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A Multi-Variable Simulation for the Design of Electric Vehicle Charging Stations

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ABSTRACT

This study addresses electric mobility, a key pillar of European decarbonisation targets. To foster the adoption of electric vehicles, a widespread and efficient charging infrastructure is essential. However, sizing charging stations remains challenging because it depends on the interaction of many heterogeneous variables that are often analysed in isolation. To overcome this limitation, this study proposes an integrated simulation model that captures these interactions within a single framework, enabling a more realistic assessment of charging-infrastructure design and operation. Following an extensive literature review, a simulation model was developed in Python environment, capable of jointly integrating the key variables identified in the literature. The model was validated against a certified software (EVerest), achieving a mean absolute percentage error of 2.7%, and against real charging session data, with a mean absolute percentage error of 4.3%. The model was then applied to a highway case study, simulating 111 served vehicles. The results show that the considered variables strongly affect quality-of-service metrics. Moreover, a simple management strategy based on a charging-time limit reduced the average waiting time by up to 97% in the tested scenarios.
Overall, these findings confirm the strong interdependence among the main parameters and highlight the need for integrated modeling approaches to support effective and realistic sizing of EV charging infrastructures.

KEYWORDS

Electric vehicle charging station; Charging management; Infrastructure optimisation; Multi-variable modelling; Dynamic simulation model; Energy management strategy.

INTRODUCTION

Climate change represents one of the most pressing global challenges, with the transport sector remaining a major contributor to greenhouse gas emissions. The deployment of electric and hybrid electric vehicles (EVs and HEVs) is widely recognised as a key strategy for mitigating these impacts due to their lower emissions, reduced noise, and improved environmental performance.

To accelerate adoption, many countries have introduced subsidies, tax incentives, and regulatory measures promoting zero-emission vehicles [1].

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Market analyses indicate rapid growth in the EV sector, with an average annual increase of 42% between 2012 and 2017 and projections suggesting that EV sales could exceed 50% of the global automotive market by 2040 [2, 3].

Achieving a large-scale transition to electric mobility requires coordinated actions among governments, manufacturers, consumers, and energy providers, with charging infrastructure playing a central enabling role. According to Piñas et al [4], the location and configuration of charging stations directly affect the penetration of electric vehicles. Moreover, the authors highlight that policy measures such as economic incentives and the strengthening of charging infrastructure have a significant impact on market penetration rates, with modelling forecasts consistent with the trends observed in European markets. As EV adoption accelerates, a well-designed Electric Vehicle Charging Station (EVCS) infrastructure becomes essential to satisfy user demand while limiting adverse effects on the power grid. Therefore, careful analysis and sizing are required to support the increasing penetration of this technology and the associated infrastructure needs.

Building on the need for a well-designed charging infrastructure, the planning and sizing of Electric Vehicle Charging Stations (EVCS) represent a complex problem involving both the transport system and the electrical grid. Charging demand is driven by mobility behaviour, while its effects materialise on the power distribution network. The literature shows that these two domains are often analysed separately, and many studies rely on simplified temporal representations that fail to capture the variability and uncertainty of demand and energy production profiles [5].

On the one hand, energy-oriented sizing models focus on station supply and grid interaction. Kassem et al. [6], for instance, propose an energy-driven approach for the optimal sizing of charging stations integrated with the grid and photovoltaic systems, applied to a university campus scenario. Their results demonstrate that accurate design can optimise energy flows and reduce grid dependence. However, the proposed model mainly focuses on the supply side, while demand is represented as a static load, thereby neglecting vehicle arrival variability, queue dynamics, and heterogeneous charging curves—factors that directly determine service quality. On the other hand, grid-focused planning studies examine impacts such as voltage drops, additional losses, and local congestion; consequently, several studies address optimal siting and grid impact assessment [7]. These analyses, however, are typically conducted at a territorial scale using aggregated load representations, without modelling the detailed internal operation of individual charging stations. At the network level, Gönül et al. [8] propose a coordinated charging strategy for highway stations that incorporates behavioural variables such as stopping probability, state of charge at arrival, and the spatial distribution of stations. This approach reduces both the required number of connectors and grid load peaks. However, it operates at a system scale, treating each station as a simplified node and neglecting internal energy management and the integration of renewable supply sources.

Other studies address the problem from the demand side using agent-based models and traffic simulations to describe user behaviour and spatio-temporal charging patterns. Multi-agent approaches can estimate the number and location of infrastructures required in complex urban contexts [9], but they do not consider the electrical sizing of individual stations, such as connection power or the capacity of storage and photovoltaic systems.

In the same vein, Wang et al. [10] investigate the spatio-temporal planning of charging infrastructure through a framework combining real traffic data, user behaviour, and grid constraints. Although the three-stage model (demand forecasting, placement optimisation, and power-flow verification) ensures overall electrical feasibility, each station is still represented as a passive load, without modelling interactions with local generation or storage resources.

Other contributions focus on the integrated sizing of station energy systems, including photovoltaic plants and storage units. Mathematical optimisation approaches, such as mixed-integer linear programming, identify cost-optimal configurations under operational constraints and, in some cases, battery degradation effects [11]. To maintain computational tractability, however, these methods often rely on representative scenarios or typical days, introducing a trade-off between temporal accuracy and model complexity.

Beyond sizing, more recently, research has addressed operational strategies such as smart charging, real-time load management, and participation in energy markets [12]. While these approaches improve operational efficiency and grid integration, they typically take the station configuration as an input rather than systematically addressing the sizing problem. Seitaridis et al. [13], for instance, propose an agent-based negotiation scheme between vehicles and stations that increases the number of served users, but operates at a high level of abstraction without modelling actual power flows, energy constraints, or renewable integration.

At the station level, dedicated simulation tools have also been developed to test management algorithms and control strategies, such as charging prioritisation and vehicle-to-grid services [14]. These tools demonstrate the effectiveness of simulation in representing station operation but are generally aimed at validating control strategies rather than supporting infrastructure design and sizing.

The integration of energy storage systems and photovoltaic generation is widely recognised as an effective solution to reduce demand peaks and mitigate grid impacts [15], with recent comparative analyses indicating that such configurations can be economically competitive with conventional grid reinforcement options [16, 17]. However, energy-oriented studies rarely incorporate behavioural and probabilistic aspects of demand, while those focusing on user behaviour often overlook internal energy management and renewable integration. As a result, key interactions between queueing performance and local energy constraints are frequently missed in single-station assessments.

This fragmentation highlights the need for an integrated approach capable of jointly combining dynamic demand modelling with local energy management to achieve a realistic representation of charging infrastructure operation. In response to this gap, the present work focuses on the single-station level and proposes a simulation model designed to support the planning and sizing of EVCS under realistic operating conditions. The framework integrates statistical demand modelling, state-of-charge-dependent charging curves, and key infrastructural constraints, such as the number of connectors and the maximum grid power, while also accounting for the integration of local resources including photovoltaic generation and energy storage with power management strategies. This approach enables a joint assessment of configuration choices and operational strategies in terms of service performance and energy flows within the station.

In line with the integrated framework described above, the development of the simulation model requires the systematic identification of all variables that characterise the system. For clarity, these variables are grouped into three main categories:

- Behavioural variables
- Vehicle variables

- Infrastructure parameters

Behavioural variables denote the stochastic characterisation of station usage (e.g., arrival patterns and requested energy) and represent a major source of uncertainty on the demand side. These variables are treated as exogenous statistical inputs in the simulations; adaptive or decision-based user behaviour is not modelled. Among them, the number of passing vehicles is fundamental for sizing, as it sets the potential demand level at the station. Moreover, charging habits depend on numerous factors and can vary significantly with regional, seasonal, and socio-economic conditions [18]. A salient example is the SoC upon arrival, which is a random variable influenced by individual preferences, the level of range anxiety, battery capacity, and the specific operational scenario [19-21].

The vehicle parameters encompass all quantities that influence the charging process. Among these, the charging curve is central to modelling, as it determines the mode and timing of the entire process. The behaviour depends strongly on the initial SoC: a high SoC at the start reduces the maximum deliverable power. In addition, the internal control performed by the Battery Management System (BMS), which regulates voltage, current, and temperature, introduces significant heterogeneity in the characteristic curves, differing for each vehicle. It is therefore necessary to specify the battery capacity and the maximum charging power supported by each model to characterise the charging profile correctly [22, 23].

The infrastructure parameters that influence system operation fall into this category. To characterise a station, it is necessary to specify the number of connectors and their associated power ratings. A crucial role is also played by the maximum power that can be drawn from the grid, which indirectly constrains the number of charging points effectively available and how they are managed. In many contexts, infrastructure constraints may cap the installable power, thereby necessitating alternative energy management strategies [24]. To increase flexibility and mitigate peaks, renewable sources and energy storage systems can be integrated to provide an additional share of available power. The infrastructure configuration and the estimation of its associated efficiencies are fundamental to an accurate description of the model. High-power charging (HPC) infrastructure often adopts a DC-connected architecture; in such cases, faithful modelling requires accounting for AC/DC and DC/DC conversion efficiencies, as well as internal thermal losses within the infrastructure [25].

Aim and novelty of the study

This paper addresses the fragmentation between transport-demand representations and station-level energy modelling by proposing a unified, validated station-scale simulation framework for EVCS planning and sizing. The aim is to support sizing and operational decisions at the single-station level by jointly capturing (i) stochastic arrivals and charging requests, (ii) realistic SoC-dependent DC fast-charging behaviour, and (iii) station energy constraints and on-site resource management.

Existing studies typically emphasise either network/territorial planning, where stations are represented as aggregated loads for siting and grid-impact analyses, or energy-system sizing/optimisation, where station demand is simplified using representative profiles or typical days to retain tractability. In contrast, the proposed framework explicitly links queueing and service quality (waiting time, throughput, utilisation) with internal energy flows and constraints (grid import limit, photovoltaic generation, battery storage operation, and conversion losses), so that operational bottlenecks and energy limitations emerge consistently from the same simulation.

The novelty of this work can be summarised as follows:

1. **Integrated station-scale coupling of demand and energy management:** the model combines stochastic vehicle arrivals (from traffic and charging frequency) with connector assignment/queue dynamics and station-level power allocation under grid and equipment constraints.

2. **SoC-dependent, heterogeneous fast-charging representation:** charging power requests are generated from vehicle-category-dependent charging curves, enabling realistic session dynamics rather than static or averaged loads.
3. **Explicit modelling of on-site resources and constraints:** PV generation and a BESS are modelled within the station power balance and dispatch logic, allowing assessment of peak shaving and operational flexibility under a binding grid limit.
4. **Quantified validation:** the model is verified against a certified charging-station platform (EVerest) and benchmarked against real charging-session data with reported error metrics, strengthening confidence in its use for planning and "what-if" analyses.

Based on the analysed studies, the quantities required to characterise the system were identified and grouped into three sets. Table 1 summarises the demand-side (behavioural) variables adopted to describe station usage and arrival characteristics. Table 2 reports the vehicle-related parameters that govern the charging process (e.g., charging curve, battery capacity, and maximum charging power). Table 3 lists the infrastructure and energy-related parameters that constrain station operation (e.g., number and rating of connectors, grid limit, and local energy resources). Together, Tables 1–3 define the input space of the simulation model introduced in the following section.

Table 1 Behavioural variables

Variable	Unit	Description
Traffic flow	veh/h	Total number of vehicles passing near the charging station per hour
Charging frequency	%	Fraction of vehicles requiring a charging session at the station
EV penetration rate	%	Share of electric vehicles within the total traffic flow
Initial SoC	%	Battery SoC upon arrival at the station
Target SoC	%	Desired battery SoC at the end of charging

Table 2 Vehicle variables

Variable	Unit	Description
Charging curve	kW vs SoC	Relationship between charging power and SoC
Battery capacity	kWh	Nominal energy capacity of the vehicle battery
Maximum charging power (EV)	kW	Maximum charging power supported by the vehicle

Table 3 Infrastructure parameters

Variable	Unit	Description
Number of connectors	-	Total number of available charging connectors
Maximum connector power	kW	Nominal power rating of each connector

Maximum grid power availability	kW	Maximum power that can be drawn from the grid connection
Storage efficiency	-	Round-trip efficiency of the energy storage system
Storage C-rate	-	Ratio between charging/discharging power and energy capacity
Storage capacity	kWh	Nominal energy capacity of the storage system
Nominal PV/wind power	kW	Installed nominal power of the renewable generation system
Station efficiency	-	Overall efficiency of the charging infrastructure (AC/AC, DC/DC, thermal losses)

METHODS

The following section describes the methodology adopted for modelling a charging infrastructure. Building on the variables defined above, we developed a Python-based simulation model to represent charging operations, queue dynamics, and station-level energy management within a single framework. The implementation follows an object-oriented approach, which simplifies the handling of charging operations and queue management.

In this work, the following Python libraries were employed: NumPy for numerical operations, pandas for data handling, SciPy for scientific computing, and Matplotlib for visualisation. In addition, the deque class from the ‘collections’ module was used to manage queue operations efficiently.

The main classes defined in the script are Vehicle and Charging Station. The logic of the main loop is summarised in the flowchart in Figure 1; the cycle is updated with a time step of 1 s, to ensure adequate resolution and avoid the loss of relevant information.

When a vehicle arrives, it is associated with the station and checks connector availability. If all connectors are occupied, the vehicle joins the queue; otherwise, it connects after a short delay $t_{w,j}$, which represents practical operations such as payment and plug-in procedures. Once connected, the charging process starts and a continuous exchange of information is established: the vehicle issues a power request, while the station determines the power that can be supplied based on the available resources and internal constraints (which may be equal to or lower than the requested level).

At each time step, every vehicle generates a power request consistent with its SoC and vehicle/connector limits, while the station determines the effectively available power by combining grid supply, renewable generation, and BESS support under operational constraints (e.g., grid import limits and BESS operating thresholds). The energy management logic distinguishes two operating conditions. When grid capacity is sufficient to meet total demand, the BESS does not discharge and may be charged using surplus renewable energy (when available), thereby reducing grid imports. Conversely, when grid capacity is insufficient, grid supply is saturated at its maximum value, renewable generation is used to minimise the residual demand, and the BESS is activated only to cover the remaining gap. At the end of each time step, energy balances and the BESS state of charge are updated.

The simulation reproduces the complete service cycle of each vehicle (waiting, connection, charging, and completion), including a technical connection delay and the automatic termination of the session upon reaching the target SoC. Upon completion, the vehicle disconnects from the station and the connector becomes available for the next vehicle in the queue.

The model assumes that all vehicles arriving at the station join the queue and are eventually served, with no abandonment or diversion to other stations. This assumption is adopted to analyse a maximum load (stress-test scenario) and to evaluate service quality under conservative operating conditions.

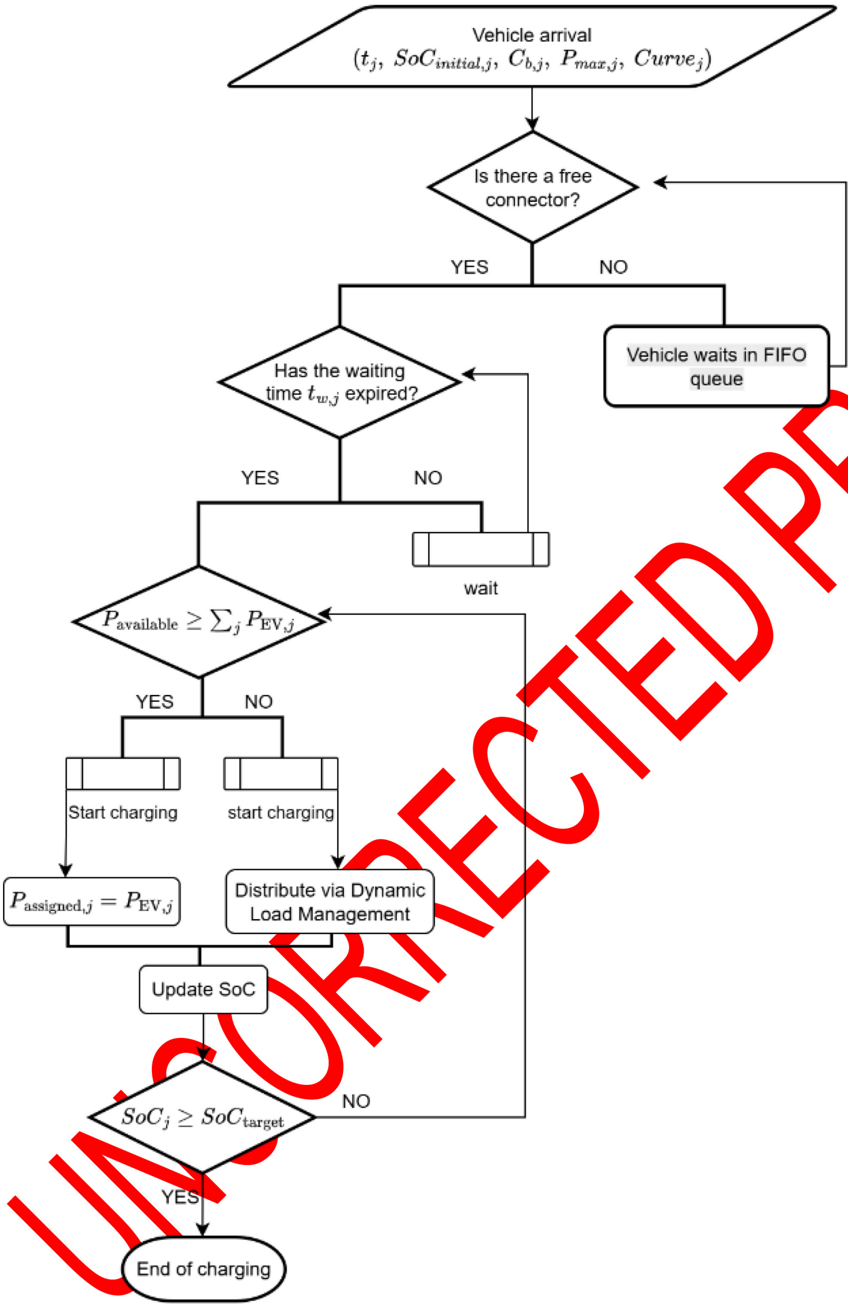


Figure 1 Flowchart of the control process

Vehicle class

The Vehicle class collects the attributes that characterise each electric vehicle, including arrival time, initial SoC, battery capacity, maximum power, and type of charging curve.

$$Vehicle = f(t_j, SoC_{initial,j}, C_{b,j}, P_{max,j}, Curve_j) \tag{1}$$

It handles the evolution of SoC during the simulation and the criteria for charging completion. The vehicle issues a power request to the infrastructure, which in turn determines the actual power allocated to each vehicle according to specified management logic.

The power requested by the vehicle ($P_{EV,j}$) is defined in accordance with the results of the National Renewable Energy Laboratory (2023) and ENEA (2017) [22, 23].

To capture the variability introduced by the Battery Management System (BMS), three representative charging-curve types were introduced, reflecting different vehicle categories and their typical DC fast-charging behaviour. This yields a power curve (kW) expressed as a function of the SoC.

$$P_{EV,j}(SoC) = f(P_{socket}, P_{max,j}, SoC_{initial,j}, Curve_j) \tag{2}$$

Charging curves were derived from experimental DC fast-charging profiles available in technical reports and public datasets, from which the characteristic points of power as a function of state of charge (SoC) were extracted. These points were subsequently fitted in MATLAB to obtain continuous functions describing the dynamic power evolution according to the typical CC–CV behaviour of lithium-ion batteries. To capture vehicle heterogeneity, the curves were classified into three types: (i) rapid-decay curves, where power decreases immediately after the initial peak; (ii) intermediate curves, characterised by a short quasi-constant power phase followed by a moderate reduction; and (iii) slow-decay curves, in which power remains close to the maximum value over a wider SoC range. The model accounts for the influence of the initial SoC through interpolation between reference profiles.
Validation was performed by comparing simulated charging times (0–80% SoC) with real charging sessions, yielding a mean absolute percentage error (MAPE) of 4.3%, which confirms the model's ability to realistically reproduce EV charging behaviour.

Figure 2 shows the resulting power–SoC profiles for the three representative charging-curve types for an initial SoC of 10%.

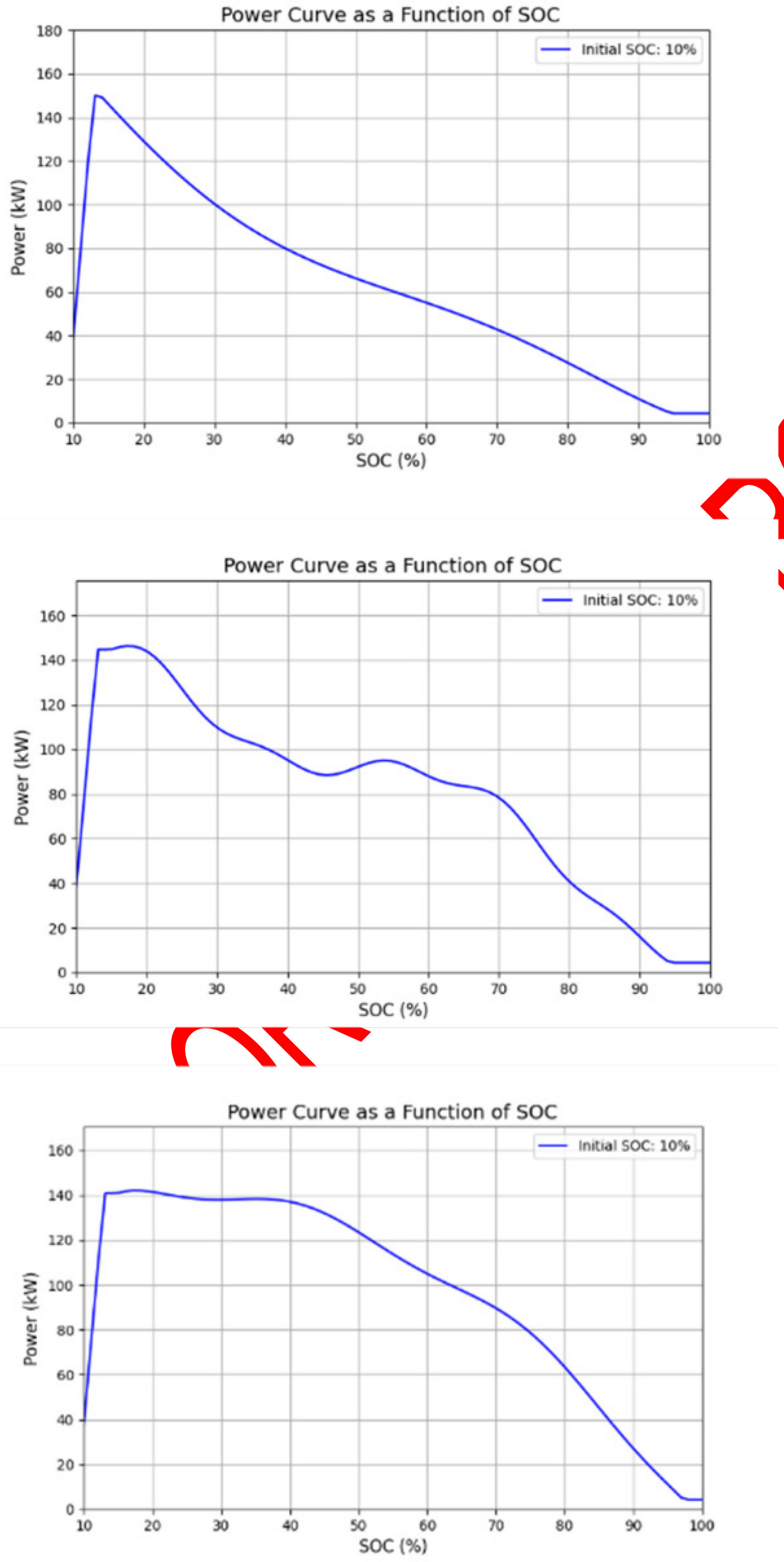


Figure 2 Power–SoC profiles of the three representative charging curve types

EV charging station class

It is the key element of the model and is responsible for governing the entire charging process. Its primary function is energy management: it assesses the available energy to supply vehicles with an appropriate amount, while respecting the system's internal constraints. To this end, it considers grid import, renewable generation, and battery storage to define priority criteria for their use and delivery, and—when necessary—redistributes power among active connectors to ensure fair allocation. The available power at any instant is given by the sum of the three contributions, as shown by Eq. 3.

$$P_{available}(t) = P_{grid}(t) + P_{BESS}(t) + P_{renewable}(t) \qquad (3)$$
$$0 \leq P_{grid}(t) \leq P_{grid}^{\max}$$

Equations 4, 5, and 6 illustrate the logic for energy redistribution.

$$P_{available}(t) \geq \sum_j P_{EV,j}(t) \Rightarrow P_{assigned,j}(t) = P_{EV,j}(t) \qquad (4)$$

$$P_{available}(t) < \sum_j P_{EV,j}(t) \quad \Rightarrow [Progressive\ Filling\ algorithm] \qquad (5)$$

$$P_{assigned,j}(t) \leq P_{EV,j}(t), \qquad P_{available}(t) = \sum_j P_{assigned,j}(t) \qquad (6)$$

If the available power is insufficient, a Dynamic Load Management (DLM) method is adopted to redistribute power fairly, while respecting all constraints of both the infrastructure and the vehicle, where energy availability makes prioritisation necessary.

When the total power requested by connected vehicles exceeds the available supply, the management system activates a redistribution logic (Progressive Filling): vehicles requesting less than the average share receive their full demand, and the remaining power is progressively redistributed among the others until the available capacity is fully utilised. This redistribution is applied at each time step based on the station-level energy management outcome (i.e., the total $P_{available}$).

Power levels within the infrastructure can, at certain times, exceed the grid's available capacity; in this context, energy storage plays a central role, not only to utilise renewable energy and secure an economic return, but also to ensure service continuity during peak demand in specific time windows [24]. The battery energy storage supplies power only when the grid cannot meet the demand. During off-peak hours, charging the battery from renewable sources is prioritised when available. Because grid availability and adjacent loads are site-dependent, selecting an appropriate management strategy requires a site-specific assessment.

In addition to the allocation strategy, system efficiencies were incorporated to account for conversion losses and thermal effects associated with the infrastructure configuration.

In the model, conversion and thermal efficiencies were implemented for the assumed AC-connected station architecture using reference values that are typical of applications of this category. As a consequence, the overall efficiency is modelled as dynamic, since it depends on both the configuration and the instantaneous energy flows [25].

Validation

After developing the model in Python, a validation phase was carried out using EVerest by LF Energy, an open-source software platform for managing electric-vehicle charging stations [26]. EVerest provides a modular firmware stack that integrates standard protocols (OCPP, ISO 15118) and local energy-management functions. As software conceived for real-world infrastructure operation, it does not support accelerated simulation.

A baseline configuration was then replicated in both EVerest and Python: an AC charging station with a total maximum power of 13.8 kW and two connectors, with active energy management to enforce the station power cap while distributing power across the connectors. To enable a direct comparison between the two models, a test vehicle flow at the station ingress was defined. By limiting each charge to a 5% SoC increment, it was possible to simulate 110 sessions over 20 hours.

The comparison between the results obtained in the two environments (Figure 3) shows a high consistency between the charging times simulated in Python and those obtained with EVerest, with a coefficient of determination of 0.9941, a mean absolute error of approximately 33 s, and a mean absolute percentage error (MAPE) of 2.72%. These outcomes confirm the validity and reliability of the developed model.

Following the validation, a comparison was conducted against real charging session data.

The reference data were collected from EVKX.net, a source that provides detailed information on charging sessions and charging curves for a wide range of electric vehicle models [27].

Ten electric vehicles representative of the main market segments sold in Italy were selected: Tesla Model 3, Audi Q4, Jeep Avenger, Mercedes EQC, BMW i4, Volkswagen ID.5, Tesla Model Y, Dacia Spring, Renault Mégane, and Peugeot 208. For each model, the nominal battery capacity and the maximum supported charging power were associated, and the time required to progress from 0% to 80% SoC was compared against the reference dataset.

The comparison with real data (Figure 4) highlights a good agreement between the simulated and observed charging times, with a coefficient of determination of 0.9101, a mean absolute error of approximately 97 s, and a MAPE of 4.32%. These results confirm the model's capability to realistically reproduce the actual charging behaviour of electric vehicles.

The obtained results are slightly less accurate than in the previous case, as charging processes can vary significantly. As also shown by real charging curves, each vehicle follows its own profile, defined by the BMS. For this reason, it is impossible to achieve a perfect match between simulated and real data. In the model, only three types of charging curves were considered, according to the vehicle category, to obtain the most versatile and representative fitting possible.

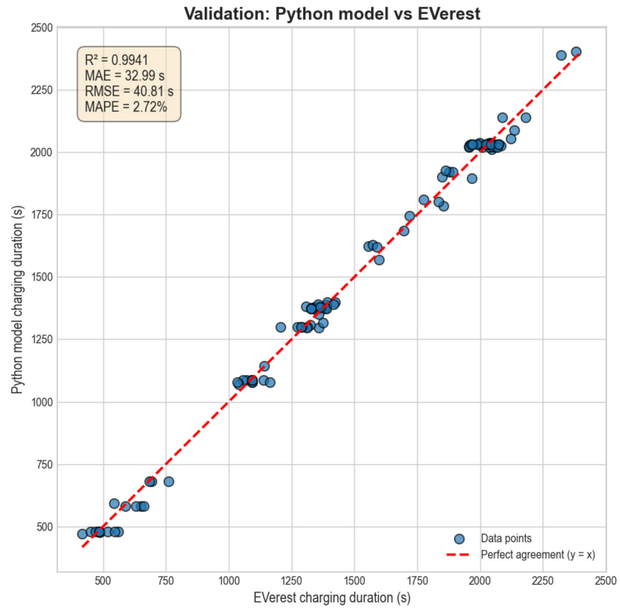


Figure 3 Validation of the Python model against EVerest

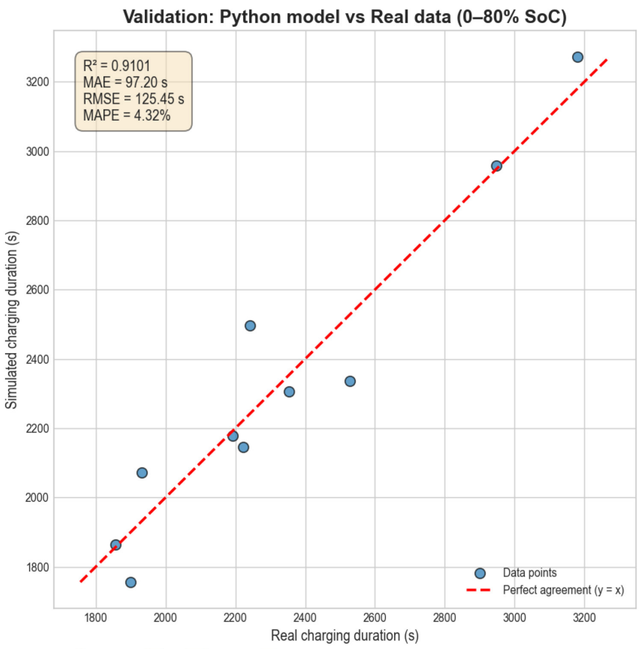


Figure 4 Validation of the Python model with real charging data (0–80% SoC)

CASE STUDY

The analysis and development methodology for charging infrastructures is highly site- and scenario-dependent. To foster the diffusion of charging infrastructures, it is essential to consider both morphological factors, such as the availability of areas suitable for conversion into charging stations, and economic, social, and infrastructural aspects.

Accordingly, the scenario type strongly influences which infrastructure typologies are feasible and prioritised. For instance, in peripheral areas, installing charging hubs is often not viable, as the limited demand does not justify investments in large infrastructures. Conversely, in major cities, on-street charging alone may prove inefficient and insufficient to fulfil the overall demand.

As highlighted by a UK Government report [28], there are significant regional disparities in the deployment of charging points. The report notes that the business case for commercial deployment can be challenging, particularly in areas with potentially low utilisation or high connection costs. At the same time, it emphasises the need to accelerate deployment to ensure sufficient charging points before demand rises, thereby supporting the transition and building public confidence. This situation is often referred to as a "chicken-and-egg" problem, where potential EV buyers are hesitant to purchase until a visible charging network is available.

As demonstrated by the study carried out by the University of Palermo in 2020 [29], the analysis of electric mobility infrastructures in Italy highlights differentiated scenarios depending on population density and the level of technological adoption. The proposed model underlines that population density represents one of the key factors in the planning of the charging network. Against this background, we selected a highway scenario to test the developed model, because traffic flows are easier to estimate and because the setting is well suited to analysing high-power charging stations, which require particularly high power levels to be drawn from the grid.

As a case study, the A2 highway, which connects Salerno to Reggio Calabria, was selected, with specific reference to the Salerno west service area. This section was chosen because it is managed by ANAS, the company responsible for the national road and motorway network, which provides detailed reports and data on the sections under concession. These data enable a realistic characterisation of highway traffic conditions and therefore support a consistent demand input for the simulations.

Input characterisation

In this first phase, the inputs required for the simulation of the selected scenario were defined and quantified.

Based on the data provided by ANAS [30], it was possible to model the vehicle flow along the considered motorway section. The simulation, performed using VISSIM software, was carried out on a weekday from 6:00 a.m. to 12:00 p.m (noon). Figure 5 shows the resulting hourly traffic profile used as input for the demand characterisation, with a peak of 3,300 vehicles at 7:00 a.m [31, 32].

The EV penetration rate was set at 25%, reflecting a forward-looking horizon consistent with the 2035 infrastructure planning framework developed by MOTUS-E for Italy and aligned with major market projections [32]. This assumption avoids sizing based on transient current conditions and instead represents a realistic future scenario.

The charging frequency (3.7%) was estimated from highway-specific reports [31] by deriving it from the average refuelling frequency on motorways and adjusting it to typical electric vehicle driving ranges. In the absence of consolidated public datasets on highway charging stops, this value should be interpreted as a scenario assumption that may vary depending on local conditions.

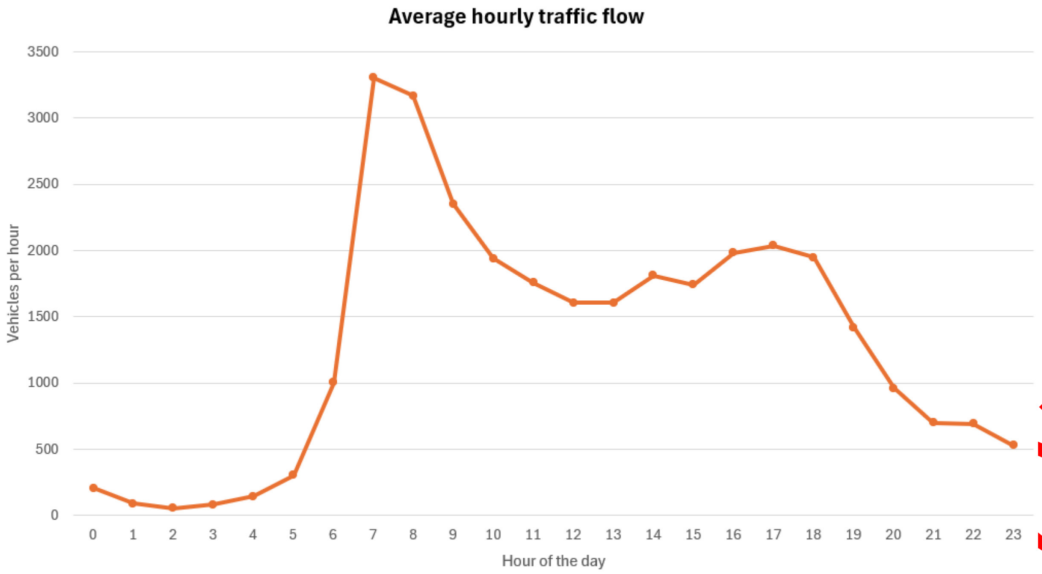


Figure 5 Average hourly traffic flow on the considered highway section

Assumptions for the initial SoC were based on the study conducted by Guo et al. [19]. This study identifies four main categories of user behaviour according to the SoC level at the start of charging, defining four different frequency distribution curves. To capture this variability in a single parametric form, a Gaussian distribution with a mean value of 35% and a standard deviation of 15% was adopted, limited to the range between 5% and 70%.

This distribution allows for a realistic representation of the dispersion of SoC values at the beginning of charging. Each charging process is considered complete once a target SoC of 80% is reached.

The vehicle fleet considered was built starting from the fifty bestselling electric vehicle models in Italy in 2023, considering their respective sales distribution. In this way, each model was assigned a weight proportional to its market share, thereby allowing a realistic representation of the composition of the circulating fleet.

Regarding the infrastructural characteristics, the analysis considered a charging station composed of eight connectors rated at 150 kW, powered by a battery storage system with a capacity of 400 kWh, a C-rate of 1, and a round-trip efficiency of 90%. The station is also equipped with a photovoltaic plant with a peak power of 270 kWp and is limited to a maximum grid power draw of 500 kW.

The internal efficiencies of the infrastructure, including both conversion and thermal efficiencies, lead to an overall efficiency of approximately 90%. This value is an effective (scenario-average) efficiency, since the efficiency varies with the instantaneous energy flows and the path followed by the current in the assumed AC-connected configuration [17].

The input values adopted for the case study are summarised in the following tables. Table 4 reports the demand-side parameters describing traffic conditions and charging behaviour, derived from traffic data and literature-based assumptions. Table 5 lists the vehicle-related inputs used to represent the composition of the circulating fleet. Table 6 presents the infrastructure configuration and energy-system parameters assumed for the analysed charging station.

Table 4 Behavioural variables

Variable	**Input**
Traffic flow	Hourly profile

	(peak of 3300 vehicles) [30]
Charging frequency	3.7% [31]
EV penetration rate	25% [32]
Initial SoC	Gaussian (μ = 35%, σ = 15%) [21]
Target SoC	80%

Table 5 Vehicle variables

Variable	**Input**
Charging curve	Fitting
Battery capacity	Market-based statistical data
Maximum charging power (EV)	Market-based statistical data

Table 6 Infrastructure parameters

Variable	**Input**	**Unit**
Number of connectors	8	-
Maximum connector power	150	kW
Maximum grid power availability	500	kW
Storage efficiency	0.9	-
Storage C-rate	1	-
Storage capacity	400	kWh
Nominal PV/wind power	270	kW
Station efficiency	≈ 0.9	-

RESULTS

This section presents the main outcomes of the dynamic simulation applied to the considered highway case study. First, the temporal evolution of power levels at both connector and station level is analysed to characterise station operation. Then the energy performance of the system is examined under two photovoltaic production scenarios and the impact of an active management strategy aimed at reducing peak-hour congestion is assessed. Finally, alternative configurations to evaluate the sensitivity of service quality to key design parameter are compared.

The dynamic simulation allows for the monitoring of all the characteristic parameters and the energy management of the charging station. This enables a detailed analysis of power evolution at both the station level and the connector level, as shown in Figure 6.

The graph allows distinguishing the charging profiles of individual vehicles. The curves vary according to the vehicle type, consistently with both the fitted power demand and the energy availability and management of the infrastructure, which makes the charging process strongly scenario-dependent and difficult to predict a priori. At certain moments, charging power shows step-like variations as a direct consequence of the redistribution logic activated during critical periods. Consequently, charging power is influenced by energy availability, station saturation, and external conditions.

The graph also allows for the assessment of the utilisation coefficients of the connectors and the identification of idle periods associated with the intentional delay $t_{w,j}$ between consecutive charging sessions.

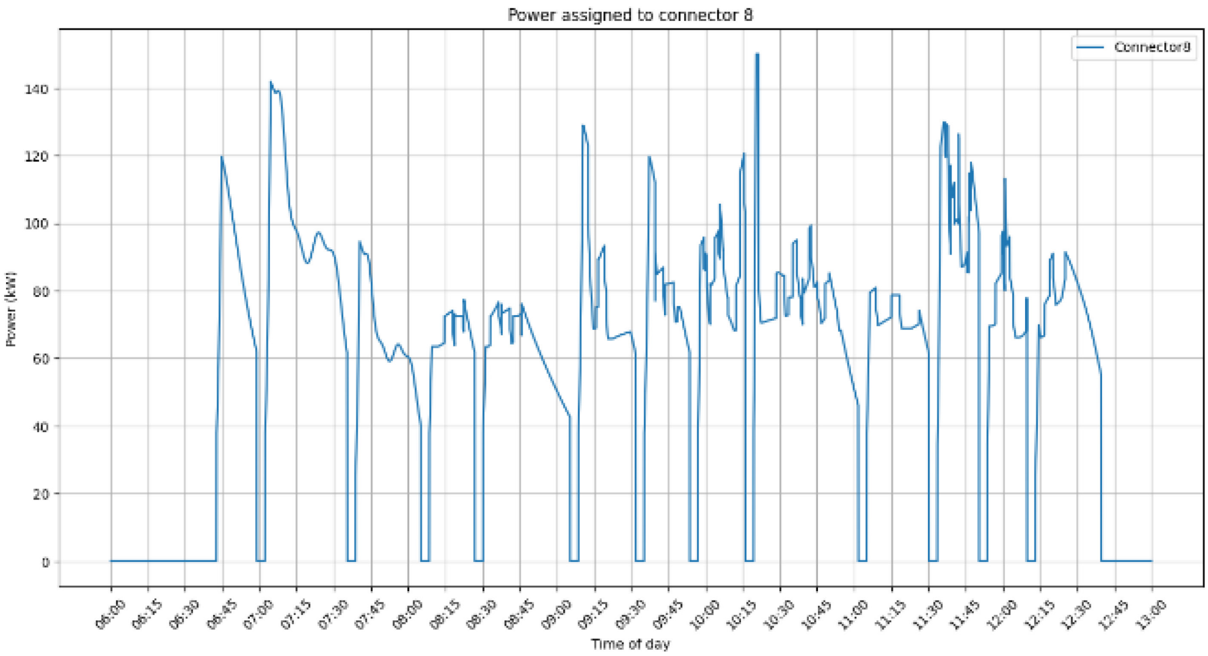
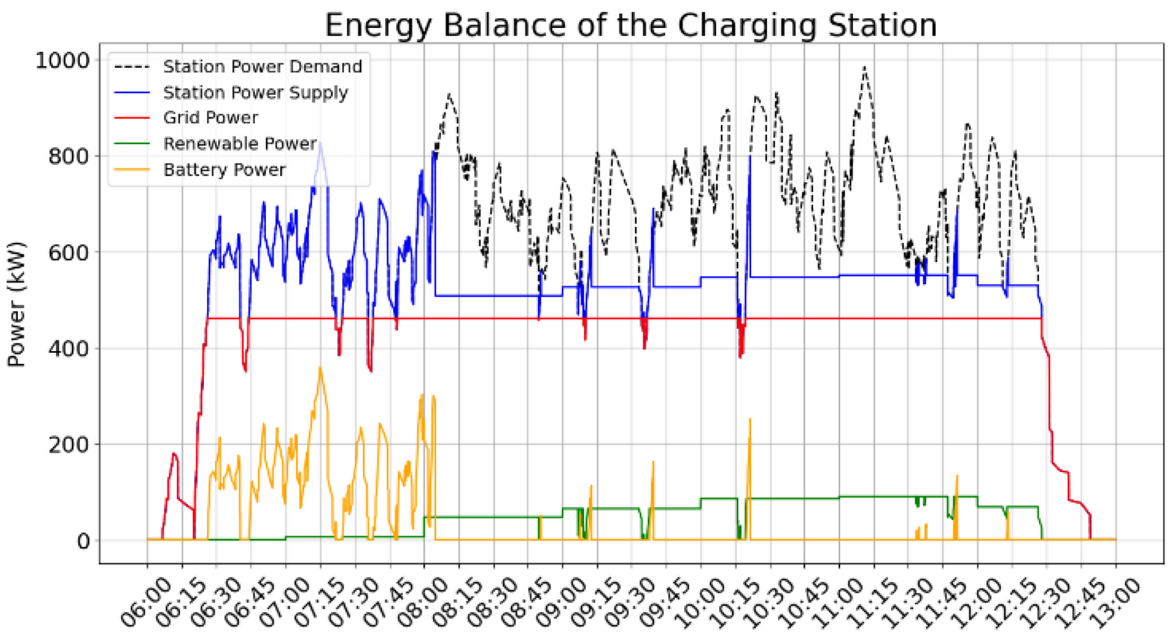


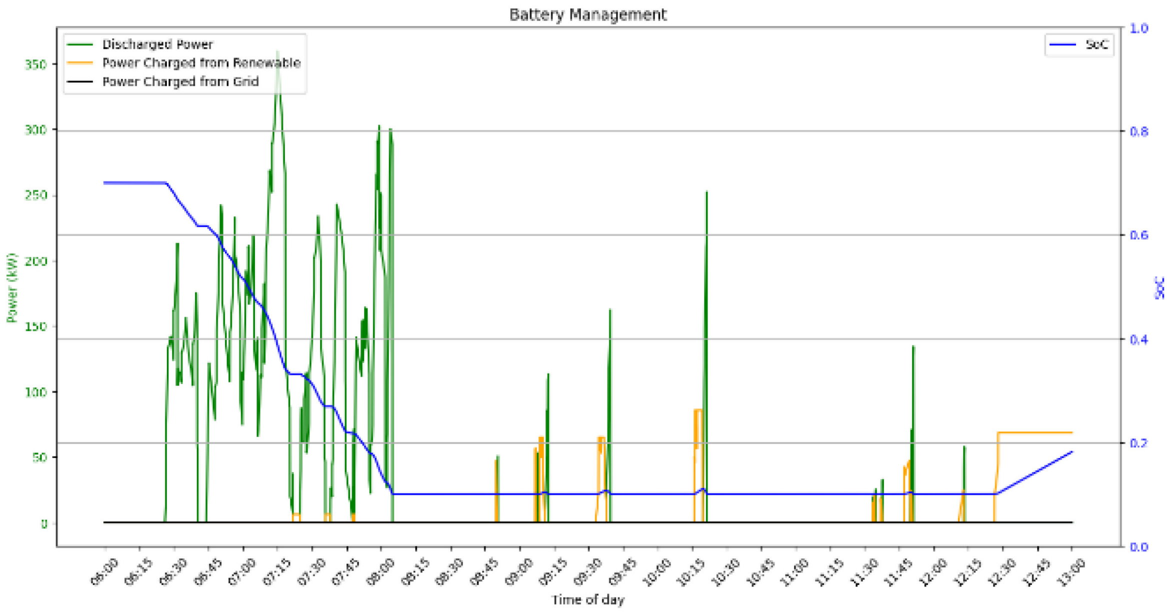
Figure 6 Power profile of connector 8

In a first simulation, a minimum photovoltaic production was considered, corresponding to the average daily generation during the month with the lowest solar availability. The resulting station energy balance is reported in Figure 7. Panel (a) illustrates the station power balance, while panel (b) reports the battery operation over the same period. It can be observed that the infrastructure operates constantly at the limit of the power that can be drawn from the grid (500 kW, net of losses), owing to the high vehicle flow and the peak of 3,300 vehicles recorded at 7:00 a.m. This condition leads the station to saturation, as the Station Power Supply curve is unable to follow the dashed line representing user demand. Under this sustained constraint, the storage battery remains insufficient (even when initialised at 70% SoC), and the limited renewable generation cannot compensate for the residual demand.

With this configuration, the infrastructure manages to charge 111 vehicles over the entire analysed period, but with an average waiting time of 45 minutes, which indicates a rather low quality of service.



(a)

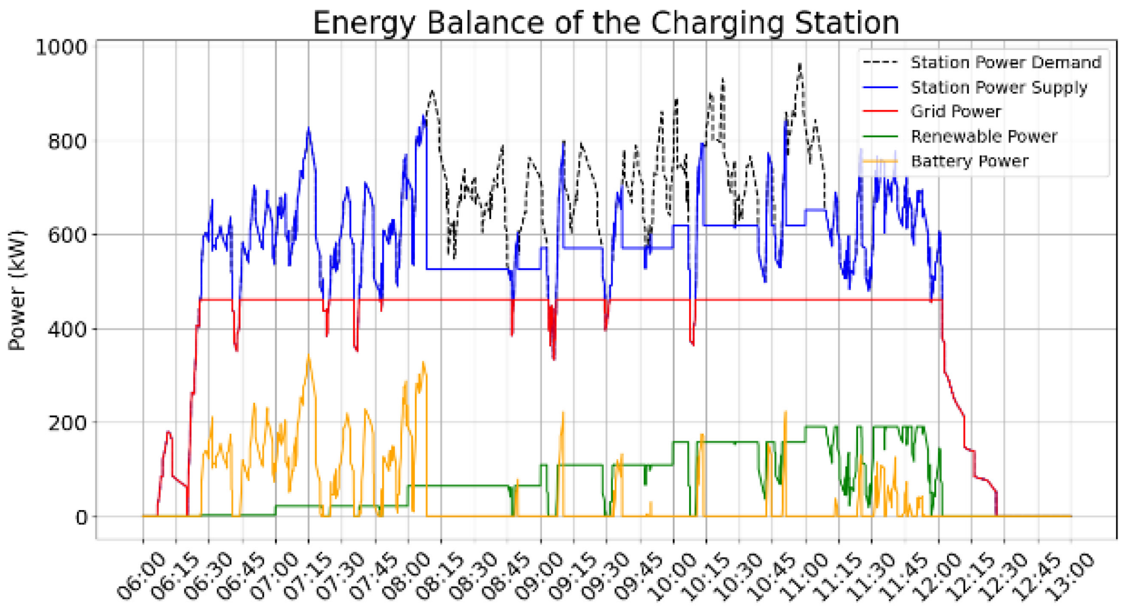


(b)

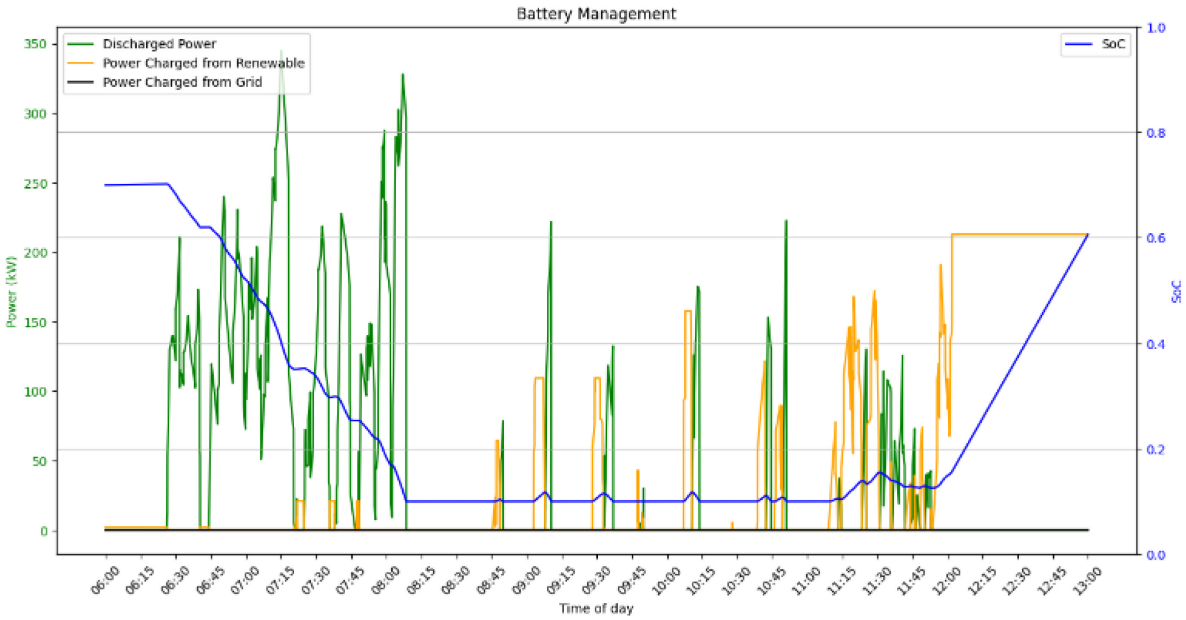
Figure 7 Energy balance (a) and battery management (b) of the proposed charging station during the month with the lowest solar production

In a second simulation, the average production of the photovoltaic field during the month with the highest solar availability is considered (Figure 8).
Although the increased photovoltaic production improves the energy balance, the station performance remains constrained by the maximum grid power availability and the high traffic demand, highlighting the importance of infrastructure sizing and power constraints in high-flow scenarios.

The infrastructure can follow the demand more effectively and recharge the battery, resulting in a 14% reduction in average waiting times and a 7% decrease in charging durations. However, the average waiting time still exceeds 40 minutes, indicating that the reference configuration remains inadequate for the considered scenario.



(a)



(b)

Figure 8 Energy balance (a) and battery management (b) of the proposed charging station during the month with the highest solar production

The analysis shows that, in a highway context and for the considered vehicle flow, the presence of eight connectors is insufficient to ensure an efficient operation of the infrastructure. The station quickly reaches saturation during peak hours, when the high number of incoming vehicles, combined with the limited number of charging points, results in average waiting times exceeding 40 minutes and a continuous redistribution of power among vehicles. Moreover, the storage system, even starting from a SoC of 70%, is unable to compensate for the 500 kW grid power constraint, and the limited renewable generation further reduces the margin available to serve simultaneous sessions.

This condition leads to an overall deterioration in the quality of service and a non-optimal use of the infrastructure. These results therefore highlight the need to explore alternative management strategies aimed at reducing congestion during the hours of highest demand.

To this end, a charging time limitation of 10 minutes was introduced as an intentionally restrictive demand-management strategy applied only during the peak period (6:30–9:30 a.m.) to isolate the theoretical effect of active congestion control. It is not proposed as a standard operational rule, but as an extreme scenario aimed at quantifying the impact of management logic on service quality.

Under this control, the average waiting time decreases to approximately 54 s and the maximum waiting time to less than 10 min, corresponding to reductions of about −97% (average waiting), −44% (average charging time), and −90% (maximum waiting) compared with the unrestricted case. From a user perspective, the average delivered energy is about 17 kWh (+25% SoC), corresponding to roughly 100 km of range, which is consistent with a top-up charge sufficient to reach subsequent service areas. More realistic implementations could include limits activated only under queue conditions, dynamic pricing, or cut-off criteria based on SoC or power rather than fixed time thresholds.

From the analysis of the station's energy balance, as shown in Figure 9, it can be observed that, compared with the previous case, the station no longer operates constantly at the limit of the maximum power drawn from the grid. The shorter charging sessions reduce the simultaneity of recharging events, meaning that fewer vehicles are connected at the same time, which in turn decreases average waiting times and queue lengths. This behaviour results in a lower average delivered power, allowing the infrastructure to better adapt to the available energy and to follow the load profile more effectively.

Consequently, the station can fully satisfy the demand without vehicle accumulation in the queue; around 11:00 a.m., the infrastructure no longer supplies power, confirming the complete clearance of the vehicle flow.

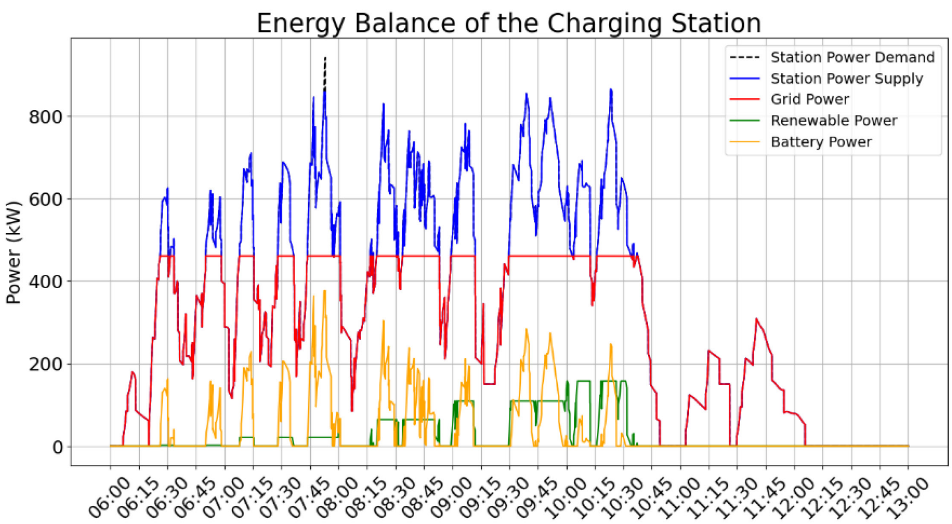


Figure 9 Energy balance in case of charging time limitations

From an energy perspective, the flows associated with the reference configuration reveal a clear dominance of the electrical grid as the primary supply source. Out of a total of approximately 2514 kWh delivered to the system, about 2122 kWh (84%) is drawn from the grid, while the contribution of the storage system amounts to roughly 267 kWh (11%) and that of renewable sources to about 125 kWh (5%). These results indicate that, although PV generation and the BESS contribute to peak shaving and temporal load balancing, they primarily act as supporting resources rather than substitutes for the grid in high-power highway scenarios characterised by a high simultaneity of charging sessions. In this context, the role of renewable generation and storage is therefore primarily to mitigate power peaks and improve the operational efficiency of the system, whereas the grid remains structurally dominant in ensuring service continuity.

Overall, these results suggest that in scenarios characterised by high vehicle flow and high-power levels, the adoption of alternative management strategies can offer significant benefits to the system, especially in cases where particularly high peaks in demand may lead to an oversizing of the infrastructure.

The study also highlighted that the sizing of a charging station depends on numerous factors and that, in the current configuration, it is complex to identify an optimal balance. Even a simple variation in the maximum power of the individual connectors can, in fact, lead to significantly different results.

The same configuration analysed previously was modified by setting five connectors at 100 kW and three at 150 kW. In this configuration, the average power delivered by the infrastructure decreases due to the reduction in the nominal power of the connectors. This condition leads to an increase in the average charging times and, consequently, to longer overall vehicle waiting times. As a result, maximum waiting times increase by approximately 40% compared with the reference case. Conversely, increasing the connector power from 150 kW to 200 kW did not yield significant benefits in terms of waiting times: the observed reduction is limited to 3% for the average waiting time and 9% for the maximum value.

From these results, a complex interdependence among infrastructural parameters emerges, leading to configurations that can differ significantly and remain difficult to predict. In the analysed highway scenario, performance degradation is primarily driven by the simultaneity of charging events under a strict grid power constraint. Under these conditions, increasing the nominal power or number of connectors does not yield proportional benefits, as the effective limiting factor is the available energy rather than the installed capacity. This finding is consistent with the literature, which highlights that HPC station performance depends not only on installed power but also on vehicle compatibility and session concurrency.

Within this context, simple operational measures — such as the temporary introduction of charging time limits during peak hours — can be interpreted as strategies aimed at increasing vehicle throughput by reducing simultaneity and queue formation, although they do not represent universally optimal solutions. Their effectiveness also depends on the presence of a sufficiently developed and coordinated charging network, ensuring that shorter sessions still allow users to reach subsequent stations.

The generalisability of these results therefore depends on the application context. While the underlying mechanisms remain valid, their effects may vary across highway, dense urban, and low-density peripheral scenarios due to differences in arrival patterns and spatial constraints. Finally, behavioural inputs remain a significant source of uncertainty, and the lack of detailed operational data limits the precise calibration of the model. To achieve a proper sizing, it is therefore necessary to analyse the joint influence of all parameters, both infrastructural and behavioural. In this context, the developed model supports rapid "what-if" analyses by allowing fast changes of configuration variables, enabling straightforward comparison across scenarios and improved understanding of parameter interdependencies. In perspective, the model could be employed to carry out sensitivity analyses, to evaluate the weight and influence of each variable on the overall performance of the charging infrastructure.

CONCLUSION(S)

An insufficient and unreliable charging infrastructure can hinder the adoption of electric mobility, particularly along highway routes, where service continuity and availability are critical. To address this issue, charging infrastructures must be properly located and sized to ensure an efficient service and foster EV adoption. Deploying many charging stations may improve perceived availability, but it can also lead to inefficient use of economic resources, since fast-charging equipment is highly expensive. For this reason, effective sizing methods are needed to balance service requirements with economic constraints and to avoid wasteful overinvestment. However, sizing a charging network is inherently complex because it depends on numerous technical, infrastructural, and behavioural parameters that must be considered jointly to ensure an efficient and sustainable design. In this context, static approaches based on average values may be misleading, as they can overestimate or underestimate both the number of stations required and their capacity. For this reason, the definition of the number of connectors must be supported by an accurate technical analysis, able to consider all relevant variables and system constraints.

Based on the simulations performed, the analysis shows that, in contexts characterised by high vehicle flows, the adoption of energy- and logic-management strategies is crucial and can yield significant benefits, often exceeding those achievable through hardware upgrades alone.

In particular, reducing connector power from 150 to 100 kW increased waiting times to more than 40%, whereas increasing power to 200 kW produced only marginal improvements (about 9% reduction in maximum waiting times). By contrast, introducing a simple time-limitation strategy during peak hours drastically reduced congestion, decreasing the average waiting time by up to 97% (from 45 minutes to 54 seconds).

Despite the charging limitation, vehicles recharge on average about 17 kWh during the controlled period, which is sufficient to reach subsequent charging stations. This suggests that, in a sufficiently dense and coordinated network, temporary peak-hour limits could help redistribute demand across neighbouring service areas and improve system-level balance. From an energy perspective, this management approach prevented the infrastructure from operating continuously at the maximum grid import limit, thereby improving overall controllability of load peaks and reducing the need for frequent power reductions at the connector level. It is important to note, however, that the 10-minute charging limitation is intentionally extreme and was introduced here to isolate and quantify the effect of active congestion management rather than to propose a universal operating rule.

The analysis also shows that identifying a truly optimal configuration remains challenging due to the strong interdependence among infrastructural and behavioural parameters. Consequently, defining effective alternative strategies requires systematic exploration of design and control options under realistic operating conditions. From this perspective, the simulation model developed in this work provides a practical tool, as it enables rapid testing and comparison of scenarios and management logics while consistently tracking service-quality and energy-flow indicators.

In the developed model, all arriving vehicles are served, and no abandonment or diversion to other stations is considered. This assumption was adopted to analyse maximum-load conditions and to assess infrastructure performance under critical scenarios, with the aim of identifying strategies capable of serving the entire vehicle flow during intense but short-duration peaks, as typically occurs in highway traffic.

In future developments, the model could be extended to include more realistic behaviours by introducing abandonment/diversion mechanisms as a function of station saturation, thereby allowing the effectiveness of management strategies to be evaluated under more variable and realistic operational conditions.

An important finding that emerged from this study concerns the need for accurate sizing, considering stochastic variables and their related infrastructural constraints. The difficulty of this process lies in the high number of factors influencing the system, many of which are difficult to define and model precisely, as they are not fully predictable.

The analysis also highlighted that user behaviour represents a crucial element for the proper design of charging infrastructures, yet it is challenging to estimate accurately.

To support this analysis and enable further scenario exploration, a Python-based software was developed as a flexible, dynamic simulator. The tool allows rapid modification of behavioural and infrastructural inputs and supports direct comparison of alternative configurations and control strategies. The theoretical aspects and reviewed studies were integrated into the simulator to provide a versatile instrument grounded in a consistent methodological framework, capable of supporting future in-depth analyses.

Electric mobility remains a recent and highly complex field. The literature does not yet provide fully consolidated sector-wide datasets, and the limited availability of real charging-session data—also due to privacy constraints—restricts extensive calibration and benchmarking against field observations. A relevant next step is to complement the technical simulator with an economic module, supported by detailed studies on installation and operating costs, to enable robust economic evaluation and comprehensive sensitivity analyses.

NOMENCLATURE

Symbol	Unit	Description
$C_{b,j}$	kWh	Battery capacity of vehicle j
$Curve_j$	-	Assigned charging curve type for vehicle j
$P_{assigned,j}(t)$	kW	Power assigned to vehicle j at time t
$P_{available}(t)$	kW	Total power available at the station at time t
$P_{BESS}(t)$	kW	Power provided by the Battery Energy Storage System at time t
$P_{EV,j}(t)$	kW	Power requested by vehicle j at time t
$P_{grid,j}(t)$	kW	Power drawn from the electrical grid at time t
P_{grid}^{max}	kW	Maximum grid power capacity
$P_{max,j}$	kW	Maximum charging power of vehicle j
$P_{renewable}(t)$	kW	Power available from renewable sources
P_{socket}	kW	Nominal power of the charging socket/connector
$SoC_{initial,j}$	-	Initial SoC of vehicle
SoC_j	-	Current SoC of vehicle j
SoC_{target}	-	Target SoC at the end of the charging session
t_j	s	Arrival time of vehicle j
$t_{w,j}$	s	Dead time before charging start for vehicle j (e.g. payment, authentication, setup)

Abbreviation	Description
AC	Alternating Current
BESS	Battery Energy Storage System

BMS	Battery Management System
DC	Direct Current
DLM	Dynamic Load Management
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
HEV	Hybrid Electric Vehicle
HPC	High-Power Charging
ISO	International Organization for Standardization
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
OCPP	Open Charge Point Protocol
PV	Photovoltaic
QoS	Quality of Service
RMSE	Root Mean Square Error
SoC	State of Charge

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