when the SOC drops below the threshold $V.\theta$. With this approach, charging occurs probabilistically: if a random draw is less than the anxiety value, the truck charges for a fixed period (e.g., 30 minutes). For example, at 10% SOC in a sparse network (density factor = 0.5), with steepness parameter $k = 10$ and threshold $V.\theta = 0.2$, anxiety ≈ 1.46, triggering certain charging (Line 8), while dense networks (density factor = 1.5) reduce this probability to 49%. This approach reflects a principle of risk aversion, in which drivers place more emphasis on the risk of battery drain than truck operational schedule. This process continues for all legs, and after the last segment, the SOC is reduced by the energy needed to reach the final station.

$$a = \frac{1}{V.\text{df}} \cdot \frac{1}{1 + e^{-k\cdot(V.\theta - r)}} \tag{2}$$

Algorithm 2 Schedule-Compliant Charging (SCC)

1: **function** SCC(Vehicle V)
2: $S \leftarrow V.S_{\max}$
3: $b \leftarrow 0.2 \cdot (V.S_{\max} - V.S_{\min})$ ▷ Energy safety buffer
4: $n \leftarrow V.\text{dt}/4.5$
5: **for** $i = 1$ **to** n **do**
6: $S \leftarrow S - V.\text{c} \cdot V.\text{v} \cdot 4.5$ ▷ $V.c$ is the energy demand per kilometer
7: $e_{\text{need}} \leftarrow \max(V.\text{c} \cdot V.\text{v} \cdot V.\text{t}_{\text{cs}} + b - S, 0)$
8: $t_{\text{c}} \leftarrow \min(e_{\text{need}}/V.P, 0.75)$ ▷ $V.P$ is the charging power, 0.75 is 45 min charging session
9: $S \leftarrow \min(S + V.P \cdot t_c, V.S_{\max})$
10: **end for**
11: $S \leftarrow \max(S - V.\text{c} \cdot V.\text{v} \cdot V.\text{t}_{\text{cs}}, V.S_{\min})$
12: **return** S
13: **end function**

2.2 Agent-based simulation

The agent-based simulation represents the core processing phase of the methodology, where vehicle agents traverse a defined road network while making autonomous decisions based on their state, journey parameters, and battery conditions.

The simulation employs a Finite State Machine (FSM) architecture for each vehicle agent, which advances through several distinct operational states. The process begins with vehicle generation (GEN), where individual truck agents are stochastically instantiated according to temporal traffic patterns derived from the input data (see **HDV traffic** in Section 2.1). Each generated vehicle is assigned key attributes including vehicle model (determining battery capacity, consumption rate, and charging power), origin of the travel, initial State of Charge (based on SOC estimation, see Section 2.1.1), and potential entry points

Algorithm 3 Anxiety-Driven Charging (ADC)

```
function ADC(Vehicle V, DC-interdistance D)
    S ← V.S_max
    t_leg ← D/v.v                              ▷ Driving time between charging stations
    n_legs ← V.dt/t_leg                        ▷ Number of legs
    for i = 1 to n_legs do
        S ← S − V.c · V.v · t_leg
        S ← max(S, V.S_min)
        r ← (S − V.S_min)/(V.S_max − V.S_min)
        a ← GetAnxiety(V, r)                   ▷ Equation (2)
        if random() < a then
            S ← min(S + V.P · 0.5, V.S_max)
        end if
    end for
    S ← max(S − V.c · V.v · V.t_cs, V.S_min)
    return S
end function
```

to the simulation area.

The ENTRY state represents the vehicle's introduction to the modeled road network at specific entry points, with transition probabilities (p_1, p_2, p_n) determining the distribution of entries across different possible ingress locations. A critical decision point occurs when evaluating whether to transition to the CHARGING state. This transition is triggered when one of two conditions is met, depending on the Charging mode (see Section 2.1.1):

- **SCC mode**: The vehicle's SOC falls below a minimum threshold (typically 30% of battery capacity)
- **ADC mode**: The driver's anxiety level exceed a stochastically sampled random threshold.

When a vehicle transitions to the CHARGING state, it interacts with a charging station agent at its current location, requesting an available charging port. If not available, the vehicle enters in a waiting queue. The charging station agent maintains a record of all connected vehicles, calculates instantaneous power demand, and tracks occupancy levels. Each vehicle's charging session is modeled with vehicle-specific parameters including maximum charging power, battery capacity, and current SOC.

The charging duration is calculated based on:

- The energy deficit (difference between current SOC and maximum battery capacity)
- The vehicle's maximum charging power
- The maximum power of the available charging port

Upon completion of charging, the vehicle transitions back to its journey, advancing toward its EXIT state where it leaves the simulation area through one of several possible exit points.

2.3 Load profiles

Even though the simulation follows an event driven approach, load profiles are sampled over the charging station at a configurable temporal resolution (typically 15-minute intervals). The output of the simulation provides aggregated charging station load profiles, visualized as temporal power demand patterns throughout the day. These profiles capture both the average behavior and statistical variations in charging demand, represented through occupancy and power demand over time. The statistical representation through boxplots and time series visualizations allows for analysis of both average behavior and extreme scenarios, supporting robust infrastructure planning that accounts for variability in daily operations.

Figure 2: The road stretch used in the case study, with entries and exits along the towns of Stjørdal and Verdal, and the location of the charging station.

Table 1: Requirements for charging stations for heavy-duty vehicles along the TEN-T network [2].

TEN-T network, per direction	**Year**	**Distance between charging stations (km)**	**Total power at station (kW)**	**Power per charging point (kW)**
Core network	2025	120 for 15% of TEN-T	1400	1·350
	2027	120 for 50% of TEN-T	2800	2·350
	2030	60	3600	2·350
Comprehensive network	2025	120 for 15% of TEN-T	1400	1·350
	2027	120 for 50% of TEN-T	1400	1·350
	2030	100	1500	2·350

3 Case study

The methodology presented in Section 2 has been applied on a case study located in an area of the highway E6 between Stjørdal and Verdal. The highway stretch is part of the TEN-T comprehensive network, and is about 60 km long. The stretch was chosen because it is located away from large urban areas, making it suitable to investigate behavior of long-haul transport without considerable noise from vehicles circulating within the area. Additionally, there are few roads branching out of the main road, with relatively little traffic, making the assumption of one exit and one entry on each endpoint more realistic. The charging station is in Gråmyra, Levanger. There exists both a fuel and a charging station there today. There also a charging station for HDVs planned in Gråmyra, which has received support from Enova [13].

The case study is based on input data from open source datasets publicly available, that make the methodology widely replicable in any context in Europe. More specifically:

- **Street topology**: The road network is modelled using a graph from the osmnx library in Python. Because the stretch is relatively short compared to the recommendations of having one fast charging station every 120 km (see Table 1, with reference to the comprehensive network), only one charging station is modelled in the simulation. The simulated charging station is modelled as two charging stations placed next two each other in two different lanes, to ensure that it is reachable from every position of the road. However, it is studied as a single aggregated charging load served by the same power system feeder. The road stretch and the location of the charging station are depicted in Figure 2.

- **Truck models:** The vehicle model types used in the simulation are based on existing electric trucks on the market. The models used in the simulation together with their specifications are summarized in Table 2. Because no distribution is found, the vehicle model of an agent is sampled from a uniform distribution. Only E-trucks with a driving range of 350 km or more are included. The rate of electrification of the fleet is obtained from the statistics reported by the Norwegian Statistics Bureau [14], which reports, for 2024, 1789 electric trucks over a total of about 66000 trucks. Based on this figure, a rate of electrification of 3% is assumed for 2025. By considering

Table 2: Technical specifications for selected electric heavy-duty trucks, compiled from official manufacturer information and publicly available independent test data.

Manufacturer	Model	Battery size [kWh]	Charging power [kW]	Range [km]	Efficiency [kWh/km]	Release year
Mercedes-Benz	eActros400	420	160	400	1.05	2021
MAN	eTGS	500	375	650	0.77	2021
Iveco/Nikola	Tre BEV	733	350	530	1.38	2022
DAF	XF Electric	525	325	350	1.50	2022
Scania	P45 Electric	520	375	395	1.32	2022
Volvo	FH Electric	540	250	395	1.37	2023
Volvo	FM Electric	450	250	380	1.18	2023
Mercedes-Benz	eActros600	600	1000	600	1.00	2024
MAN	MAN eTruck	520	750	700	0.74	2024

a growing rate of electrification of the trucks fleet (12.5% of new trucks sold in 2024 in Norway were electric), a rate of 10% is assumed as a realistic value for a future scenario set in 2030.

- **HDV traffic**: Several National Road Administrators (NRAs) provide free access to traffic historical data. In Norway, the Norwegian Public Roads Administration (Statens Vegvesen) provides traffic records from a system of inductive loops deployed in Norwegian streets and highways through a public API [15].
- **Transport routes** The Synthetic European Road freight transport describes estimated European truck traffic flows between 1,675 regions all over Europe and is based on the publicly available ETISplus project from 2010 [16, 17]. The project collected Europe-wide freight volumes and calibrated the resulting origin-destination matrices with real world traffic flows. With Stjørdal and Verdal being own nodes in the synthetic road freight transport dataset, the choice of the two also simplified the traffic flow modelling.
- **Driving patterns**: The SOC estimation framework distinguishes between two driver types: a schedule-compliant model (SCC mode), where regulated fleets charge predictably at mandated intervals, and an anxiety-driven model (ADC mode), where individual drivers make stochastic charging decisions based on the simulated anxiety level. For more details, see Section 2.1.1.

The case study aims at determining the expected load profiles from long-haul trucks charging demand utilizing the charging station located in the observed area. Two scenarios are analysed based on Table 1:

- **Case 1**: The first scenario is set in 2025, with a fleet electrification rate of 3% and a charging station every 160 km, characterized by a total power of 1400 kW per lane and a single charging point of 350 kW each.
- **Case 2**: The second scenario is set in 2030, with a fleet electrification rate of 10% and a charging station every 100 km, characterized by a total power of 1500 kW per lane and two charging points of 350 kW each.

For each case, two different SOC estimation models are used: the Schedule-Compliant Charging (SCC) model (**sub-case a**) and the Anxiety-Driven Charging (ADC) model (**sub-case b**). The impact of the two different SOC estimation models on the load profiles is comparatively analysed. The simulation considers a time horizon of 3 months (the input traffic data includes the interval from March to June 2024), and the results are aggregated with a time resolution of 15 minutes. The results are presented and discussed in Section 4.

4 Results

Figure 3 presents the simulation results for both SOC modeling approaches for Case 1, whereas Figure 4 reproduces the simulation results for Case 2. The load profiles patterns reveal notable divergences as electrification rates and infrastructure capabilities evolve between 2025 and 2030, and between the sub-cases representing the two different SOC estimation models.

The comparison between Schedule-Compliant Charging (SCC) and Anxiety-Driven Charging (ADC) models demonstrates remarkable consistency in the 2025 scenario. Both approaches generate similar load patterns with peak demands of approximately 800 kW during the 10:00-14:00 period, though the SCC model occasionally produces outliers approaching 900 kW (Figure 3a). The aggregated statistical indicators (mean, median, and quartiles) exhibit strong correspondence between the two models, suggesting that despite their fundamentally different behavioral frameworks, the expected charging patterns under the limited electrification conditions in 2025 are consistent.

As fleet electrification increases by 2030, the results between the two modelling approaches diverge significantly. The SCC model predicts substantially higher power demands (Figure 4a), with peaks reaching 2200 kW compared to the 1500 kW maximum predicted by the ADC model. This disparity extends to station occupancy, where SCC projects concurrent charging for up to 10 trucks, while ADC estimates a maximum of 6 simultaneously charging vehicles (Figure 4b). The statistical moments likewise reflect this divergence across both load demand and occupancy metrics.

4.1 Discussion of results

The divergence in 2030 projections likely stems from the increased density of charging infrastructure mandated for this period. In the ADC model, enhanced station availability reduces driver anxiety levels, enabling more flexible charging decisions and potential postponement to subsequent stations. This behavioral adaptation is not captured in the SCC model, which maintains rigid compliance with regulatory breaks regardless of infrastructure density.

These findings highlight the sensitivity of load forecasting to behavioral assumptions, particularly as electrification scales. For grid planning purposes, the SCC model may provide more conservative estimates suitable for capacity planning, while the ADC model offers insights into how actual behavior might distribute load more efficiently across an expanded network.

Future validation against empirical data will be essential to determine which model more accurately represents heavy-duty vehicle charging patterns and to calibrate parameters accordingly. The acquisition of historical charging data from early electric truck deployments represents a critical next step for refining these projections.

5 Conclusion

This study presented an agent-based modeling approach for simulating high-power charging station load profiles for long-haul electric trucks. Based on open-source publicly available data and EU regulations for infrastructure development, the methodology incorporated two distinct driver behavior models: Schedule-Compliant Charging (SCC) and Anxiety-Driven Charging (ADC).

A Norwegian highway corridor served as the case study, analyzing two time horizons (2025 and 2030) and comparing resultant 15-minute resolution load profiles aggregated over a three-month simulation period. The results revealed that while both behavioral models produce similar load patterns in early adoption scenarios, they diverge significantly as electrification and charging infrastructure density increase, with implications for grid capacity planning and investment strategies. This differentiation highlights the importance of behavioral characterization in charging infrastructure planning.

Future work should focus on validating these models against empirical data as it becomes available and further refining the agents' parameters based on real driver behavior studies.

Acknowledgments

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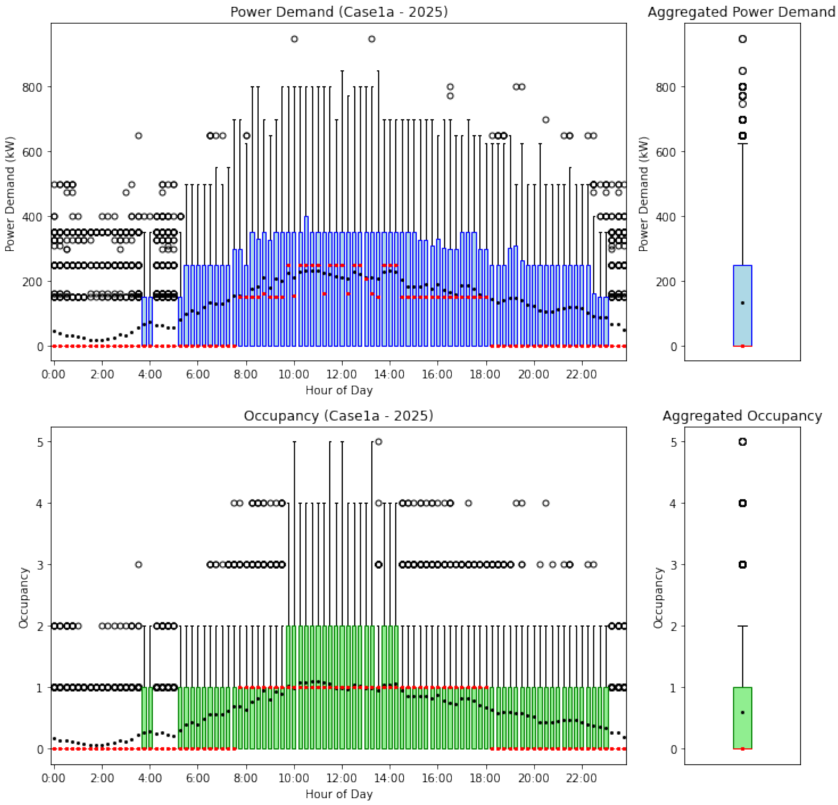
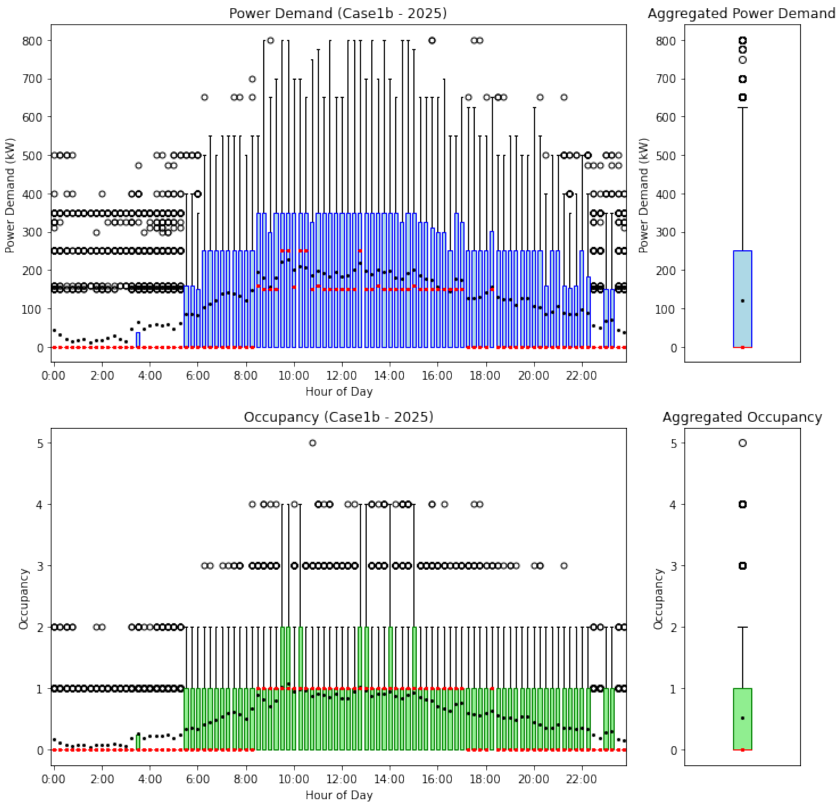
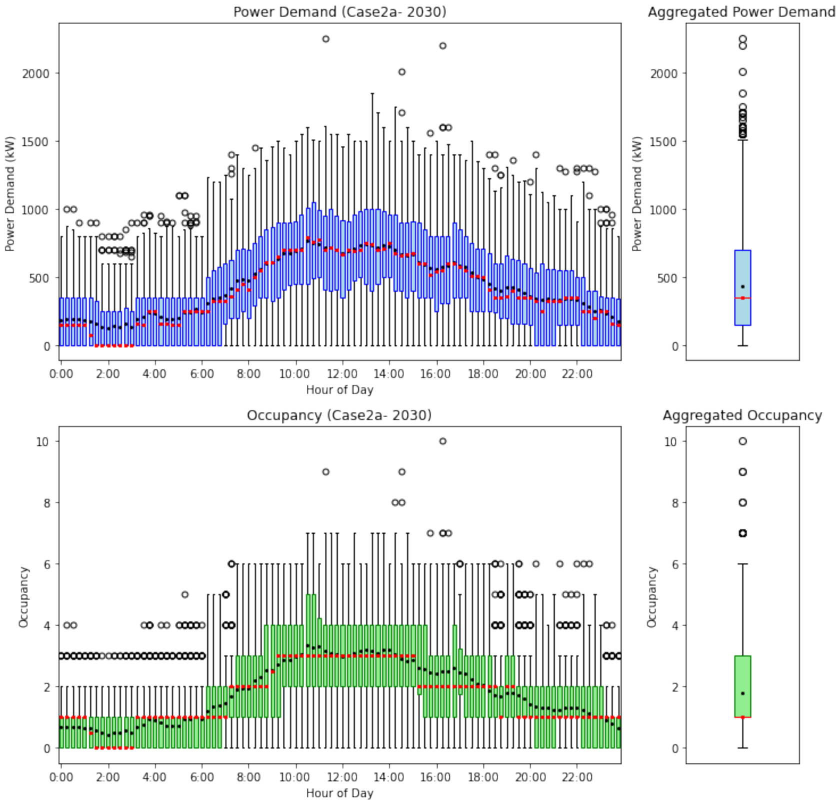


(a) Case 1a: SCC Mode

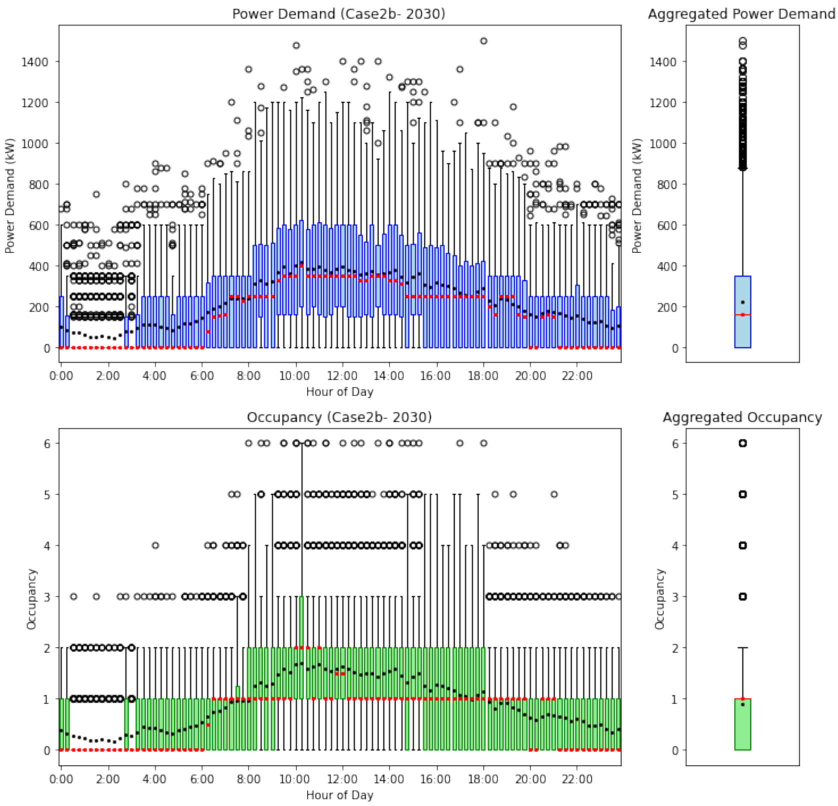


(b) Case 1b: ADC Mode

Figure 3: Results of the 2025 scenario simulation for the two SOC modeling approaches: (a) Case 1a-Schedule-Compliant Charging (SCC); (b) Case 1b-Anxiety-Driven Charging (ADC). Red squares represent the median values, while black squares denote the mean values for each time interval.



(a) Case 2a: SCC Mode



(b) Case 2b: ADC Mode

Figure 4: Results of the 2030 scenario simulation for the two SOC modeling approaches: (a) Case 1a-Schedule-Compliant Charging (SCC); (b) Case 1b-Anxiety-Driven Charging (ADC). Red squares represent the median values, while black squares denote the mean values for each time interval.

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