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Investigating the Impact of Electrifying Heavy-Duty Trucks on Power Grids Using Agent-based Simulation and Probabilistic Load Modelling

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Executive Summary

This paper presents an integrated simulation framework that combines agent-based transport modeling with probabilistic power flow analysis to assess the grid impact of heavy-duty vehicle electrification. The approach is applied to a case study of fully electrified long-haul road freight in the Skåne region of Sweden, using high-resolution transport demand data and an actual power grid model. The agent-based model produces probabilistic charging demand profiles for each station, which are then used as input to a probabilistic load flow simulation. The simulation estimates the resulting loading of substation transformers, including the probability of transformer overload. The simulation results show that in one-third of the studied substations, the maximum transformer loading exceeds 100% following the introduction of truck charging. Peak charging demand typically occurs from late morning to noon, aligning with the early stages of logistics operations. Interestingly, truck charging can reduce reverse power flows and mitigate the risk of curtailment in areas with high wind power penetration. These findings highlight the value of integrated transport–energy simulations for planning resilient infrastructure and guiding targeted grid reinforcements.

Keywords: Electric Vehicles, Heavy Duty electric Vehicles & Buses, Fast and Megawatt charging infrastructure, Modelling & Simulation, Power Electronics system

1 Introduction

To realise a zero-emission transportation fleet, a potent action is to electrify. Electrification can be realized through various energy carrier technologies (e.g., batteries or fuel cells) and re-energization (e.g., plug-in fast charging, charging while driving, battery swapping, or hydrogen refilling). According to EU regulation AFIR [1], member states must deploy plug-in fast-charging stations along the Trans-European Transport Network (TEN-T) core and comprehensive road network by 2025. Projecting the future charging demand generated by a fully electric transport fleet requires comprehensive datasets regarding transport movement, valid assumptions for vehicle energy consumption, and potential route changes imposed by fewer charging opportunities compared to refueling with conventional fuels, as well as shorter driving ranges. Due to the system-level impacts of electrification — such as changes in vehicle routing behavior, infrastructure usage, and energy demand patterns — agent-based simulation and modeling are essential tools for assessing and providing detailed guidance on charging and power grid infrastructure planning.

1.1 Literature review

The electrification of transportation introduces new demands on the electric grid, particularly due to the potential for concentrated and unpredictable charging loads [2]. To address this, some studies have coupled detailed electric vehicle modeling with power system simulations to assess grid impacts under different charging scenarios, such as Hu et al. [3]. Another study by Zhou et al. [4] integrates travel demand estimation and grid constraints into optimizing charging infrastructure. These studies demonstrate the effectiveness of using detailed transport models to understand the impact of electrification on the power grid; however, they rely on simplified or aggregated representations of vehicles. This limits their ability to capture the spatial and temporal variation of a large-scale real-world scenario.

Additional studies have explored the interaction between truck charging profiles, electromobility transport behavior, and their impact on the power grid. From a transportation modeling perspective, Shoman et al. [5] assess the infrastructure needs for truck charging within a European context, using transport demand models to estimate charging demand requirements. Similarly, Walz et al. [6] present a probabilistic approach to constructing truck-charging load profiles, offering insight into demand variability. However, both studies omit power grid simulations, thereby limiting their applicability to integrated infrastructure planning.

Some studies address this by combining charging demand modeling with grid simulations. Safdarian et al. [7] integrate power grid analysis with the estimated charging demand of both light- and heavy-duty vehicles derived from travel surveys and trip data, illustrating the potential of coupling transport and grid domains. However, their approach lacks detailed transport simulation and energy consumption modeling at the vehicle level, as the study relies on a simplified energy consumption model that uses constant values of energy use per mile rather than accounting for variations due to vehicle speed and road slope. In contrast, Borlaug et al. [8] simulate charging demand from depot-based freight operations and analyze its impact on the distribution grid, particularly at the substation level. While this work offers detailed insights into depot charging, it does not extend to en-route charging estimation or broader freight travel behavior.

1.2 Paper contribution

Previous studies have highlighted the value of integrating the transport and energy domains while also pointing to a research gap: the need for detailed simulations that account for trip-level energy consumption, en-route charging patterns, and spatial-temporal impacts on the electric power system. This motivates further research that couples high-resolution transport models, which capture charging demand for a given charging infrastructure, with power grid simulations to support planning for large-scale truck electrification.

Several studies explore charging infrastructure planning and demand modeling using both empirical data and simulation-based approaches. However, challenges remain in capturing the detailed movements of electrified vehicles and addressing the availability of existing charging infrastructure.

This paper addresses these challenges by introducing a novel combination of two methods: an agent-based simulation of transportation flows and a probabilistic power grid load simulation, which together provide a detailed understanding of the impact of electrified vehicles on the total power grid load.

Given the level of detail required in the underlying data and the authors' access to it, this study focuses solely on the effect of long-distance, heavy-duty trucks on a specific region in Sweden, namely Skåne. The method is, however, easily replicable for other regions if sufficient data is provided. The main contributions of this paper are:

- The integration of an agent-based transport simulation with a one-to-one representation of long-haul truck transport and a probabilistic load flow (PLF) model for the actual power grid.
- The generation of high-resolution, probabilistic charging demand profiles for heavy-duty vehicles at the station level.
- A regional case study of Skåne, Sweden, demonstrates how spatially distributed charging demand from electrified freight transport affects average and peak transformer loading in a real power grid model.
- A modeling approach can be adapted to other regions or vehicle segments, given suitable transport and grid data.

2 Methodology

This paper utilizes two separate models to simulate both the goods transportation and the power grid. In this section, both methods and their combined interaction are described.

2.1 Agent-based modeling and simulation

To generate a comprehensive spatio-temporal power demand for the probabilistic power grid simulation, a model providing a detailed insight into goods transport in Sweden is needed. Creating a synthetic representation of the transport flow enables a realistic simulation of daily transportation patterns.

2.1.1 Modeling a fully electrified Swedish goods transport

The modeled population, representing a fully electrified daily long-haul transport of long-haul truck agents, is produced from the Swedish Transport Administration's Swedish National Goods model, Samgods [9], output. Samgods generates optimized goods transport flows based on data on aggregated monetary flows between companies in Sweden. Goods are categorized, and the model selects the most cost-efficient transport mode for every monetary flow within a category. The resulting output specifies the annual number of trips for origin-destination (OD) pairs related to goods transportation, including both domestic and international (imports and exports) transports. In this study, trips originating from foreign positions are relocated to the most suitable border entry point into Sweden, considering both road and ferry options.
To convert these aggregated annual transport flows into daily trips for synthetic agents, enabling transport simulation of a typical day, OD pairs are first filtered and then assigned probabilistically to individual agents based on the likelihood of their occurrence. This process generates a statistically likely average day from the annual data. All OD pairs with a daily number of trips higher than once daily will always be included in the typical day. There are, however, two limitations arising from using yearly data. Firstly, since no data on day-to-day variations is available, there is no accurate description of how one day affects the next. This makes it impossible to simulate a statistically correct sequence of days accurately. Secondly, the temporal variation of departure times during a day is unavailable when converting annual trips to daily ones. The second limitation has successfully been mitigated by obtaining data containing probability distributions of vehicle type and trip length-specific departure times, provided by truck manufacturers Scania CV AB and Volvo Trucks AB. Since the case study is limited to the Skåne region in Sweden, a regional filter is applied to the dataset to include only those trips that intersect the area at any point along their route.
Using available information and a dynamic vehicle simulation model created in MATLAB and Simulink, vehicle characteristics, such as battery capacity and energy consumption maps dependent on speed and road inclination, are assigned to each agent. All agents' OD trips are processed simultaneously, generating detailed data on energy consumption and battery levels in space and time. Since no data is available to statistically link one day to the next, variations in the modeled population are introduced by simulating agents across multiple versions of an average day, each with different battery capacities (i.e., driving ranges) and initial states of charge (SOC). A conditional assignment of initial SOC values is based on the trip origin. For trips originating domestically, the initial SOC is drawn from a range of 80% to 100%, reflecting the possibility of overnight charging. In contrast, the initial SOC is more uncertain for trips entering the system from foreign origins. It is therefore drawn from a broader range of 20% to 100%, representing variability in charging conditions prior to border entry. Thereby, the agents' conditions alter from one day to the next. A reconstruction of the modeled population is performed at every rerun of the transport simulation, ensuring that trips not occurring daily are assigned probabilistically according to their likelihood of occurring. Each simulated day produces a detailed time series of charging power for each charging station. An overview of the general approach to simulate variations of an average day is seen in Fig. 1.
The modeled population is processed on the Swedish road network, with information gathered from OpenStreetMap. The agents are allowed to charge at the locations where truck charging stations are built or will be built in 2025 as part of the governmental subsidy program ”Regionala Elektrifieringspiloter” [16]. Since the scenario investigates the impact of public charging infrastructure for a fully electrified long-haul transport sector, the current infrastructure in 2025 is assumed to be insufficient regarding the number of available charging points. Therefore, only the planned station locations are considered, and each station is assumed to have an unlimited number of charging points, each rated at 1 MW. This ensures that every truck requiring a charge will always be able to do so without waiting. It will also give the necessary charging demand at each charging station. While analyzing the effects of queuing or power grid limitations is undoubtedly relevant, it requires assumptions about both the number of charging points per station and the capacity of the local electricity grid. Estimating the former is challenging given the limited available data and detailed information about grid capacity, which is classified in Sweden, making such an analysis infeasible at this stage.

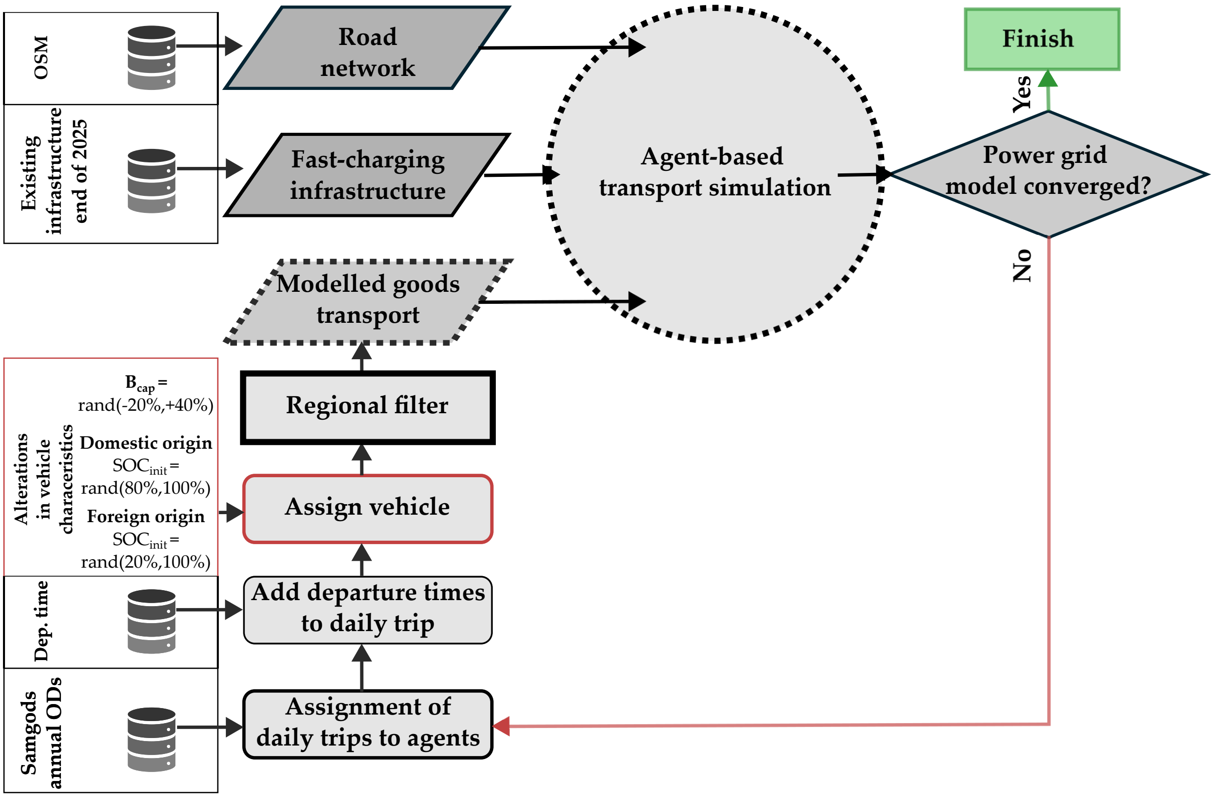

Figure 1: Simulation procedure showing the process of varying the modelled population to create daily variations.

2.1.2 Simulation of Swedish goods transport

The modeled population of agents is simulated for a total of 24 hours in a mesoscopic transportation simulation environment called MATSim [10]. MATSim is a simulation framework capable of handling large-scale transport simulations while also keeping a high level of detail for each simulated transport. The daily plans of all modeled truck drivers are simulated simultaneously. They are iteratively refined based on predefined behavioral rules, converging toward a stable state where agents no longer benefit from changing their plans. The iterative simulation process does not aim for a global optimum and instead focuses on optimizing individual agents. This makes the simulation process particularly suitable for this paper's study, which aims to simulate the self-interested decision-making of truck drivers. The MATSim runs are iterated until convergence in daily plans is observed, with an additional buffer of iterations applied afterward, resulting in a total of 20 iterations.
Each agent's behavior can be mathematically described using a scoring function S as follows:

$$S = \sum_{i=1}^{n} U_{\text{freight}} - \sum_{j=1}^{m} P_{\text{travel},j} - P_{\text{battery}} - P_{\text{delay}} \tag{1}$$

where:

- $U_{\text{freight},i}$ is the truck activity i at the start or end of the day during loading or unloading ($n = 2$).
- $P_{\text{travel},j}$ represents the penalty incurred by traveling along route segment j from origin to destination. This is summed for all m route segments. This penalty incentivizes minimizing travel time.
- This work uses a P_{battery} to apply a discrete penalty, which is put relative to one hour of travel time. This ensures that no plans with detours longer than one hour will be chosen over a plan with battery depletion.
- P_{delay} inflicts a discrete high penalty if the agent fails to reach its second activity on time. This standard feature of MATSim ensures that the agent is penalized if it never leaves its first activity, which is possible in rare circumstances.

In this work, charging activities are pre-planned in a pre-simulation phase, where the agent's SOC is estimated spatially along the road network. When the estimated SOC reaches below a randomly selected threshold between 15% and 40%, which applies to the first 80% of the MATSim iterations. This approach ensures that multiple charging station options are explored. In the final 20% of iterations, charging decisions are fixed based on the five highest-scoring plans.
For each MATSim run, each agent will create a route that includes the most efficient charging activities, provided that sufficient charging infrastructure is available. Each charging activity's energy transfer and time are logged. This information is aggregated for all agents, and hourly power demand curves are generated for each charging station. These demand curves are used as input to the power grid simulation.

2.2 Interface between simulation models

The interface between the simulation models is described in Fig. 2, which describes the ingoing data and the resulting outputs from the transportation simulation feeding the probabilistic load flow simulation.

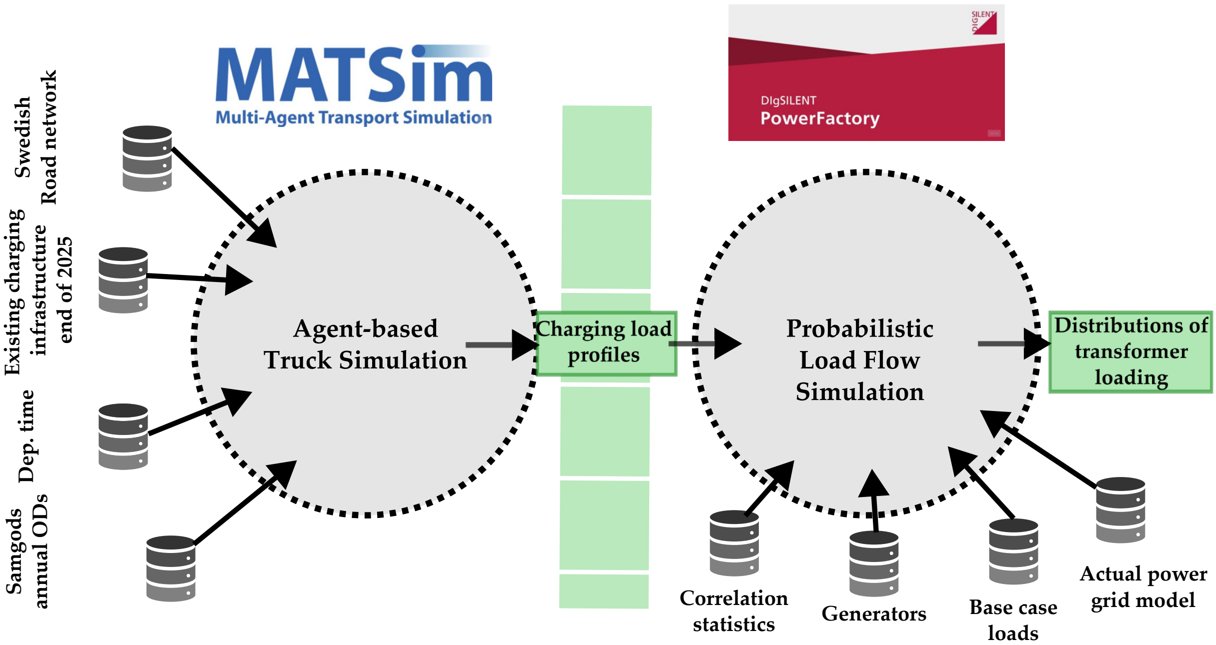

Figure 2: Total overview of the data inflow and outflow when combining the simulation procedures.

2.3 Power grid simulation

A probabilistic load flow (PLF) simulation is run using the simulation tool DIgSILENT PowerFactory [11] to analyse how truck charging impacts the grid capacity. The grid model used is the actual transmission (400 kV) and sub-transmission (135 kV) grid model used by the grid owners in the study area. Due to security constraints, the model can not be shared openly, but some key statistics are listed in Table 1. The grid has a meshed topology.

Table 1: Grid elements in grid model used.

Element Type	Elements in Study Area	Element Type
Bus	378	Static
Load	150	Input
Generator	79	Input
Line	198	Output
Transformer	169	Output

The inputs to the PLF simulation are distributions of truck charging loads, base case loads, and generators in the system. The bootstrapping method [12] is applied to draw random values from the truck charging load time series generated by the MATSim simulation. For the base case loads, 10 years of historical hourly data is available, on which the bootstrapping method is applied to draw random values.

The generators in the study area mainly consist of distributed wind power and combined heat and power (CHP) plants. Parameterized probability distributions to model wind power plants have been developed in [13] and are used as input in this study. Wind power generators are modeled using Weibull distributions, as in:

$$f(x) = \frac{k}{\lambda} \cdot (\frac{x}{\lambda})^{k-1} \cdot \exp\left(-(x/\lambda)^k\right) \tag{2}$$

where $\lambda = 0.22 \cdot P_{rated}$ (P_{rated} being the rated power of the wind power plant) and k = 0.85. These parameters were calculated in [13] based on historical wind power data in the study area. The CHP plants are modeled using uniform distributions as described by:

$$f(x) = \begin{cases} \frac{1}{P_{max}-P_{min}}, & \text{if } P_{min} \leq x \leq P_{max}, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

where P_{max} is the maximum and P_{min} the minimum power of the plant.

The different input parameters to the PLF simulation can not be assumed to be independent. Studies have previously shown that EV charging loads from cars are highly correlated to other loads in the system [15], which implies that the same may be true for truck charging loads. This is considered by calculating a correlation matrix from the generated truck charging profiles and the 10-year datasets of basecase loads. The correlation is then captured in the PLF simulation by using Gaussian copulas [14]. Based on Sklar's theorem, a copula C links the random variables X and Y, which have continuous cumulative distribution functions (CDFs) F_X and F_Y, if their joint distribution can be expressed as

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)). \tag{4}$$

The PLF simulation uses 5000 iterations, and the adequacy of this number was decided based on a visual convergence test.

3 Results and discussion

The combined simulations provide detailed information regarding the charging demand for each agent and station, as well as the impact of charging stations on the nearest primary substation transformer.

3.1 Charging Load Profiles

As the conditions of the simulated population vary, so does the demand for charging. The resulting charging demand across all stations is shown in Fig. 3. Peak demand occurs between 9:00 and 12:00, driven by differences in initial battery levels and vehicle ranges. This time-resolved charging demand data, capturing within-day variations, is used as input to the power grid simulation.

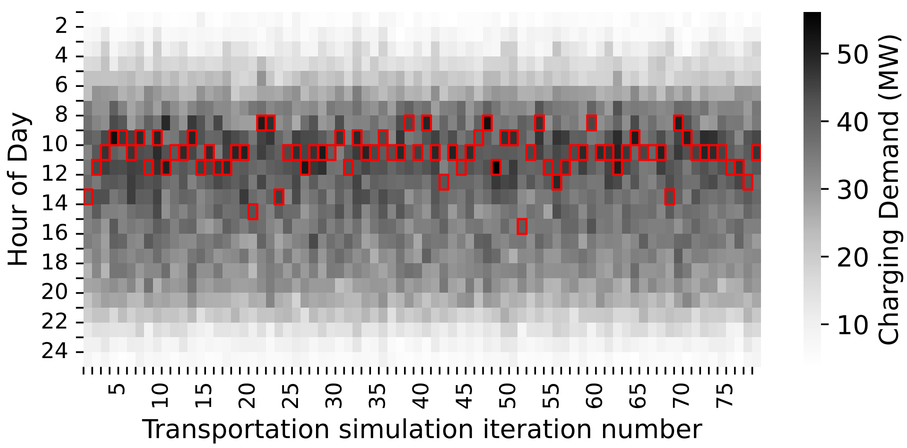

Figure 3: Charging demand for long-haul trucks for all stations across all iterations. The hour of peak power demand is highlighted in red.

It is important to note that passenger car data is omitted primarily due to the lack of detailed statistics on departure times for trips. Origin and destination matrices are available for long-distance travel and light-duty transport. Whilst an essential addition to understanding the full scope of the impact of electrification on the power grid, assumptions made without a statistical basis for agents' departure times will dilute the accuracy of the presented results. This statistical basis could be reached, for example, through a comprehensive travel survey or the gathering of mobile phone data.

3.2 Grid Capacity Impact

The PLF simulation generates results in the form of probability distributions of transformer and power line loading. To check the convergence of the PLF simulation, a visual convergence check was made of the rolling average and standard deviation of the loading of all transformers in the study area. This is presented in Fig. 4, which shows converging results already at 2 000 PLF simulation iterations.

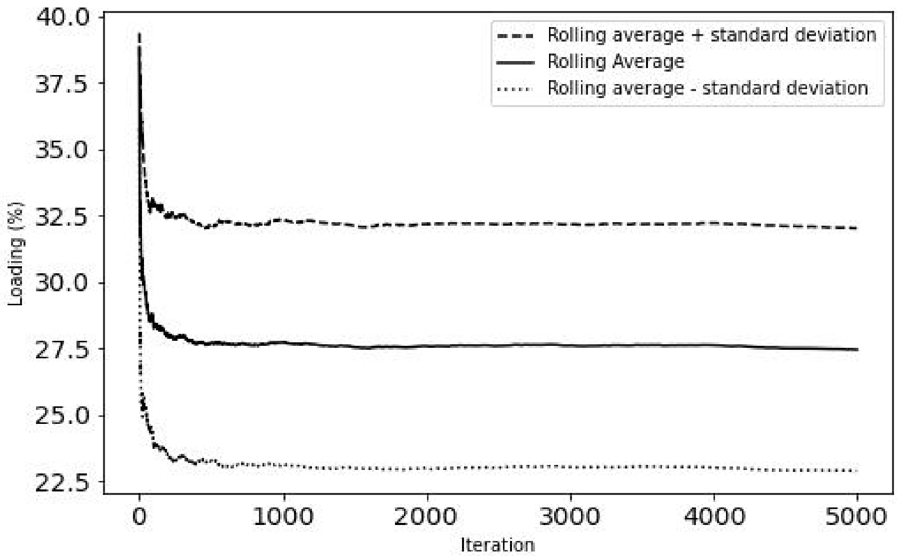

Figure 4: Convergence plot of the rolling average loading of analyzed transformers.

The PLF simulation shows that the introduction of public truck charging will increase the average and maximum loading of the primary substation transformers in most cases. Fig. 5 shows the substation transformers' maximal loading before and after introducing truck charging. In 6 out of the 18 transformers where truck charging is introduced, the maximal loading exceeds 100 %. However, there are also two cases (Substations H and R) for which the introduced truck charging results in a lower substation loading. This can be explained by the presence of distributed wind power generation at those substations, which causes a risk of high reverse power flows. In this study, some of that power is used to charge the trucks, thus lowering the loading on the substation. In other cases, the distributed generation may need to be curtailed to prevent overloading. The simulation in this study does not capture this curtailment but instead quantifies these risks of high transformer loadings. Fig. 6 plots the average transformer loading, which increases in all of the substations after the truck charging is introduced.
The grid capacity impact is highly dependent on the size of the primary substation transformer and its base case loads and generation. This can be seen in Fig. 7, which compares the average truck charging load per substation with the average loading of the substation transformer. From this graph, it is evident that the transformer loading does not depend only on the truck charging load. The three substations with the highest average truck charging load (A, C, and L) do not directly correspond to the three substations with the highest average transformer loading (G, B, and A). This highlights the need for power systems simulations and good knowledge on the power grid studied when assessing the grid impact from new loads on the system.

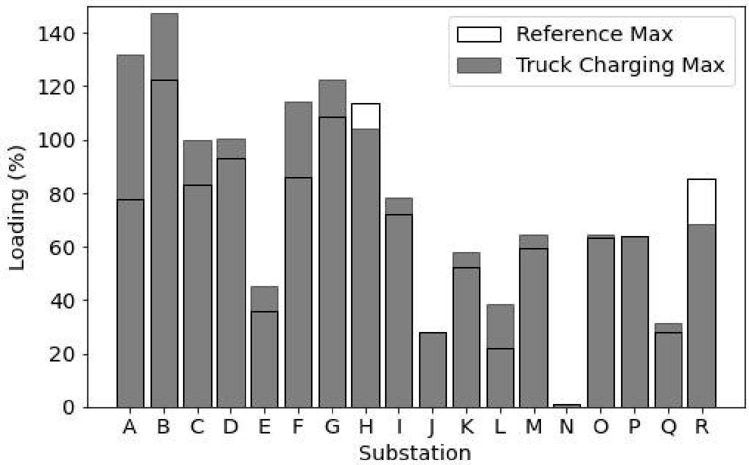

Figure 5: Maximum loading of transformer stations in with introduced truck charging (gray) compared to the reference case (white).

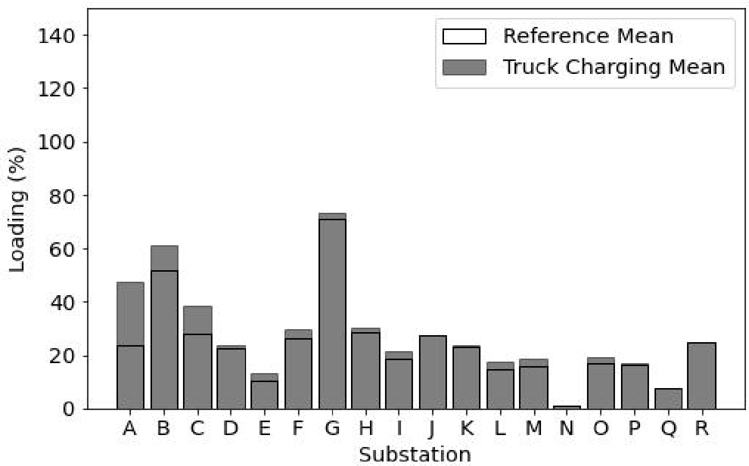

Figure 6: Mean loading of transformer stations in with introduced truck charging (gray) compared to the reference case (white).

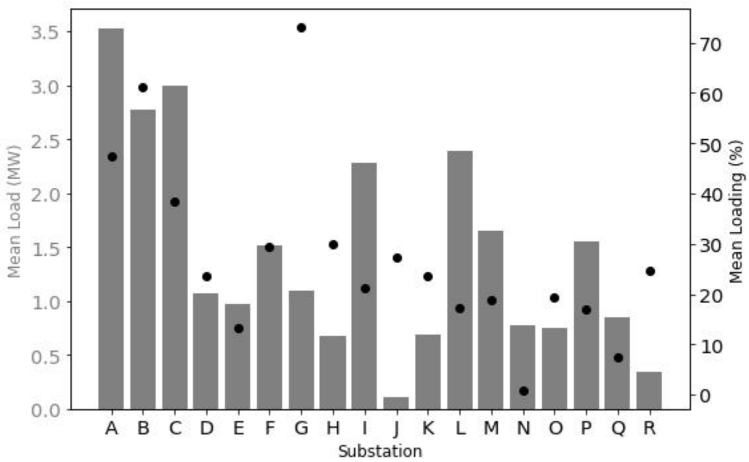

Figure 7: Comparison of average truck charging load (grey) and mean transformer loading (black).

4 Limitations and future work

The data source represents today's goods transport demand, and it is vital to understand how this might change in the future. The Swedish Transport Administration has, since the simulation work of this paper was conducted, presented prognoses for the evolution of goods transport until 2045. A natural improvement on this work would be to update the dataset to contain their projected future goods transport demand. Moreover, this combined modeling approach presents several branching research directions. The impact of different technologies on the power grid can be analyzed by introducing other charging possibilities, such as electric road systems and battery swapping. Altering the logistic flows to minimize charging peak power demand to understand what could be done is also a topic to expand this work upon.

5 Conclusion

This study demonstrates a combined simulation approach that integrates detailed agent-based transport modelling with a probabilistic power system load flow analysis to assess the impact of large-scale truck electrification on the power grid. The approach enables a detailed estimation of spatial and temporal charging demand from electric long-haul trucks, which is an essential input for power grid impact assessments.

The transport simulation results reveal that the charging demand varies significantly depending on the initial SOC and driving range assumptions. The peak charging demand occurs mainly during the late morning hours until noon. The method captures possible charging patterns for a detailed origin-destination set with a supplementary dataset with departure times. These are subsequently used as input to a regional power grid PLF analysis.

The PLF simulation results show that introducing public truck charging leads to increased average and peak loading in several primary substation transformers, with six out of eighteen transformers experiencing loadings exceeding 100%. However, the study also identifies instances where truck charging mitigates reverse power flows caused by local wind generation, highlighting the complex interactions between new loads and existing distributed generation. These results reinforce the need for localised, data-driven power system modelling when evaluating the grid impact of transport electrification.

The analysis highlights the importance of accurate and detailed input data. While the current study focuses on long-haul freight due to available statistical support, including passenger vehicle demand would be a valuable next step, requiring more robust data on departure times. Additionally, incorporating future goods transport forecasts, as the Swedish Transport Administration provided, would strengthen the relevance of such simulations for long-term infrastructure planning.

Finally, the modelling framework presented here is extensible and opens several branches for future research, including the evaluation of alternative charging strategies (e.g., battery swapping or electric road systems), logistic adaptations to reduce power peaks, and coordinated planning between transport and energy sectors. These directions will be crucial in supporting a resilient and scalable electrification of heavy-duty transport.

Acknowledgments

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Presenter Biography

Mattias Ingelström obtained the M.Sc. in mechanical engineering with a major in computational mechanics from Lund University in 2019. He is a PhD candidate at Lund University's technical faculty in the Electrical Engineering and Automation division. His research specializes in agent-based simulation of transport systems to highlight a potential charging infrastructural need if the transport sector is electrified. His work so far has been conducted as part of the project E-Charge, which aims to demonstrate the feasibility of electrifying long-haul heavy-duty transport using battery technology and fast charging.