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An integrated mobility and energy simulation framework for assessing the impact of bus opportunity charging strategies on the power grid

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ABSTRACT

Electric buses (EBs) play a crucial role in achieving global greenhouse gas emission targets. However, efficiently operating an electric bus fleet (EBF) requires a comprehensive approach that considers both mobility and energy systems, particularly when implementing opportunity charging strategies. Existing literature and many real-life implementations often focus on only one of these systems, oversimplifying the other, which can lead to inefficiencies, operational challenges, or even unfeasible implementations. To fill this gap, we propose a framework to assess the impact of bus opportunity charging strategies on the power grid by integrating a traffic simulation model (SUMO) and a power grid simulation model (Gaia). SUMO evaluates the energy consumption and charging needs of the EBs, while Gaia assesses the impact of the transformer load in the distribution grid. The integrated method is applied to Rotterdam's bus line 36 to demonstrate the practicality of this approach. Results indicate that designing an electric bus route with opportunity charging is feasible only when both mobility and energy systems are carefully coordinated.

1. Introduction

Public transportation is essential for sustainable urban development, and electric buses (EBs) play a key role in reducing greenhouse gas emissions. By replacing diesel-powered buses, EBs not only improve air quality but also support efforts to decarbonize public transport. In the Netherlands, government policies strongly promote the adoption of EBs, aiming for all new buses to be emission-free within the coming years and transitioning the entire fleet to electric by 2030.[1] These commitments highlight the critical role of EBs in achieving a sustainable and resilient urban mobility system.

Recognizing these advantages, extensive research has focused on optimizing various aspects of electric bus fleet (EBF) operations, such as charging infrastructure optimization, charger placements, charging schedules, vehicle routing, and overall fleet investments (Liu et al., 2021; Alamatsaz et al., 2022; Wang et al., 2016; Zhou et al., 2022; Perumal et al., 2022; Zhang et al., 2024). For instance, Messaoudi and Oulamara (2019) developed an optimization model that simultaneously schedules buses and allocates charging times, aiming to reduce the number of buses used and minimize charging costs. Li et al. (2020) introduced a model that minimizes total operational costs by optimizing the placement of buses and charging stations. While these studies aim to reduce the costs and improve the operational efficiency of EBF operations, they often overlook the significant and intermittent electricity demands that EBs place on local grids, particularly during *opportunity charging*, where buses recharge at stops along their routes.

As indicated by Zhang et al. (2020) and Unterluggauer et al. (2022), effectively managing an EBF requires addressing the interplay between mobility and energy systems. These systems are deeply interconnected, as the charging demands of EBs can place considerable stress on local power distribution grids, potentially compromising grid stability and operational efficiency. Insights from personal EV research may help bridge this gap, as studies have extensively explored the effects of residential EV charging on power grids, focusing on strategies such as neighborhood charging schedules and centralized parking (Chudy et al., 2022; Dougier et al., 2023; Mohamed et al., 2017; Rogge et al., 2015). However, EBs charging presents unique challenges due to its higher power requirements and concentrated daytime loads under opportunity charging strategies. This can present significant challenges for grid infrastructure, which may not be prepared to accommodate such intense loads.

Recent developments in the Netherlands further highlight the practical consequences of these challenges. Public transport operators (PTOs) have struggled with insufficient grid capacity and underestimated

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[1] https://www.government.nl/topics/mobility-public-transport-and-road-safety/public-transport/goals-of-public-transport/sustainable-public-transport.

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charging times, leading to significant operational disruptions. For example, in Twente, a combination of inadequate charging infrastructure, grid limitations, and underestimated charging requirements resulted in delays and service interruptions (Omroep Flevoland, 2023; OVPro, 2023; NOS, 2023). These delays often occur when buses cannot charge on schedule, leaving them unprepared to meet their planned routes. Such experiences highlight the risks of focusing solely on the transportation systems while neglecting energy infrastructure. To overcome these challenges, an integrated simulation framework that considers both mobility needs and energy constraints is essential for ensuring the effective and reliable deployment of EBFs.

To this end, we propose an integrated approach that connects a traffic simulation method (SUMO) and a power grid simulation method (Gaia) for EB opportunity charging. SUMO is used to assess EB opportunity charging needs based on detailed data regarding vehicle movements, traffic signal interactions, and the effects of traffic management strategies, such as traffic priority measures, on travel times and energy efficiency. Complementarily, Gaia evaluates the impact of EB opportunity charging on local distribution grids using real-life consumption data and GO-E archetypes[2] derived from anonymized grid data from Dutch postal codes. Gaia enables a detailed analysis of how opportunity charging affects grid stability and capacity. By combining the capabilities of SUMO and Gaia, our approach offers a comprehensive decision support system for EB opportunity charging strategies. This integrated simulation framework allows exploring how different mobility and energy strategies interact, leading to more informed and robust decisions.

The main contributions of this work are as follows:

- We develop an integrated mobility and energy simulation framework that combines a traffic simulation model (SUMO) with a power grid simulation model (Gaia) to assess the impact of electric bus opportunity charging strategies on local distribution grids. The framework incorporates real-world grid data and GO-E archetypes, which represent anonymized consumption profiles, to evaluate the effects of opportunity charging on grid capacity and stability.
- We validate this framework using a real-world case study of bus line 36 in Rotterdam, the Netherlands. Five distinct charging strategies, varying in charging capacities, and schedules are tested. These strategies are assessed based on their ability to meet the operational demands of the bus fleet while minimizing the impact on the local power grid. The case study is used as an empirically grounded example to demonstrate the framework; the quantitative results are specific to this line and its local distribution grids, but they illustrate the type of insights that the approach can provide to public transport operators.

The remainder of this paper is structured as follows. Section 2 reviews related studies. In Section 3, we present the conceptual framework for integrating the traffic simulation model with a power grid simulation model. Section 4 describes the real-world case study, with results analyzed in Section 5. Finally, Section 6 concludes the paper and highlights future research directions.

2. Literature review

EBF management involves coordinated decisions on charging infrastructure, bus planning, vehicle scheduling, and routing. Two main charging strategies have been widely studied: depot/terminal charging, where buses recharge at depots or major terminals between trips, and on-route (opportunity) charging, where buses recharge during service at intermediate stops equipped with high-power chargers (Hu et al., 2022). This section reviews four relevant research lines, optimization models for depot/terminal charging, optimization for opportunity charging, simulation-based approaches, and grid impact studies.

2.1. Optimization for depot charging

Extensive research has focused on optimizing depot and station-based charging systems to enhance fleet efficiency and reduce operational costs. For example, Rogge et al. (2018) developed models that integrate fleet sizing and scheduling with heterogeneous infrastructure requirements. Liu and Ceder (2020) focused on minimizing the number of required EBs and stationary chargers at depots using integer programming models. These approaches primarily address operational efficiency but often simplify the energy demands on local power grids. Zhang et al. (2022) developed a bi-level integer programming model to determine the number of fast chargers and charging scheduling of EB fleet. These approaches effectively capture operational constraints, however, they often simplify the power system by assuming fixed electricity prices or total power limits, without explicitly modeling the local distribution grid. To address this limitation, recent work incorporates power network constraints directly into the optimization process for depot charging. Najafi et al. (2025) propose an integrated model that jointly optimizes bus schedules, charging infrastructure, and the sizing of on-site renewable generation and storage, while ensuring feasibility with respect to low-voltage grid constraints. Their case study demonstrates that adding local energy resources reduces operational cost and maintains compliance with distribution system limits. However, their framework only allows charging at depots and bus stations between trips, and not during trips.

2.2. Optimization for opportunity charging

Even though depot and terminal charging systems are widely adopted for their simplicity and straightforward implementation, opportunity charging has gained increasing attention due to its potential to enhance operational flexibility and minimize downtime. Opportunity charging employs fast chargers at bus stops, allowing buses to recharge during service routes. He et al. (2019) examined the deployment of fast charging stations at terminals and on-street stops, considering different charger types and electricity demand charges. Building on this, He et al. (2020a) proposed an optimization model to minimize total charging costs by scheduling charging operations and determining actual charging power under fixed charger and depot locations. Guschinsky et al. (2021) addressed the combined challenges of fleet sizing and charging infrastructure placement, specifically focusing on fast chargers at bus stops. Hu et al. (2022) investigated the joint optimization of charger locations and charging schedules for electric bus fleets utilizing opportunity charging. Wang et al. (2024) developed a joint optimization model to plan charger placement and fleet configuration, incorporating considerations for heterogeneous vehicles, opportunity charging operations, and battery degradation.

Despite these advances, most research on opportunity charging focuses primarily on mobility optimization, often overlooking the broader implications for local power grids. Fast chargers, which range from 50 kW to 500 kW, generate significant power peaks that can strain grid capacity, particularly in urban areas with high congestion.

To reduce the impact of opportunity charging on power grid, existing literature primarily focuses on optimizing charging costs through variable tariff models, assuming that cost reductions are directly correlated with grid impact reduction. For example, Wu et al. demonstrated a 25.88% reduction in costs alongside a 7.2% reduction in grid power loss, although these reductions are not always directly proportional (Wu et al., 2019). Research on personal electric vehicles provides

[2] The GO-E archetypes are a classification system developed within the Gebouwde Omgeving Elektrificatie (GO-E) research project by a consortium of energy and research-related companies to address privacy concerns surrounding energy consumption data (see van Noort (2024) Section 3.3 on Page 25 for detailed explanation.).

valuable insights into managing distributed energy loads (Sundstrom and Binding, 2011; Tan et al., 2016), but its direct applicability to EBs is limited. Unlike personal electric vehicles, which typically follow residential charging patterns, EBs require higher power demands and operate under concentrated daytime loads (Gong et al., 2012; Elnozahy and Salama, 2014; Prencipe et al., 2022). These unique operational profiles necessitate tailored approaches for opportunity charging systems.

2.3. Simulation and grid impact studies

Simulation studies complement optimization models by allowing detailed evaluation of electric bus operations under realistic traffic or infrastructure conditions. For example, Peng et al. (2024) developed a data-driven micro-simulation of the Shenzhen transit network to compare infrastructure scenarios for battery-electric and hydrogen buses. This work helps explore operational trade-offs under spatial and temporal demand variation, they often do not model the electricity system explicitly.

From the energy systems perspective, another body of work assesses the impact of electric bus charging on distribution networks. These studies simulate voltage profiles, transformer loads, and power losses to identify conditions that may require grid reinforcement or load management. For instance, Al-Saadi et al. (2022) evaluate the effects of ultra-fast electric bus charging and highlight the risks of transformer overloading during peak service hours. Their results show that even high-power pantograph charging (up to 350 kW) does not currently violate the limits. However, these studies do not capture mobility-related variables such as headways, dwell time windows, or operational constraints, and they do not assess feeder capacity limits under various charging strategies.

2.4. Research gap: the connection between mobility and energy in EB service design

Although extensive research has been conducted on optimizing EB charging infrastructure, vehicle scheduling, and fleet investments, the interaction between these operational decisions and the local power grid remains underexplored. Most studies either focus on the mobility aspects, optimizing charging schedules and vehicle routes, or on the energy aspects, modeling grid impacts in isolation. However, the combined challenges of managing EB fleet operations and mitigating grid impacts, particularly with opportunity charging, have received limited attention. Additionally, while there is significant literature on personal EV impacts on residential grids, the unique demands of EB charging and the role of opportunity charging strategies remain understudied.

3. Methodology

In this section, we present our integrated simulation framework that combines traffic simulation (SUMO) and power grid simulation (Gaia) to simultaneously address the mobility requirements and energy constraints of EB opportunity charging.

3.1. Overview

The Fig. 1 illustrates the proposed framework, which consists of two primary components: a mobility simulation model and a power grid simulation model. SUMO, a microscopic traffic simulation tool, models the movement and energy consumption of individual electric buses in real time, taking into account factors such as traffic conditions, stop durations, and route schedules. It uses inputs such as bus and route characteristics and charging strategies (detailed in the following section) to generate outputs, including travel times for completing a trip and detailed energy requirements for buses along their routes. Gaia, a macroscopic low-voltage grid simulation tool, evaluates the grid's ability to meet the energy demands provided by SUMO. It takes transformer characteristics and GO-E archetypes as inputs, assesses transformer load rates to determine whether the grid can support the required energy (which is indicated as required charger capacity for operation) for charging without destabilization. The interaction between SUMO and Gaia is facilitated through the exchange of data: SUMO provides Gaia with the power needs required at different points, while Gaia returns feedback on whether the grid can support these demands.

3.2. SUMO

In this study, SUMO is used to model the traffic network and simulate the energy consumption of EBs under various operational strategies. The case study network includes bus routes, traffic signals, and charging stations, all configured within SUMO. EBs are modeled using SUMO's electric vehicle module, with parameters such as energy consumption rates, battery capacities, and charging dynamics (Kurczveil et al., 2014). Following Kurczveil et al. (2014), at each simulation step, the model updates battery energy from a longitudinal-dynamics balance that depends on the simulated speed and acceleration, road gradient and curvature, aerodynamic and rolling resistance, and constant auxiliary power; charging contributes energy according to station power, efficiency, and dwell time. Hence, energy use is dynamic and emerges from traffic conditions rather than a fixed consumption rate.

Charging stations are also customized with parameters like charging speed, duration, and delays, representing the time required for buses to initiate charging after a complete stop. Traffic priority measures are dynamically integrated to optimize EB operations. This setup enables the analysis of how different traffic management strategies and charging configurations affect the energy consumption and operational efficiency of the EB fleet.

3.3. Gaia

Gaia is a software solution for planning, designing, and managing low-voltage electricity grids. Power grid operators (PGOs) can configure their grids within the software and calculate metrics such as system voltage, current (in Amperes), transformer load rates (as percentages), and network safety parameters (Phase to Phase, 2024). The simulation requires demand profiles for connections, as well as the characteristics of the cables used in these connections.

Gaia typically uses three demand profiles: a generic weekday, Saturday, and Sunday. This simplified subdivision reflects standard practice among PGOs and allows for monthly adjustments to account for seasonal variations. For instance, in winter, weekday heating demand peaks when people return from work, whereas weekend demand is more evenly distributed. The software models demand either through probability distribution functions or predetermined profiles. Probability distributions represent unpredictable components, such as PV modules or other household devices, allowing Gaia to simulate best- and worst-case scenarios by calculating 5th and 95th percentile thresholds. This approach helps evaluate the variability of grid performance under different demand conditions. An example of a probability distribution for household demand is shown in Fig. 2, which displays the probability curves for power demand from a PV system (red), heat pump (yellow), and a privacy-protected consumption pattern (green). The data shows higher power generation from PV systems in summer and higher demand from heat pumps in winter, reflecting seasonal trends.

In addition to probability distributions, Gaia uses predetermined demand profiles to model component demand over time. These profiles range from 0 to 1, representing a percentage of the component's maximum demand. For example, a 200 kW EV charger with a profile value of 0.6 would draw 120 kW from the grid. Fig. 3 shows a typical weekly demand profile for an EV charger, with weekday peaks when users return home and reduced power draw overnight as the battery

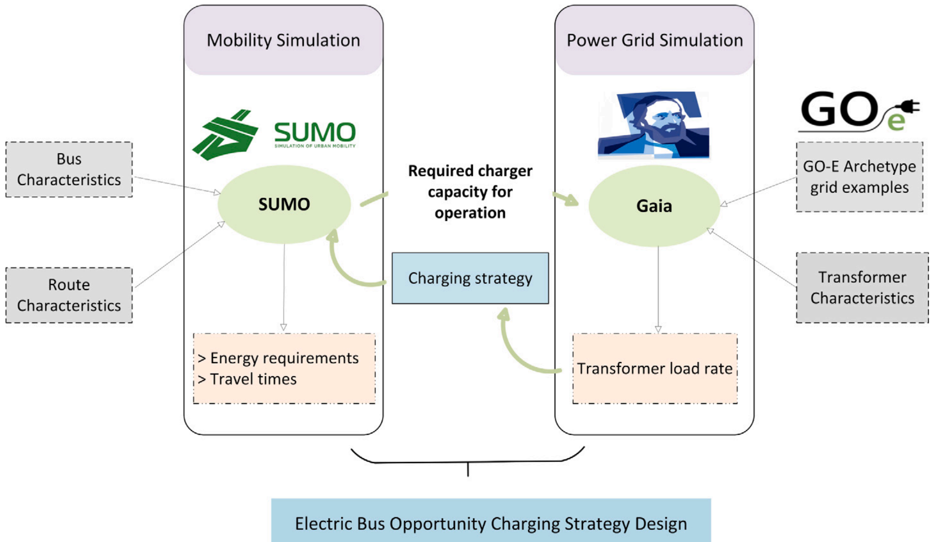


Fig. 1. The overview of the framework.

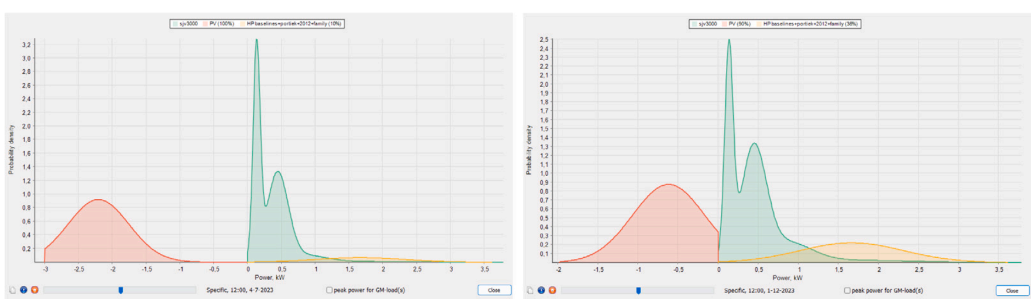


Fig. 2. Consumption patterns of a household on a generic workday in July (left) and December (right) at 12:00. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

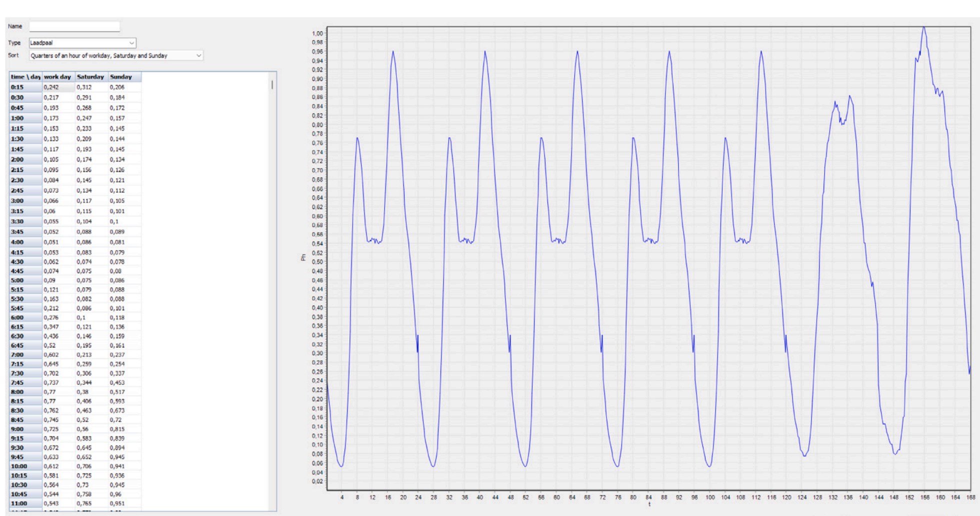


Fig. 3. Weekly demand profile of an example EV charger.

reaches full capacity. Using both demand probability distributions and profiles, Gaia simulates grid loads at 15-minute intervals for each of the three generalized day types (weekdays, Saturdays, Sundays) over the course of the year. These simulations help assess grid quality by examining voltage, current, transformer load rates, and overall network safety.

Opportunity chargers can be manually added to the grid within Gaia by assigning specific demand profiles, and their inclusion is factored into the overall grid demand calculations. This allows for a detailed analysis of how such chargers influence grid stability and capacity. Furthermore, Gaia ensures data privacy by employing GO-E archetypes—anonymized consumption patterns developed collaboratively by energy companies and research institutions. These archetypes enable the incorporation of real-world data into simulations while protecting sensitive information, ensuring that the grid's demand is modeled accurately without compromising user privacy.

3.4. Gebouwde Omgeving Elektrificatie (GO-E) archetypes

Gaia uses grid data as input to evaluate the quality and performance of low-voltage electricity grids. To use real-life data in this research, privacy-protected data is required due to the sensitive nature of energy consumption information. Within the GO-E project, a consortium of energy and research-related companies developed a methodology to subdivide the Netherlands into eight different grid archetypes. These archetypes are based on data made available through the implementation of smart grids and smart meters. Given the privacy-sensitive nature of energy consumption data, energy companies are legally obligated not to share such data beyond what is required for their operational tasks (De Nederlandse Overheid, 2012). However, for research on grid operations and innovations, the use of real-world data is highly beneficial. Additionally, generalized assumptions derived from archetypes can improve grid management for other regions. This need led to the development of the GO-E archetypes.

The archetypes classifies every postal code region in the Netherlands into one of the following eight categories: Pre-1920 residences, Pre-war residences, Post-war terraced houses, Post-war tenements, Corporation residences, Detached houses, Rural area, and Limited population & industry (Westerga and Emde, 2023). Each postal code is assigned to an archetype based on several parameters, including: Percentage of families with children, Energy label distribution, Average household size, Percentage of cooperative residences, Distribution of rental vs. owned properties, Build year of the area, Density of addresses, Percentage of gas connections and access to district heating, Percentage of 3-phase grid connections. Since not all postal code regions perfectly match their assigned archetype, a goodness-of-fit analysis was conducted to assess how well the energy patterns within each archetype align with its defining characteristics. This analysis evaluates the uniformity of energy patterns among postal codes within the same archetype. It measures how representative or "archetypical" these patterns are for the given archetype, reflecting the degree to which the observed energy behaviors conform to the archetype's defining attributes. Fig. 4 illustrates this goodness-of-fit, showing how well postal code regions align with their archetype.

Each archetype in Gaia is associated with six example grids from three different PGOs, with two example grids per PGO. These grids are real-world representations, stripped of all privacy-sensitive information, allowing for generalized conclusions about the grids in neighborhoods assigned to the archetypes. Gaia provides two versions for each grid: one for 2023, representing the current grid state, and another for 2030, based on predictive models used by the PGOs. Although the specifics of these predictive models are not disclosed due to non-disclosure agreements, they help forecast future grid demands.

For this simulation, the grid for 2030 is used. The decision to use the 2030 grid model is based on the timeline required for infrastructure development—investments in new grid infrastructure can take several years to implement. Additionally, the 2030 grid scenario represents a more congested system with higher power consumption and production, providing better insights into transformer load rates and the importance of traffic priority measures to reduce grid stress.

4. Case study: fast charging stations along a bus route in Rotterdam

The following sections detail the selection of the case study based on specific criteria, including the route and bus characteristics. Additionally, the implementation of the charging technology and the method used for opportunity charging are discussed.

4.1. Criteria for selecting a bus route in the case study

To implement the methodology outlined in Section 3, a single bus route will be selected to evaluate different charging strategies. The criteria for selection, along with their corresponding hypotheses, are as follows:

- *At least 10 intersections*: The number of intersections is crucial for assessing the impact of traffic priority on bus energy consumption. Energy use is affected by how often the bus needs to decelerate and accelerate (Huan et al., 2019). A minimum of 10 intersections provides enough locations where traffic priority could reduce these events, allowing for measurable differences in energy consumption.
- *At least 10 bus stops*: The number of bus stops determines the potential locations for opportunity charging stations. Locating chargers near transformers significantly reduces installation costs, which are generally much higher than the cost of the chargers themselves (Benmenni, 2021). Although direct investment costs are not the focus of this study, placing chargers close to transformers is a practical consideration. Having at least 10 bus stops offers flexibility for cost-effective placement.
- *Minimum 15-minute intervals between buses*: We select a line where there are at least 15 min between consecutive bus arrivals at the opportunity-charging stop. This choice is driven by the time discretization of Gaia, which computes transformer loading as average power over fixed 15-minute intervals. With at least 15 min between arrivals, each charging event can be mapped to a separate 15-minute interval in Gaia and represented by a single on/off state of the charger. Lines where buses arrive more frequently, or where several lines share the same charger, would require a more detailed aggregation of multiple charging events within one 15-minute interval or a grid model with a finer temporal resolution. This is beyond the scope of the present demonstration but is an important direction for future work.
- *Route crossing at least 3 GO-E Archetypes*: The route must pass through at least 3 GO-E archetypes, as described in Section 3.4. These archetypes are a key input for Gaia, and including multiple archetypes broadens the applicability of the research findings. Of the 4 archetypes with a high goodness-of-fit, at least 3 should be included to ensure that the results are relevant to other areas with similar characteristics and ensure widespread applicability.

4.2. Case study selection

The selection of the case study is based on the criteria outlined in previous sections. The choice of the bus route for modeling in SUMO takes into account both the route characteristics and the goodness-of-fit of the archetypes along which the bus operates. The city of Rotterdam was selected as the case study area due to the availability of relevant data. The selection process involved comparing Rotterdam's archetype distribution map with the public transport network of the city.

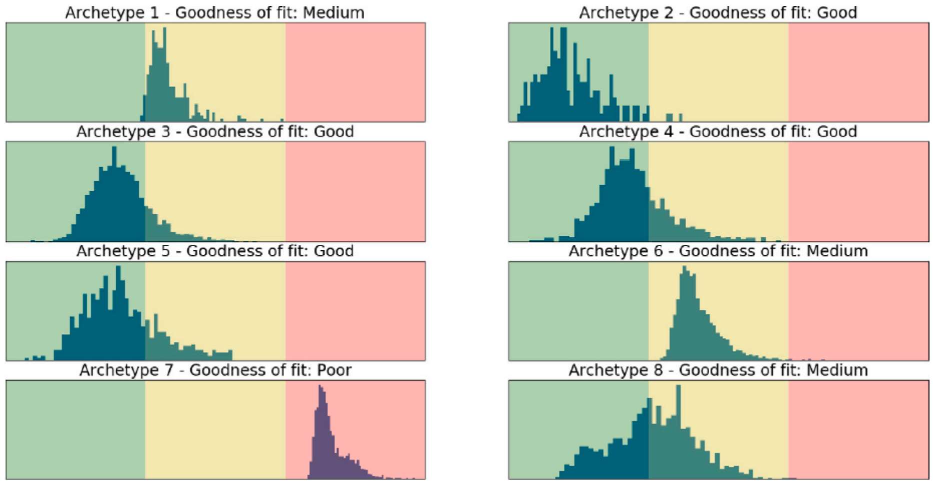


Fig. 4. The Goodness-of-fit for the 8 GO-E Archetypes. For each archetype, the histogram shows the distribution of distances between neighborhoods and the centroid of their archetype cluster in the principal-component space used in GO-E. Smaller distances indicate neighborhoods that are more "archetypical"; archetypes 1–5 therefore have the highest overall goodness-of-fit.

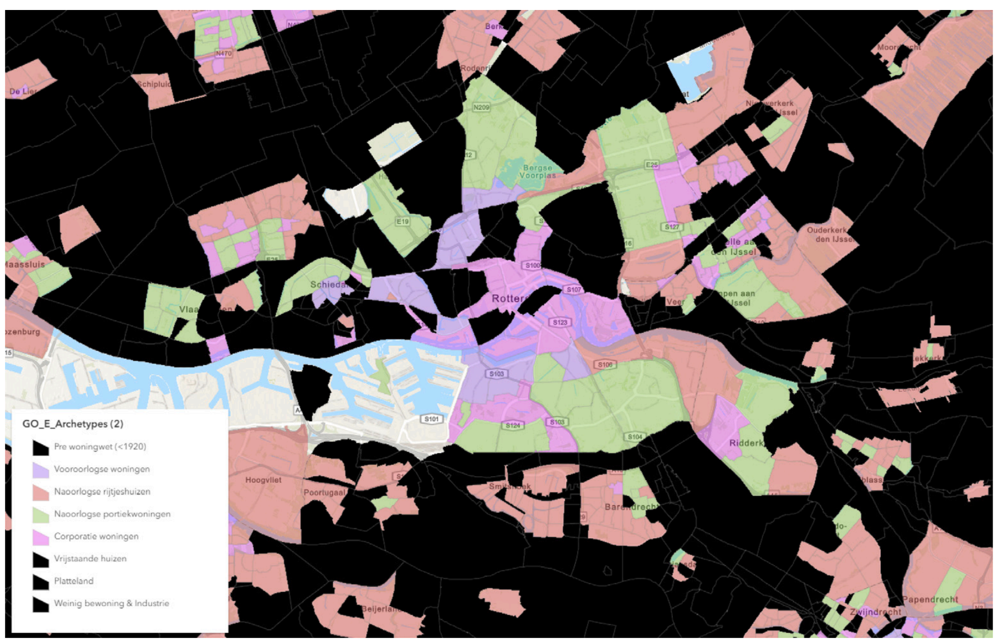
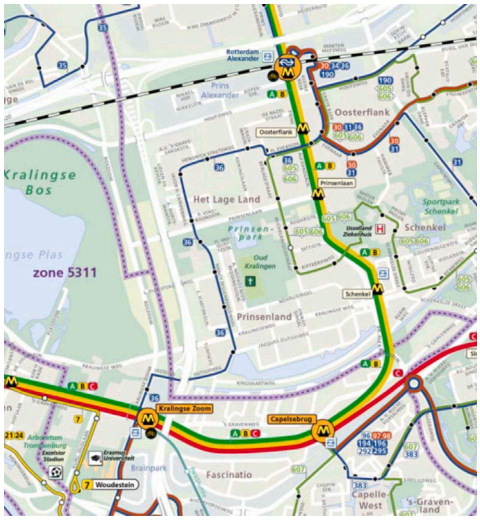


Fig. 5. The archetype distribution of Rotterdam excluding the GO-E archetypes with a poor or medium goodness-of-fit, purple = Pre-war residences, red = Post-war terraced houses, green = Post-war tenements, pink = corporation residences. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 5 presents the maps of Rotterdam displaying the GO-E archetypes, excluding those with medium and poor goodness-of-fit. The city center offers a variety of transportation options, including trams, metros, cars, buses, cyclists, and pedestrians. However, only a few bus routes travel exclusively through areas with the highest-quality archetypes. Additionally, manually modeling the complex intersections in the city center would lead to oversimplifications, potentially reducing the accuracy of energy consumption calculations in SUMO for buses.

As a result, the Rotterdam Alexander area, located in the city's northeast, was selected for its simpler intersections, allowing for more precise modeling. Bus line 36, which runs between Rotterdam Alexander station and Kralingse Zoom metro station, was chosen as the case study. This route passes through three distinct archetypes: Archetype 3 (Post-war terraced houses), Archetype 4 (Post-war tenements), and Archetype 5 (Corporation residences). Figs. 6(a) and 6(b) display the route on the PT map and the corresponding archetypes.

Bus line 36, although shorter (approximately 6 km) and not typically used for opportunity charging (which is common on longer routes around 25 km), is suitable for this study. This is because the focus is on local distribution grid impacts, where congestion is more of an issue. Longer routes tend to connect with less congested grids outside of neighborhoods. Additionally, the closely spaced stops on a city bus line like line 36 reduce infrastructure costs by placing chargers closer to transformers. Furthermore, traffic and priority issues are more prominent in the city center, where line 36 operates, making it a relevant choice. In contrast, long-distance routes usually face less traffic and pass through rural GO-E archetypes, which are less informative for studying grid congestion. Please note that, we use line 36 as a representative urban test bed to apply and illustrate the proposed framework. The aim is not to study the complete Rotterdam bus network, but to examine in detail how a realistically modeled bus line interacts with several low-voltage grids belonging to different



(a) Bus line 36 in the PT map of the RET

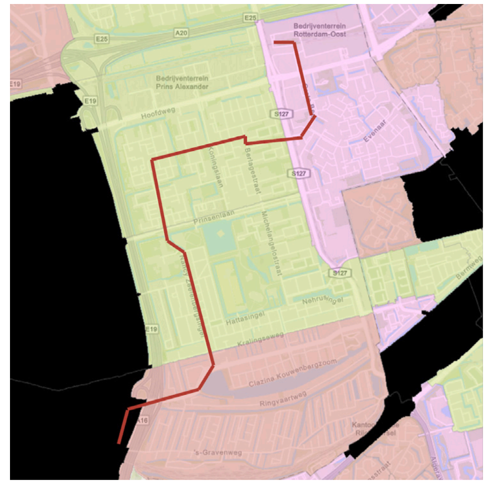

(b) Bus line 36 shown on the archetype map of Rotterdam

Fig. 6. Bus line 36 and its location relative to public transport and urban archetype layers in Rotterdam.

GO-E archetypes. Consequently, the numerical thresholds obtained for charger power, dwelling times and timetable adjustments should be interpreted as context-dependent for this route and set of inputs, the underlying mechanisms identified, such as transformer overload during evening peaks when high-power chargers are used, are expected to occur whenever similar charging profiles are imposed on comparable distribution grids.

An integrated approach to decision-making requires a solid understanding of the current practices and characteristics of the research area. The following subsections will cover the practices of Rotterdamse Elektrische Tram (RET), the PTO in the study area, and the input characteristics required for simulation.

4.3. Current charging strategy of RET

RET, the public transport operator in the study area, is in the process of transitioning to a fully electric public transport system, with the aim of achieving full electrification by 2030. At present, 100 electric buses, accounting for 40% of the total fleet of 250 buses, are in operation and rely on pantograph charging systems.

These buses are primarily charged at the Kleiweg depot during the night, ensuring that they start daily operations with a full charge. In addition to depot charging, buses are charged during the day at five terminal stations: Rotterdam Centraal, Krimpen aan den IJssel, Station Schiedam, Vlaardingen West, and Overschie (van Noortwijckstraat). These terminal stations are important transit hubs where multiple bus lines and modes of transport intersect. Since these stations often serve as the starting and ending points of bus routes, they provide the necessary longer dwell times for opportunity charging.

For buses that do not pass through these terminal stations, additional charging is required during the day. In such cases, buses return to the depot, leading to what are known as deadhead trips—non-revenue trips made solely for the purpose of charging. The pantograph chargers used by RET are illustrated in Fig. 7, and the fleet of electric buses is supplied by the manufacturer VDL.

4.4. Route and bus characteristics

For the SUMO simulation, detailed inputs on both the route and bus characteristics are essential. The route characteristics include key elements such as road network design, lane speeds, priority lanes, dedicated bus lanes, traffic regulation systems (TRS), and bus station locations. These details are manually entered into SUMO by using data

Table 1
EB characteristics used in the simulation.

Parameter	Value
Maximum battery capacity	216 kWh
Maximum power output	160 kW
Vehicle mass	15,000 kg (average)
Front surface area	8 m^2
Air drag coefficient	0.6
Internal moment of inertia	0.01 kg m^2
Radial drag coefficient	0.5
Rolling resistance coefficient	0.01
Constant power intake	5.5 kW
Propulsion efficiency	90%
Recuperation efficiency	15%
Stopping threshold	0.1 km/h

from sources such as Open Street Maps, Google Street View, and site visits.

In terms of bus characteristics, the values used in the simulation are provided by the bus manufacturer VDL, as the RET operates VDL's electric buses in Rotterdam. Table 1 outlines the vehicle specifications, including parameters like battery capacity and weight. The only exception is the recuperation efficiency, which is based on literature. Research suggests that a recuperation efficiency of around 15% is a reasonable estimate for electric buses (Ma et al., 2019). In addition, the total vehicle mass is fixed at the value 15,000 kg, as shown in Table 1 and represents an average operating condition of the bus, including a typical passenger load. This mass is kept constant throughout the simulation; time-varying passenger occupancy is not explicitly modeled. As a result, the simulated energy use represents an average loading condition.

Along with the route and bus characteristics, SUMO allows the integration of chargers. The specific technology and charging methods implemented in the simulation are outlined in the following subsections.

4.5. Charging strategies and opportunity charger implementation

Pantograph chargers range in capacity from 50 kW to 500 kW (He et al., 2020b). In this research, two charger capacities are considered: a 200 kW charger, representing a mid-range option, and a 450 kW charger, the maximum capacity used by the RET buses (VDL, 2023).

Daytime depot charging is excluded from this study due to the inefficiency of deadhead trips, where buses must return to the depot

Fig. 7. An RET pantograph charger at the central station of Rotterdam.

solely for recharging purposes (Alamatsaz et al., 2022). Instead, the focus is on evaluating the effects of opportunity charging during bus operations. The initial battery capacity for each trip is assumed to be 90%, accounting for the energy consumed when traveling from the depot to the starting point of the route. The battery should not drop below 30% at the end of the route to ensure the bus can safely return to the depot without running out of charge.

For opportunity chargers, the implementation involves two key steps: determining their locations and integrating them into the Gaia simulation. The location of each charger is chosen based on its proximity to transformers and to ensure that all three GO-E archetypes in the study area are covered. Proximity to transformers is crucial due to the high costs of infrastructural investments, as discussed in Section 4.1. Although direct investment costs are not included in this study, placing chargers near transformers is a realistic preference to minimize potential expenses. Fig. 8 illustrates the process used to determine the charger locations. For each bus stop along the route, the distance to the nearest transformer was analyzed, and the stops closest to transformers were selected for charger installation. In cases where multiple bus stops had similar distances to transformers, the stop that caused the least interference with traffic was chosen. Extended charging times at locations with heavy traffic could disrupt flow, so minimizing traffic interference was prioritized.

The pantograph chargers are represented in Gaia using a simplified on–off demand profile. Gaia operates with a fixed 15-minute time step and interprets the profile as a fraction of the charger's rated power in each interval. For this case study, we set the profile to 1 in the 15-minute interval that contains a charging event in SUMO, and to 0 otherwise. Gaia therefore assumes that, in an 'on' interval, the charger draws its full rated power (200 kW or 450 kW) for the entire 15 min. In reality, dwell times at the opportunity-charging stops in SUMO are around 1–2 min, so the total energy taken from the grid during a visit is lower than this upper bound. We use this representation only to check whether the local distribution grids can accommodate the additional peak power associated with the opportunity-charging strategies; detailed charging durations and state-of-charge trajectories are modeled in SUMO. Extending the framework to weight the Gaia profile by the fraction of the 15-minute interval during which the charger is active, or to use a grid model with a shorter time step, is left for future work, especially for stops where several lines share chargers and arrivals are more frequent.

5. Experiment design

To understand the connection between mobility and energy systems in EB operation, various strategies of the case study need to be simulated, which requires adjusting specific simulation variables. This section details the simulation variables, strategy configurations, and the criteria used to assess whether these strategies meet mobility and energy requirements.

5.1. Simulation variables and strategies

The strategies are configured based on the following simulation variables:

- *Traffic intensity and priority*: Traffic conditions are manually configured in the simulation, assigning higher traffic volumes to major roads compared to residential streets. Traffic volumes are modeled using Poisson processes with random seeds to capture variability across 100 simulation runs. In certain strategies, traffic priority is introduced to reduce EB energy consumption by minimizing acceleration and deceleration events. Traffic priority, in this context, gives preferential treatment to the EB to reduce its stops at intersections and traffic signals. This approach simulates real-world priority lanes or signal priority systems, where the EB receives green lights at intersections or benefits from reduced congestion in priority lanes.
- *Dwelling time*: The time spent at stops (dwelling time) is set at 20 s for regular stops based on Rau et al. (2019). At stops equipped with opportunity chargers, the dwell time is treated as an adjustable parameter and kept constant within each strategy. As summarized in Table 2, we test dwell times of 20 s (Strategies 1–2), 130 s (Strategies 3–4) and 90 s (Strategy 5). These values are selected offline to explore how additional time at charger stops affects both energy intake and timetable adherence. For Strategy 5, we reduce the dwell time at charger stops from 130 s in steps and re-evaluate the simulation until the battery charge and timetable requirements are both satisfied; the resulting value is 90 s. No formal optimization routine is embedded in the simulation—the dwell time at charger stops is varied between scenarios rather than adjusted dynamically during operation.
- *Charging capacity*: A baseline charging capacity of 200 kW is used, with a maximum of 450 kW following RET guidelines (VDL, 2023). This capacity is linked with the Gaia model to assess interactions between EB charging needs and the power grid.

Based on these variables, five different strategies are configured, as summarized in Table 2. These strategies will be assessed to identify the most effective configurations that support electric bus opportunity charging while meeting mobility and grid requirements.

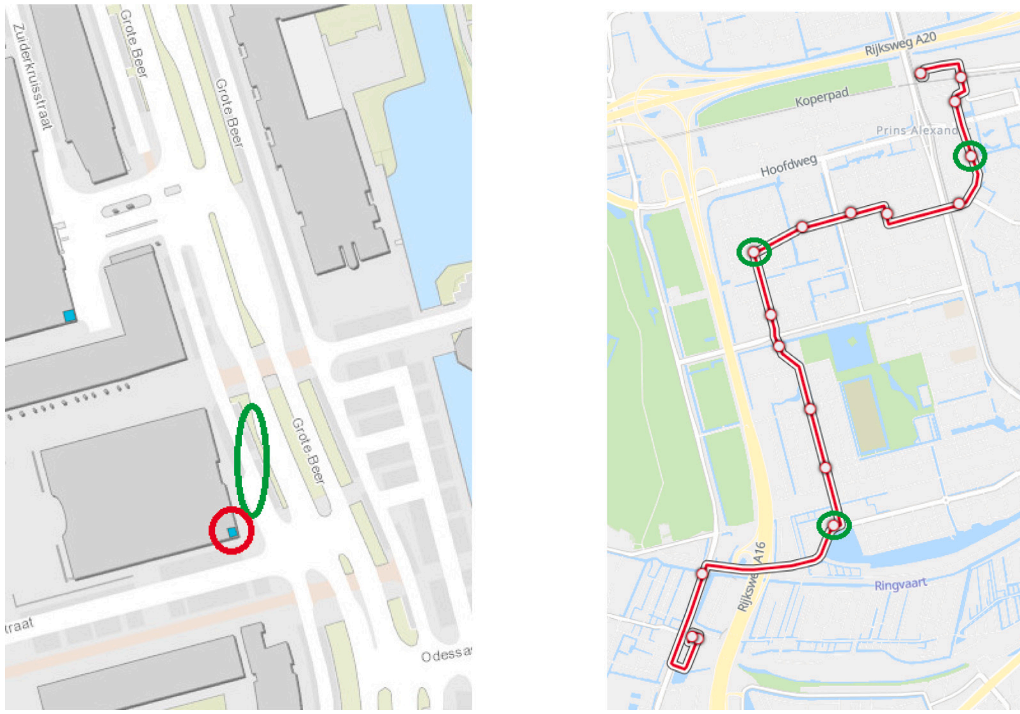


Fig. 8. The determination of charger locations. The left picture shows the location of the transformer (red encircled) and the location of the charger (green encircled). On the right, the green circles indicate the charger locations along the route. The left picture shows the determination of the location of the upper right charging location. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Summary of simulation strategies based on key variables.

Strategy	1	2	3	4	5
Charger capacity (kW)	450	200	200	200	200
Dwelling time (s)	20	20	130	130	90
Traffic priority	No	No	No	Yes	Yes

5.2. Evaluation criteria

The evaluation of the different strategies is guided by the operational requirements of the mobility and energy systems.

For the **mobility system**, the primary objective of the public transport operator (PTO) is to meet demand as efficiently as possible. This work assumes that the current timetable and route design sufficiently meet demand, so any changes to the existing design should be minimized. These objectives are expressed as two key requirements:

- *Energy limit per trip*: For each trip, the net battery energy decrease must not exceed 8.64 kWh. This ensures that the bus, starting its route at 90% battery capacity, retains at least 30% by the end of the day to return to the depot. This limit is based on the usable battery energy of 216 kWh, allowing a 60% charge difference over the course of 15 trips:

$$\frac{216\,\text{kWh} \times (0.90 - 0.30)}{15} = 8.64\,\text{kWh} \tag{1}$$

- *Minimal impact on timetable*: Any adjustments to dwelling time at charging stops will impact arrival times at intermediate stops. The goal is to keep changes within a 10% increase to the current total route time of 2520 s. While no strict limit is established in the literature, Fridgen et al. (2021) suggest keeping additional travel time low to maintain service reliability.

For the **energy system**, to maintain a safe and stable grid, transformers should not regularly exceed their maximum load capacity of 100% (Mohamed et al., 2017). While transformers can handle loads above their rated capacity, operating at levels higher than 100% can lead to accelerated degradation of the transformer and the cables connected to it, resulting in reduced operational lifespan (Mohamed et al., 2017).

The simulations in Gaia and SUMO will be run on an HP Z-Book 4th generation with an Intel® Core™i7-10750H CPU @ 2.60 GHz. The SUMO simulation, shown in Fig. 9, models only the intersections of the road network, as the areas beyond intersections do not significantly affect the bus's performance but would increase computation times. With this setup, simulating one full operating day of line 36 for a single charging strategy takes roughly two seconds on this machine, so a few hundred strategies can be evaluated within about ten minutes.

For the Gaia simulation, the following grids and transformers are used, each with complete and accurate data:

- Archetype 3 (Post-war terraced houses): 1 grid with 5 transformers.
- Archetype 4 (Post-war tenements): 2 grids with a total of 6 transformers.
- Archetype 5 (Corporation residences): 2 grids with a total of 5 transformers

6. Results

In this section, we first present the simulation results of SUMO, conducted using the configurations outlined in the above section. Then, we present the Gaia results to verify the impact of the simulated strategies on the transformer across different archetypes.

6.1. SUMO

The average results of different strategies in SUMO is summarized in Table 3, which provides insights into their ability to satisfy the key requirements of battery charge, and timetable adherence. We use red

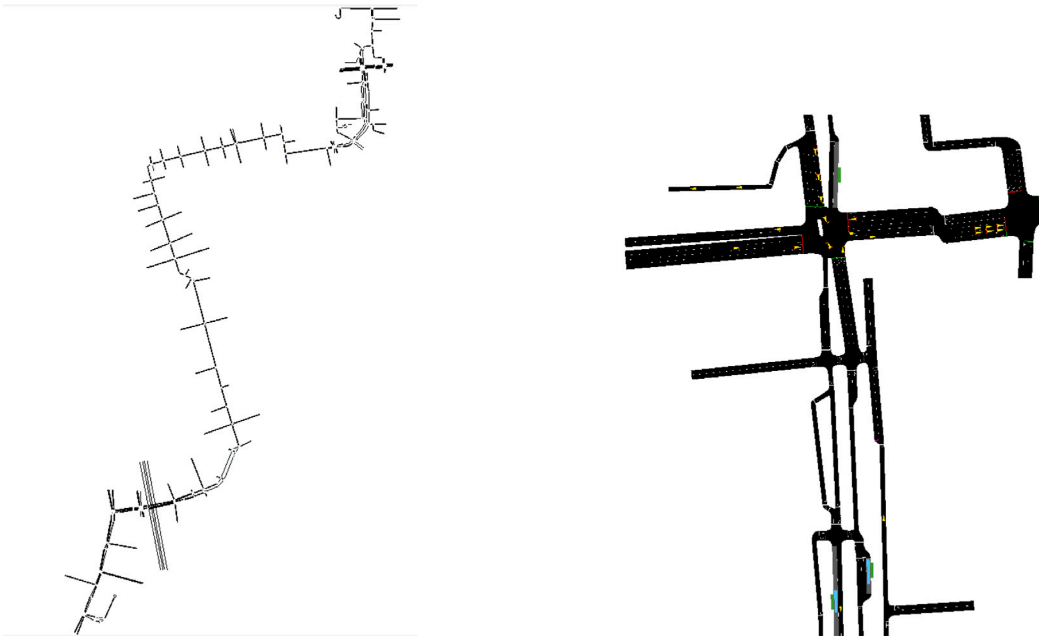


Fig. 9. An overview (left) and closeup (right) of the simulation in SUMO, the EB is white and the blue bars indicate a charger. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
The average results of 100 runs of the different strategies in SUMO.

Strategy	1	2	3	4	5
Charger capacity (kW)	450	200	200	200	200
Dwelling time (s)	20	20	130	130	90
Traffic priority	No	No	No	Yes	Yes
Travel time (s)	2502.90	2502.90	3194.10	2881.43	2634.98
Total energy consumed (kWh)	38.92	38.92	40.13	38.32	37.89
Energy regenerated via braking (kWh)	2.23	2.23	2.25	1.84	1.86
Energy charged by chargers (kWh)	14.25	6.33	41.17	41.17	28.5
Net battery energy change (kWh)	22.42	30.35	−3.28	−4.69	7.53

color to highlight the evaluation criteria that are not satisfied by the simulation strategy.

For strategy 1, as shown in Table 3, the average travel time of 2502.9 s aligns well with real-life expectations, as a round trip typically takes around 42 min (2520 s) (RET, 2024). However, as outlined in Section 5.2, the net battery energy decrease per round trip is 22.42 kWh, exceeding the allowable limit of 8.64 kWh (refer to function (1)). Thus, from mobility perspective, strategy 1 does not meet the battery charge requirement, with energy consumption exceeding what the bus can sustain over a full day of operation.

For strategy 2, we set the charging capacity to 200 kW, and kept the dwelling time and traffic priority the same as strategy 1. The results show that the average travel time of 2502.9 s aligns well with real-life expectations, as a round trip typically takes around 42 min (2520 s). However, similar to strategy 1, under the requirements outlined in Section 5.2, the net battery energy decrease per round trip (30.35 kWh) exceeds the 8.64 kWh limit. Strategy 2 did not meet the battery charge requirement, with energy consumption levels higher than what the bus could sustain over a full day of operation.

In strategy 3, the charging capacity was kept at 200 kW, but the dwelling time at charging stations was extended from 20 s to 130 s. This extended dwelling time allowed the bus to recover enough charge to meet the battery requirement, resulting in a net battery energy increase of 3.28 kWh per round trip. Even though this strategy addressed the energy demands, it came at the expense of increased travel time, which rose to 3194.1 s, a significant deviation from the timetable.

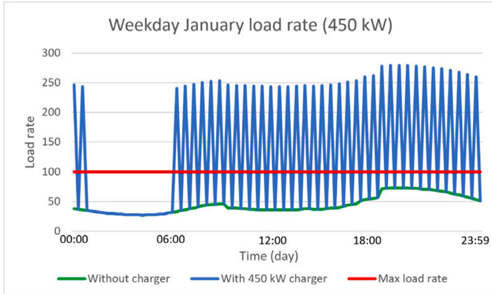
To address the timetable delays in strategy 3, strategy 4 introduced traffic priority to reduce energy consumption and travel time. Traffic priority minimized acceleration and deceleration events, reducing overall travel time by 9.8% and lowering energy consumption by 4.5%. This setup resulted in a net battery energy increase of 4.69 kWh per trip. However, travel time remained slightly longer than ideal, indicating that further adjustments in charging or timing are needed to fully meet battery and timetable requirements.

Strategy 5 refined the approach by reducing dwelling time to the minimum needed to satisfy battery requirements, setting it at 90 s, while incorporating traffic priority. This adjustment achieved a balanced result, with total travel time only 5.3% longer than the baseline scenario. From the mobility system perspective, strategy 5 successfully met both battery and schedule needs.

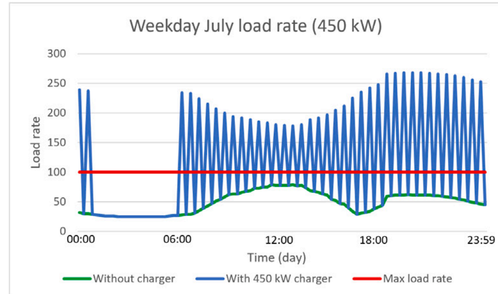
After analyzing the SUMO results, the next subsection presents the simulation results from Gaia. Since Gaia only requires charger capacity as an input, it is unnecessary to simulate all five strategies independently. Strategies 2 through 5 share the same 200 kW charger capacity, resulting in identical grid impacts. Therefore, the analysis is simplified by classifying the strategies into two groups: one using a 450 kW charger (strategy 1) and the other using a 200 kW charger (strategies 2–5). This grouping allows us to examine how different charger capacities affect transformer loads across various archetypes.

6.2. Gaia

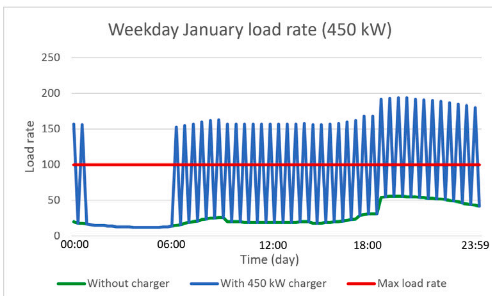
The 450 kW charger imposed excessive strain on the transformer across all archetypes, as shown in Fig. 10. In this figure, the transformer load with the charger (blue) is compared to the load without the charger (green) across various conditions: in January and in July. The



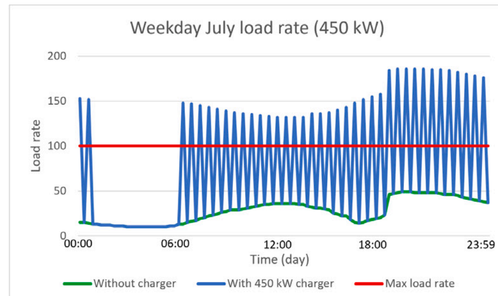
(a) Archetype 3: January



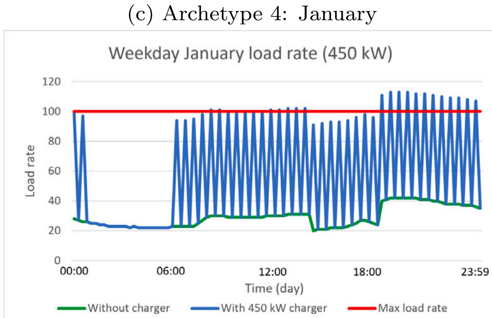
(b) Archetype 3: July



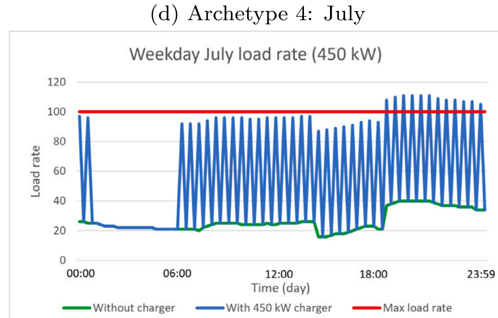
(c) Archetype 4: January



(d) Archetype 4: July



(e) Archetype 5: January



(f) Archetype 5: July

Fig. 10. The impact of a 450 kW charger on the grid of archetypes 3, 4 and 5: post-war terraced houses, post-war tenements, and corporation residences. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

red line marks the 100% load threshold, which ideally should not be exceeded. The figure shows that each archetype's grid encountered overloads under different seasonal conditions:

- Archetype 3: As shown in Figs. 10(a) and 10(b), the grid in archetype 3 could not support a 450 kW charger, frequently exceeding the 100% load threshold. Even in summer, when Photovoltaic (PV) modules contribute additional power, the grid struggles to handle the increased demand, leading to continuous overloads that compromise transformer stability.
- Archetype 4: Similarly, as shown in Figs. 10(c) and 10(d), archetype 4's grid is unable to manage the 450 kW charger effectively. Although PV energy offers some support, it is insufficient to meet the high demand, especially during peak hours, resulting in frequent overloads.
- Archetype 5: As shown in Figs. 10(e) and 10(f), the grid in archetype 5 can support the 450 kW charger from midnight until 18:00. However, during evening peak hours from 18:00 to midnight, the load regularly exceeds transformer capacity, making the charger unsustainable during these times. While summer conditions are slightly more favorable, the evening demand remains a barrier.

Based on these results, the 450 kW charger was found unsuitable across all archetypes due to the consistent transformer overloads.

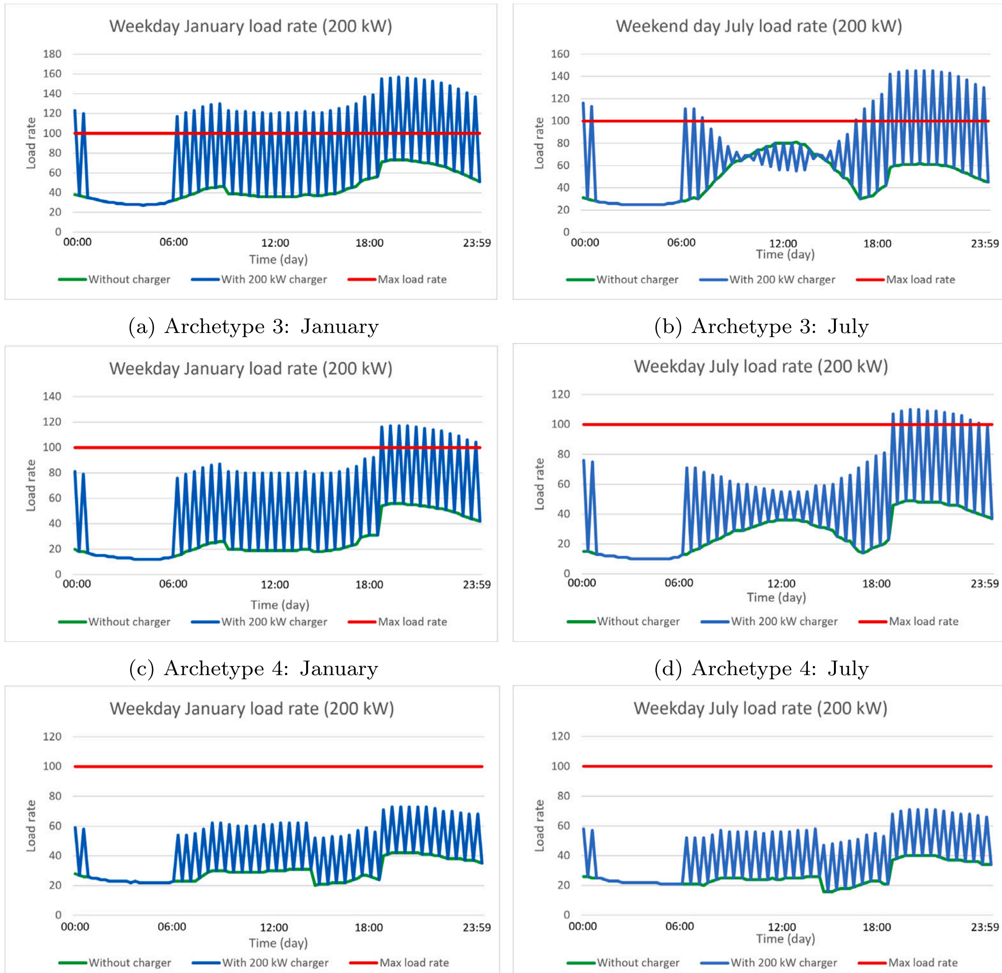
For the transformer impact of the 200 kW charger, the effects are consistent across all strategies (1, 3, 4, and 5). Each archetype's grid has varying capacities to handle this load under different seasonal conditions, as can be seen in Fig. 11:

- Archetype 3: As shown in Figs. 11(a) and 11(b), the grid struggles with a 200 kW charger in winter, frequently exceeding the 100% threshold. In summer, however, the grid manages better, particularly during daylight hours when PV modules provide additional power, reducing strain on the transformer.
- Archetype 4: As shown in Figs. 11(c) and 11(d), the grid generally supports the 200 kW charger but occasionally exceeds capacity during evening peaks from 18:00 to midnight.
- Archetype 5: As shown in Figs. 11(e) and 11(f), this grid consistently supports the 200 kW charger year-round without exceeding the load threshold or facing major issues.

With archetype 5 supporting 200 kW chargers, 200 kW charger capacity satisfies the grid requirement.

6.3. Discussion

After analyzing the results from SUMO and Gaia, strategy 5 successfully meets both mobility and transformer load requirements. Table 4 provides a summary of requirement satisfaction across all strategies.



(a) Archetype 3: January (b) Archetype 3: July

(c) Archetype 4: January (d) Archetype 4: July

(e) Archetype 5: January (f) Archetype 5: July

Fig. 11. The impact of a 200 kW charger on the grid of archetypes 3, 4 and 5: post-war terraced houses, post-war tenements, and corporation residences.

Table 4
Assessment of requirement satisfaction for mobility and energy systems across five strategies.

Strategy	1	2	3	4	5
Charger capacity	450 kW	200 kW	200 kW	200 kW	200 kW
Dwelling time	20 s	20 s	130 s	130 s	90 s
Traffic priority	No	No	No	Yes	Yes
Requirement: Satisfied?					
Battery energy decrease ≤8.64 kWh/round trip	No	No	Yes	Yes	Yes
The timetable should not substantially be interfered with, with a maximum increase of 10%	Yes	Yes	No	No	Yes
The transformer should not exceed 100% regularly or continuously	No	Yes	Yes	Yes	Yes

From a mobility perspective, the successful deployment of EBFs depends on charging strategies that maintain schedule reliability. Strategy 5 demonstrates that incorporating traffic priority and optimizing dwelling times can provide sufficient charging opportunities without disrupting timetables. From an energy perspective, grid stability must be maintained by ensuring that charging demands remain within transformer capacity limits. This study highlights that uncoordinated charging, particularly in residential neighborhoods, can result in transformer overloads, emphasizing the need for strategic planning and careful timing of charging sessions.

It is worth noting that our results have both route-specific and more general aspects. The exact combinations of headway, charger power and dwell time that satisfy all requirements are specific to line 36 and to the 16 transformers from the three GO-E archetypes in our case study. However, the patterns observed in SUMO and Gaia is consistent across archetypes and seasons: concentrating high-power pantograph charging in residential areas quickly causes transformers above their nominal capacity, and lower charger powers can only be applied where the grid still has sufficient spare capacity. This shows the kind of interaction between service design and grid constraints that the integrated framework can reveal and suggests that the feasibility of opportunity charging in similar contexts is largely driven by three factors: service frequency, charger power and local grid capacity.

6.4. Limitations and policy implications

There are several limitations of this work. First, on the energy side, Gaia operates with a fixed temporal resolution of 15 min and represents demand as an average power over each interval. Pantograph chargers are modeled with a simplified on–off profile at this time step: when a charging event occurs in SUMO, the corresponding Gaia profile is set to one for that 15-minute interval and to zero otherwise. In this study we accept this approximation because Gaia is used only to assess whether the local low-voltage grids can accommodate the additional high-power demand under a conservative assumption. A more detailed representation of charging within the 15-minute interval, or a grid model with a shorter time step, would be needed to study short duration peaks and to align energy balances more closely across the two simulators. Moreover, on the grid side we report only transformer loading as the indicator of stress. Extending the analysis to additional Gaia outputs such as cable loading and node voltage profiles to construct a richer set of electrical safety indicators is left for future work.

Second, charger locations and operating strategies are treated as predefined scenarios rather than as decision variables in an optimization model. Charger locations along line 36 are fixed a priori at selected bus stops, and each charger is connected to the nearest low-voltage transformer in the GO-E archetypes. This proximity-based siting is a practical simplification: it may lead to clustering effects and checks transformer capacity only ex post, and it ignores economic and operational siting criteria such as costs, layover opportunities, land-use constraints and passenger demand. A full siting study would treat charger placement and sizing as decision variables in an optimization model, here, fixed charger locations are used only as a test case to demonstrate the integrated mobility–energy framework. The strategies then combine a small set of charger capacities, dwell times at charger stops and traffic priority settings. In particular, the dwell time at charger stops is not adapted dynamically during the simulation but chosen offline as a scenario parameter. This scenario-based approach is sufficient to demonstrate how the integrated framework can be used to compare alternative operating strategies, but it does not search systematically over the full space of possible charger locations, power levels and timetable adjustments.

Third, the analysis focuses on a single bus route. Line 36 in Rotterdam is selected because it combines a realistic urban operating environment with a limited set of overlapping low-voltage grids, which makes it suitable as a test case for the framework. However, this choice also means that the quantitative conclusions regarding feasible charger capacities, dwell times and the interaction between opportunity charging and transformer loading are specific to this route and to the distribution grids it traverses. Extending the analysis to multiple routes with different lengths, service frequencies, stop densities and charging concepts would be required to derive network-level guidelines.

Fourth, the SUMO and Gaia models are configured and linked manually using open data and operator input. This manual setup is practical at the line level but would need to be automated to extend the framework to a full bus network or city. From a computational perspective, however, the simulations are light: a single-day run for one charging strategy completes in a few seconds on a standard laptop, so a few hundred strategies can be evaluated within minutes. The main scalability constraint is therefore the manual preparation of the traffic and grid models, rather than computational time.

Despite these limitations, the framework has clear practical value. It allows public transport operators and distribution system operators to test whether proposed charger powers, locations and operating strategies are compatible with local distribution-grid capacity before implementation. The line 36 case illustrates that mobility-driven choices such as higher charger power or longer dwell times must be checked against transformer limits, and that operational measures (e.g. traffic priority and modest dwell extensions) can help, but only within the bounds set by the grid. The same type of analysis can be applied to other routes or networks to support infrastructure planning and operational guidelines for bus electrification.

7. Conclusion

This study presents a comprehensive framework for evaluating the feasibility of electric bus (EB) opportunity charging by integrating mobility and energy system simulations. Applied to Rotterdam's bus line 36, the framework highlights the critical need for aligning mobility and energy requirements to ensure the successful implementation of charging strategies.

The results show that, from a mobility perspective, charging strategies must meet energy demands without disrupting operational schedules. Strategies with extended dwelling times (e.g., 130 s) satisfied battery requirements but caused significant timetable delays, demonstrating the trade-off between charge sufficiency and schedule adherence. From an energy perspective, higher charging capacities, such as 450 kW, reduced net battery energy loss but consistently led to transformer overloads, highlighting the importance of managing grid impacts. The most effective strategy combined a 200 kW charger, a reduced dwelling time of 90 s, and traffic priority, achieving a balanced solution. This approach resulted in only a 5.3% increase in travel time, within acceptable limits, at the same time meeting all battery, transformer load, and schedule requirements.

The framework is generic and can be applied to other routes and urban areas where detailed traffic and grid data are available. Extending the analysis to multiple lines with different lengths, headways and stop densities, and to different grid configurations, would make it possible to derive network-level guidelines for opportunity charging and to test the robustness of the findings. The main modeling assumptions and implementation constraints are summarized in Section 6.4.

CRediT authorship contribution statement

Jie Gao: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Siebren van Noort:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Jop Spoelstra:** Writing – review & editing, Conceptualization. **Gonçalo Homem de Almeida Correia:** Writing – review & editing, Conceptualization, Supervision.

Declaration of competing interest

The authors declare no competing financial or personal interests that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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