

Article

A Digital Sandbox Approach: Simulating and Forecasting Charging Demand of Electric Two-Wheelers for Risk-Informed Infrastructure Planning

Yiru Yang *, Huijun Hong, Jiahe Chen, Qiyang Ruan, Zhengcheng Min and Jiaying Hu

Guangzhou Haizhu Power Supply Bureau of Guangdong Power Grid Co., Ltd. Guangzhou 510220, China; honghuijunwhu@163.com (H.H.); chenjiahewhu@163.com (J.C.); ruanqiyangwhu@163.com (Q.R.); minzhengchengwhu@163.com (Z.M.); hujiayingwhu@163.com (J.H.)

* Correspondence: lotustougao@163.com

Abstract

The rapid surge of Electric Two-Wheelers (E2Ws) in high-density urban villages imposes severe strain on low-voltage residential distribution networks. Unlike formal Electric Vehicles, E2W charging is decentralized and highly constrained by short pedestrian walking thresholds, frequently forcing users to adopt non-compliant “fly-wire charging” when public facilities are scarce. Traditional top-down load models fail to capture these localized, micro-behavioral single-phase grid impacts. To address this deficit, this study proposes a GIS-integrated “Digital Sandbox” simulation framework that projects individual behavioral mutations directly onto feeder networks via a hyper-granular “particle tracking” mechanism, treating each E2W as an autonomous agent. As a case study focused on a representative urban-village area, we validate the model using field data from the site. A 30-day simulation reveals that unmanaged fly-wire charging generates a peak load of 17.64 kW (nearly double the public station peak) and accounts for 38.9% of aggregate energy consumption—concentrated within the top 10 buildings and coinciding with evening peaks, inducing severe phase imbalance. While the numerical results are case-specific, the framework itself is transferable to other service areas through re-calibration against local data. This foundational digital twin blueprint shifts E2W planning from guesswork to particle-level risk prediction.

Keywords: Electric two-wheelers (E2Ws); digital sandbox simulation; charging demand forecasting; agent-based modeling; spatio-temporal analysis

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1. Introduction

With the continuous advancement of the urban transportation green transition, E2Ws have experienced a rapid surge in ownership within densely populated areas, such as urban villages, owing to their convenience and cost-effectiveness, becoming a primary mode for residents’ short-distance travel [1]. However, the planning and construction of the corresponding charging infrastructure, particularly in these unique urban spaces, lags [2]. Unlike centralized and relatively well-regulated charging stations for Electric Vehicles (EVs), E2W charging demand exhibits distinct characteristics of being “widely distributed, low in single-unit power, yet substantial in aggregate volume” [3,4]. Their charging behavior predominantly occurs at the residential endpoint, directly coupled with low-

voltage distribution transformer areas. Consequently, the aggregated load generated has a non-negligible impact on the already fragile distribution networks in urban villages [5,6].

Urban villages are characterized by high building density, narrow access methods, and outdated electrical wiring planning. The construction of public charging facilities faces the dual constraints of physical space and electrical capacity, resulting in limited charging interface availability and difficulty in deploying large-scale, centralized charging points [2,7]. This “supply shortage” directly leads to the proliferation of non-standard charging practices, such as “fly-wire charging.” Such behavior not only poses severe electrical fire safety hazards [1], but more critically, its disordered and stochastic single-phase connection patterns serve as a key contributor to the exacerbated three-phase imbalance in the low-voltage distribution network. This, in turn, increases additional losses in lines and transformers and leads to excessive supply voltage deviation, among other power quality issues [8,9]. In the long term, this accelerates equipment aging and may even trigger a protection malfunction, threatening the power supply reliability of the transformer area [6].

Current research on E2W charging loads within the specific context of urban villages remains in its nascent stage [3]. Existing studies have primarily focused on the macro-level planning of charging facility layouts [2] or areas such as Vehicle-to-Grid (V2G) interaction for EVs [5,10]. There is a notable lack of refined modeling and analysis concerning the micro-level spatiotemporal distribution characteristics of E2W charging behavior under the unique physical and social fabric of urban villages [4], its coupling mechanism with the operational state of the distribution transformer area [7,11,12], and methodologies for optimizing the charging-facility configuration under high constraints [13,14]. In particular, the failure to effectively differentiate between the distinct properties and impacts of “fly-wire charging” as an unauthorized load versus “standard charging” as a controllable load hinders the formulation of governance strategies that effectively balance safety, economic viability, and practical feasibility [15].

Based on previous research utilizing survey data analysis, we gained initial insights into the charging patterns and spatial distribution of E2Ws [16,17]. However, these approaches are constrained by their inability to support long-term, continuous human observations at the district level, and they lack the dynamic perspective needed to capture evolving charging behaviors [18,19].

To predict infrastructure strain, the current literature relies on data-driven statistical modeling and micro-simulation frameworks. While machine learning approaches [20] effectively decode massive driving datasets, existing studies primarily focus on formal EVs [21–23]. Direct application of these EV-centric paradigms to E2Ws in dense urban villages creates severe mismatches. Unlike EVs using regulated stations, E2W charging is ubiquitous, low-power, and hyper-concentrated at residential endpoints. Driven by short walking thresholds and facility congestion, users often pivot to informal “fly-wire charging.”

To bridge this gap, this study shifts focus to E2W spatio-temporal behavioral evolution, introducing a GIS-integrated “Digital Sandbox”. Here, we formally define the “Digital Sandbox” as a high-fidelity, closed-loop virtual evaluation environment that couples static geospatial constraints with dynamic multi-agent decision heuristics. Distinct from conventional macro-traffic layout simulations or pure statistical load forecasting, the “sandbox” mechanism is characterized by three core tenets: (i) Spatial Container Isolation, which bounds the non-linear interaction of entities within a high-density, real-world topology; (ii) Behavioral Emergence Tracking, which treats macroscopic network strain as an evolutionary consequence of bottom-up, micro-level human decisions; and (iii) Scenario Mutability, allowing for the plug-and-play testing of various counterfactual infrastructure planning schemes without real-world risk. By transforming static spatial simu-

lation into a dynamic spatio-psychological decision framework, this sandbox reveals how charging infrastructure scarcity cooperates with localized spatial grids to aggravate peak loads and network imbalance.

The remainder of this paper is organized as follows. Section 2 discretizes the topological information of the study area, incorporating the spatial distribution of E2W ownership across residential buildings and the existing charging station layout, followed by a preliminary supply-demand analysis. Section 3 establishes the digital sandbox model of E2W charging behavior coupling the hunger mechanism, and performs parameter calibration together with sensitivity analysis. Section 4 presents and discusses the simulation outputs and their potential impacts on the low-voltage distribution network. Section 5 concludes the paper by summarizing the model's features and limitations, and outlines directions for future optimization.

2. Spatial Network and Behavior-Integrated Framework for E2W Charging in Urban-Village Feeders

2.1. Study Area

As shown in Figure 1, the prototype for this study was located in a typical urban village in Southern China. The power distribution transformer area in question is characterized by extremely high-density buildings and populations with pronounced electrical safety risks. The available land for constructing centralized charging facilities is severely limited, resulting in an almost complete absence of dedicated charging stations for E2Ws.

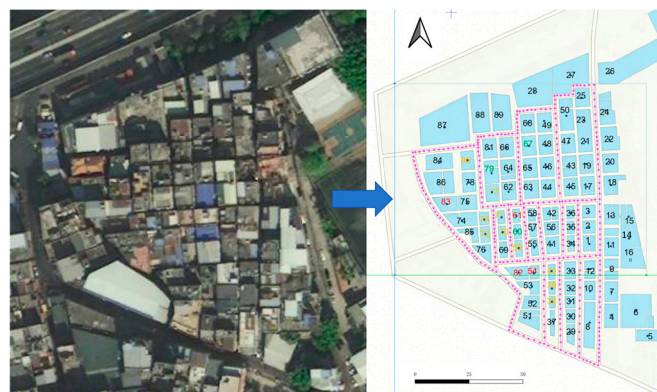


Figure 1. Study Area and Its Discretisation Topology.

As shown in Figure 2, existing charging stations are installed on buildings with limited scale and primarily distributed sporadically (typically no more than five chargers per station). Due to the scarcity of charging resources, some residents resort to non-standardized sockets privately connected from indoor residential circuits, a practice commonly referred to as “fly-wire charging.”



Figure 2. Forms of Charging Installations within the Study Area.

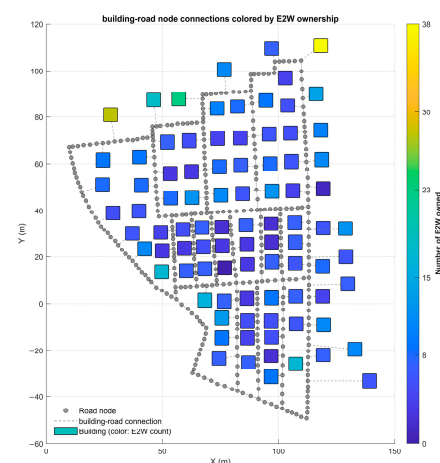
2.2. Spatial Topology Network Construction

2.2.1. Node Definition

A discretized network was constructed based on field survey data. As shown in Figure 3, a major road intersection within the study area was designated as the coordinate origin (0, 0) to establish a planar Cartesian coordinate system. The due east direction is defined as the positive x -axis, and the due north direction is defined as the positive y -axis. All coordinates were determined using actual measured relative distances (m).

Road Nodes: The accessible pathways within an urban village are discretized. Nodes were placed at approximately uniform intervals along the centerlines of roads and alleys to represent viable travel paths. The effect on the user route choice is considered negligible when the actual distance between adjacent road nodes is very short (less than 5 m).

Building Nodes: Each building is abstracted as a node located at the geometric center of the structure. Key attributes are assigned to each building node, including the E2W ownership count, number of existing “fly-wire” charging sockets, and the maximum allowable number of standard charging ports. The building nodes serve as both sources of charging demand and points of load integration.



2.2.2. Edge Definition

The nodes are interconnected by edges to form a network topology, with the edge weights representing the travel distance.

Road Connectivity Edges: Consecutive road nodes along the same road are connected by edges. The weight of this edge is the measured Euclidean distance between two nodes.

Building Access Edges: As shown in Figure 3, each building node is connected to its nearest road node via a direct edge. The weight of this edge is the shortest straight-line distance from the building to the road access point, simulating the pedestrian path from the building to the road network.

Figure 3. Building Access Edges.

Inter-Building Effective Distance: As shown in Figure 4, the effective travel distance between any two building nodes is not a straight-line distance. It is calculated as the distance from Building A to its nearest road node + the shortest network path distance between the two nearest road nodes and the distance from Building B to its nearest road node.

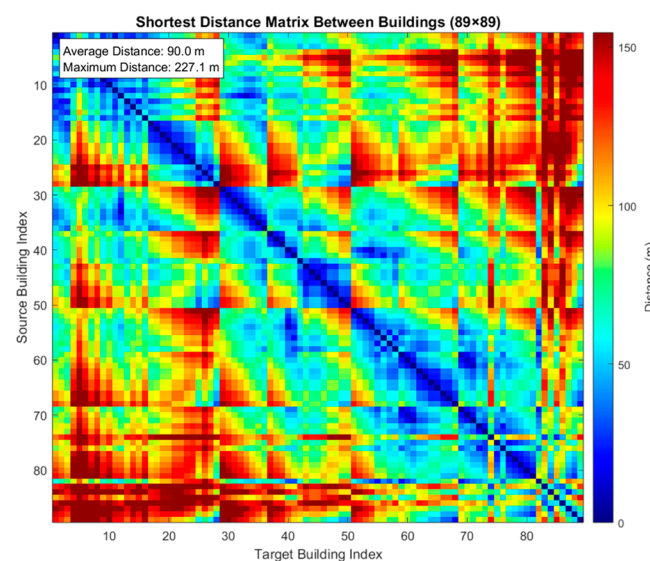


Figure 4. Distance between buildings.

2.2.3. Structural Interpretation

Through the above rules, the complex physical space of an urban village is abstracted into an undirected graph. This discretized network model preserves the critical spatial adjacency relationships between buildings and roads. It transforms the continuous problem of charging service accessibility into a computationally efficient graph-based analysis, laying the structural foundation for the subsequent evaluation of charging port service coverage, user walking accessibility, and the spatial distribution of electrical loads.

2.3. Spatial Characterization of E2W Charging Demand and Informal Access Behavior

The study area comprises 89 residential buildings, with a total of 694 E2Ws. Currently, 13 charging stations are operational, equipped with 44 charging piles (average 3.38 piles per station). The road network topology was constructed from geographic data, and each building was mapped to its nearest road node using a path-based distance calculation (Floyd–Warshall algorithm). This section begins with a preliminary analysis of the existing charging infrastructure in the study area, drawing upon the available GIS data.

As shown in Figure 5, the coverage of buildings and E2Ws varies noticeably with the acceptable walking distance D_a . When D_a ranges from 20 m to 40 m, coverage rises sharply and delivers the highest marginal gain. The growth slows down between 40 m and 70 m,

and coverage eventually plateaus above 70 m, where further extending walking distance brings no practical improvement.

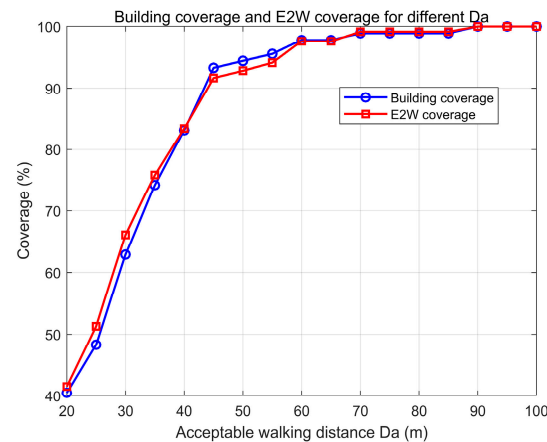


Figure 5. Building coverage and E2W coverage for different D_a values.

Since the mean nearest distance from buildings to charging stations is 26.28 m, and adopting a 25-m threshold yields an overall coverage rate of approximately 50%, this study accordingly selects 25 m as the accessibility threshold. It should be noted, however, that this threshold may vary across different areas; the value adopted here serves primarily for illustrative purposes in the present case study. The distance from each individual building to its nearest station is provided in Figure 6 for reference.

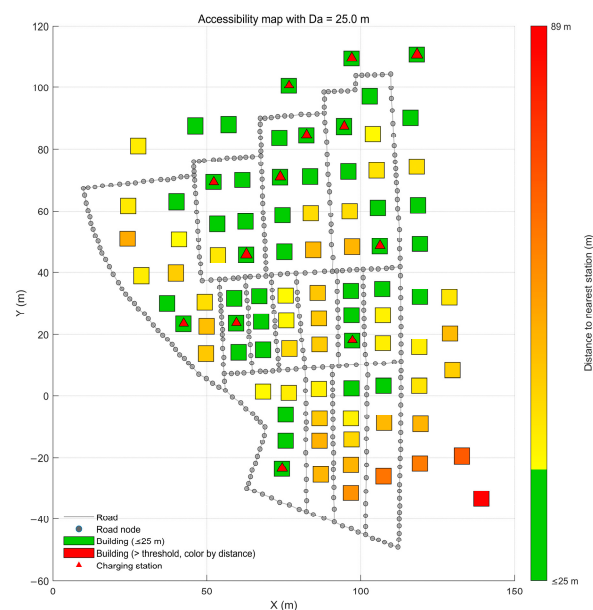


Figure 6. Accessibility map.

Under this setting, only 43 buildings (48.3%) remain reachable, serving 356 E2Ws (51.3%). Consequently, 46 buildings (51.7%) with 338 E2Ws (48.7%) are classified as unreachable. The specific distance statistics are shown in Figure 7. The mean nearest distance to a station is 26.28 m (median 26.32 m, standard deviation 15.66 m), with a maximum of 88.59 m and a minimum of 4.08 m. The equivalent coverage radius of individual stations ranges from 20.75 m (Station 13) to 39.90 m (Station 2), reflecting heterogeneity in the spatial distribution of surrounding buildings.

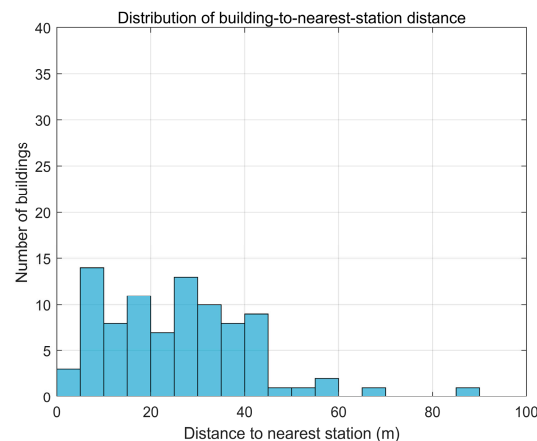


Figure 7. Distribution of building-to-nearest-station distance.

As shown in Figure 8, the area is divided into $25\text{ m} \times 25\text{ m}$ cells. Each cell's color represents the total number of E2Ws (e-bikes) in buildings located within that cell.

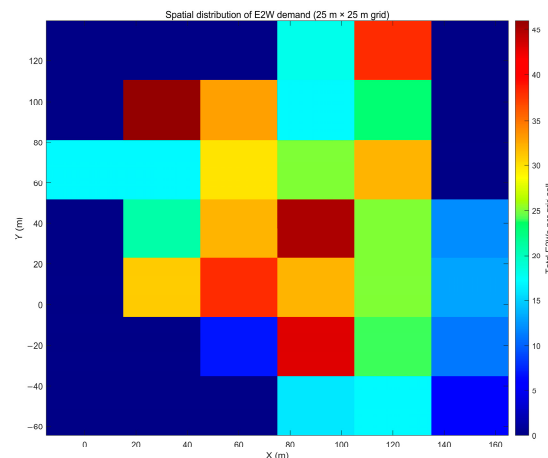


Figure 8. Spatial distribution of E2W demand.

28 grid cells contain at least one building. The highest demand cell contains 46 E2Ws, located around $X = 38\text{ m}$, $Y = 88\text{ m}$.

The heatmap reveals spatial clusters of high E2W density, which may guide optimal placement of new charging stations.

As shown in Figure 9, buildings were clustered using K-means ($k = 3$) on three normalised features: (i) number of E2Ws owned, (ii) distance to the nearest charging station, and (iii) reachability under $D_a = 25\text{ m}$ (binary).

The resulting clusters exhibit distinct profiles:

Cluster 1 (45 buildings, 50.6%)—characterised by zero reachability under $D_a = 25\text{ m}$, an average distance of 38.37 m to the nearest station, and a relatively low average E2W count (6.9). This group represents the most underserved buildings.

Cluster 2 (4 buildings, 4.5%)—the highest-demand cluster (average 26.8 E2Ws per building). Despite having a relatively short average distance (20.45 m) and 75% reachability, its small size suggests isolated high-density points.

Cluster 3 (40 buildings, 44.9%)—the best-covered cluster (100% reachable under $D_a = 25\text{ m}$), with the shortest average distance (13.27 m) and a low average E2W count (6.9).

The spatial distribution of clusters shows that Cluster 1 buildings are mainly located at the periphery, while Cluster 3 occupies central areas close to stations.

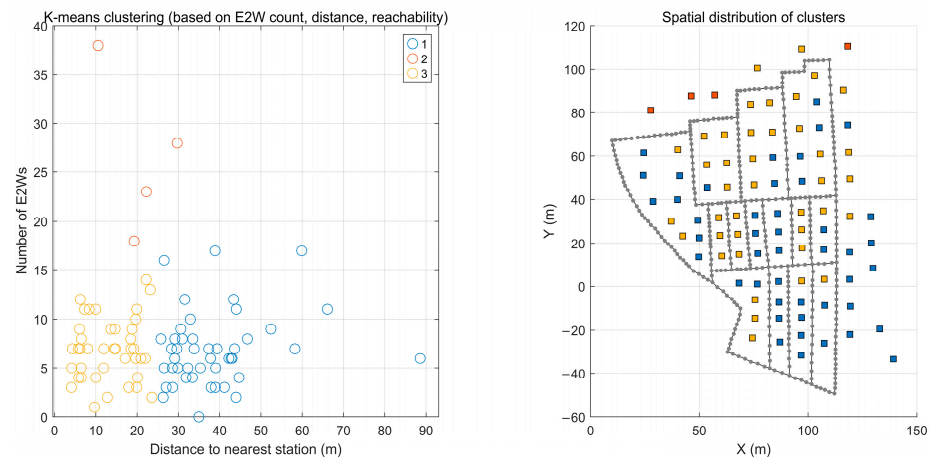


Figure 9. K-means clustering results.

3. Spatio-Temporal Evolution Model of E2W Charging Demand Based on Digital Sandbox

In previous studies, based on field research and historical data analysis, we preliminarily revealed the charging demand characteristics and spatial distribution patterns of E2Ws within the study area. However, traditional surveys and static data analysis methods have some inherent limitations. On the one hand, manual observation struggles to achieve long-term, large-scale, and high-frequency continuous monitoring, with high data collection costs and susceptibility to subjective influences. However, static data cannot fully reflect the dynamic evolution of charging demand, particularly the interactions and emergent effects of micro-level individual behaviors across temporal and spatial dimensions.

To overcome the aforementioned challenges and make full use of the existing data on E2W usage habits, this study proposes the concept of a digital sandbox. This model aims to construct a high-fidelity virtual simulation environment by employing agent-based modeling techniques to simulate the charging decision-making process and the spatial movements of each E2W. Consequently, it projects the spatiotemporal evolution trends of the charging demand under conditions where sustained human observation is impractical. The introduction of the digital sandbox not only addresses the shortcomings of traditional methods, but also builds upon the actual usage patterns of E2Ws and simulates charging behavior responses under different infrastructure configuration schemes. This provides data-driven decision support for precise planning and dynamic expansion of charging facilities, thereby guiding the construction of a more scientific, economical, and safe charging infrastructure.

3.1. Model Framework and Core Concepts

This model constructs a multilevel digital sandbox simulation system consisting of a spatial base layer, a building unit layer, an individual vehicle layer, and a behavioral rule layer. The spatial base layer integrates road network topology and building spatial distribution; the building unit layer characterizes the physical attributes and charging facility configuration of each building; the individual vehicle layer simulates the battery status and behavioral characteristics of each E2W; and the behavioral rule layer defines the logical flow of charging decisions. The layers are dynamically coupled through bidirectional interaction mechanisms, collectively driving the spatiotemporal evolution of the charging demand. Within this multi-level architecture, the “Digital Sandbox” is explicitly defined as a high-fidelity behavioral simulation container. Its exclusive academic connotation lies in capturing the granular, spatio-temporal dynamics of decentralized agents under re-

source scarcity, where the aggregated outputs of individual behaviors (such as time of arrival, building node location, and single-phase connection choice) are directly mapped and projected onto the low-voltage feeder networks as dynamic electrical loads and three-phase unbalance profiles.

As shown in Figure 10, the model follows a “bottom-up” individual modeling philosophy, with its core concept being that macroscopic charging demand is an emergent phenomenon arising from the aggregation of microscopic individual behaviors. Each E2W acts as an independent agent, making charging decisions based on its battery status, spatial location, and environmental conditions. These decisions interact with the individuals to form macroscopic charging patterns. This modeling approach effectively captures the nonlinear characteristics and spatial heterogeneity of the charging behavior.

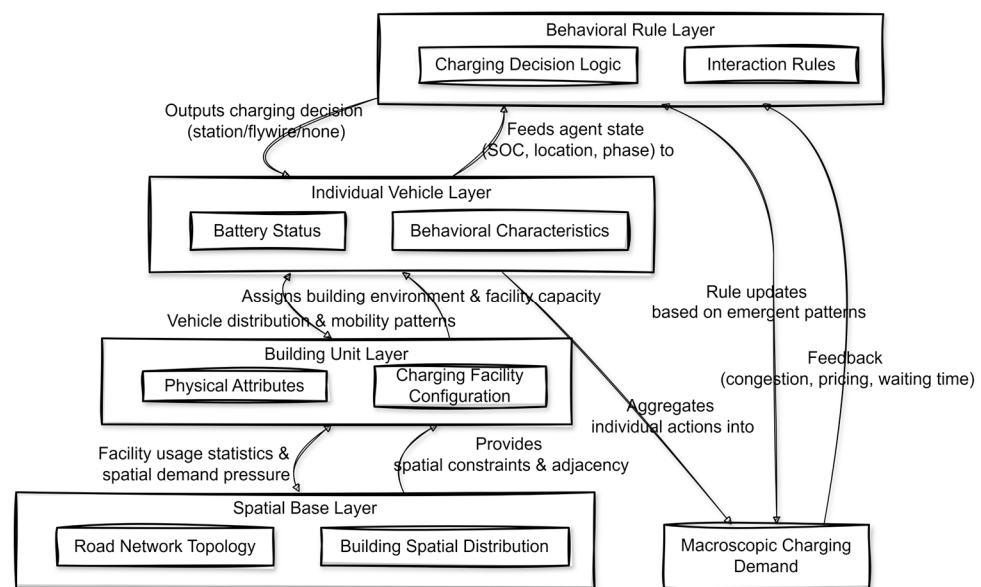


Figure 10. Bottom-up model structure.

3.2. Spatial Base and Building Unit Modeling

3.2.1. Spatial Base Construction

The spatial base of the model was constructed using high-precision Geographic Information System (GIS) data, comprising two core elements: the road network and building polygons. The road network was represented as a node-edge structure using graph theory, with the Dijkstra algorithm employed to calculate the shortest path distances between buildings, thereby realistically reflecting pedestrian accessibility. The building polygons were abstracted as point features, with each point possessing the following attributes:

Building identifier (BuildingID): Unique identifier.

Spatial coordinates (X, Y): Coordinates of the building's centroid.

Number of standard charging ports (StandardPorts): The number of standardized charging interfaces configured in the building.

E2W ownership (E2WCount): The average daily number of vehicles was calculated based on the time-series data.

3.2.2. Quantifying Neighborhood Relationships

Based on the distribution characteristics of the road network in the study area, the shortest path distance matrix between buildings is first calculated, denoted as $D = [d_{ij}]_{n \times n}$. Here, n represents the total number of buildings in the study area, and the matrix element

d_{ij} is specifically defined as the shortest path distance from the i th building to the j th building (unit: m). The elements on the main diagonal of the matrix, d_{ii} , are all 0, meaning that the distance from a single building to itself is 0.

To quantify the walking accessibility between buildings, combined with the actual needs of walking trips, an acceptable walking range threshold of D_a was set. Based on this threshold and the aforementioned shortest path distance matrix D , an adjacency matrix $A = [a_{ij}]_{n \times n}$ is further constructed to characterize whether any two buildings are within the acceptable walking range. Its elements are defined as follows:

$$a_{ij} = \begin{cases} 1, & \text{if } d_{ij} \leq D_a \text{ \& } d_{ij} \neq -1 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

In the formula, $a_{ij} = 1$ indicates that the shortest path distance between the i -th building and j -th building is within the acceptable walking range, and the two have walking connectivity; $a_{ij} = 0$ indicates that the shortest path distance between the two buildings exceeds the acceptable walking range, or they are the same building (without practical connectivity significance), and the two do not have walking connectivity.

This matrix quantifies the spatial accessibility relationship between buildings, and serves as an important basis for charging decisions.

3.3. Individual E2W Modeling

The model operates on a double-loop structure of “day-time step”. Its core mechanisms include vehicle initialization and energy consumption updating, charging demand generation, public charging station assignment, hunger-count-driven mandatory fly-wire charging, and three-phase load calculation.

3.3.1. Vehicle Initialization and State Parameters

Let num_b be the number of E2Ws owned by building b . The total number of E2Ws is $N_{vehicle} = \sum_b num_b$. Each E2W i is characterized by the following parameters: its associated building b_i , charging power P_i (kW), battery capacity C_i (kWh), health factor $H_i \in [0, 1]$, state of charge $S_i \in [0, 1]$, and fly-wire phase $\phi_i \in \{A, B, C\}$. The parameters are initialized as:

$$P_i \sim U(180, 270), C_i = 1.2, H_i \sim U(0.7, 1.0), S_i^{\text{init}} \sim U(0.2, 1.0), \phi_i \sim \text{Uniform}\{A, B, C\} \quad (2)$$

3.3.2. Energy Consumption Model

At the beginning of each day, any E2W that is not currently charging and is not marked as “skip discharge” consumes an amount of energy:

$$E_{\text{day}} = E_0 \cdot (1 + \varepsilon(2r - 1)), r \sim U(0, 1) \quad (3)$$

where E_0 (kWh) is the baseline daily energy consumption and ε is the energy consumption fluctuation coefficient. The corresponding reduction in SOC is:

$$\Delta S_i = \frac{E_{\text{day}}}{C_i \cdot H_i} \quad (4)$$

The SOC is then updated as $S_i \leftarrow \max(0, S_i - \Delta S_i)$. A vehicle that experiences consecutive charging failures is flagged with `skip_discharge = true`, meaning it will not discharge on that day, thereby preventing its SOC from dropping too low.

3.3.3. Charging Demand Generation

Two types of charging demand are generated daily.

- (1) Regular demand: When $S_i < S_{low1}$ and the vehicle is neither charging nor skipping discharge, a demand is generated with probability:

$$P_{req} = \frac{S_{low1} - S_i}{S_{low1}} \cdot \alpha \cdot \gamma_w \quad (5)$$

where $\alpha = 0.8$ is a base coefficient and $\gamma_w = \gamma_{weekend} \cdot \gamma_{rain}$ (product of weekend and rainy day factors) captures the amplifying effect of weather and rest days on users' willingness to charge.

- (2) Mandatory demand: When $S_i < S_{low2}$ and the vehicle is not charging, a demand is generated with certainty. After two consecutive station allocation failures, the vehicle performs fly-wire charging on the third day.

The arrival time window for all demands is fixed between 17:30 and 20:00 each day, corresponding to a set of time-step indices T_{arr} . For regular demands, the arrival step is chosen uniformly at random from T_{arr} . For mandatory demands, the arrival step is sampled according to an exponentially weighted distribution that depends on the vehicle's "hunger count" k (the number of consecutive charging failures). The probability mass function is:

$$p(t) = \frac{\exp(-\lambda(k) \cdot (t - t_{min}))}{\sum_{\tau \in T_{arr}} \exp(-\lambda(k) \cdot (\tau - t_{min}))}, \lambda(k) = \lambda_0 + \beta \cdot \min(k, 5) \quad (6)$$

with $\lambda_0 = 0.3$ the baseline decay rate, $\beta = 0.1$, and t_{min} the first time step of the window. This design makes vehicles with higher hunger counts more likely to arrive earlier, mimicking adaptive user behavior.

3.3.4. Charging Station Assignment and Hunger Counting

Upon arrival, a user first tries to use a public charging station. The walking distance from building b to station s is:

$$d_{b,s} = d_{b,node} + d_{path}(n_b, n_s) \quad (7)$$

where $d_{b,node}$ is the distance from the building to its assigned road node, and d_{path} is the shortest-path distance between road nodes. Stations are visited in increasing order of $d_{b,s}$. If $d_{b,s} \leq D_a$ (the user's acceptable walking distance) and the station has an available pile, the assignment succeeds. The required number of time steps for charging is:

$$N_{step} = \left\lceil \frac{(1 - S_{before}) \cdot C_i \cdot H_i}{P_i} \cdot \frac{60 \text{ mins}}{\Delta t} \right\rceil \quad (8)$$

After assignment, the vehicle enters the station-charging state. If mandatory demand assignment fails, $k \leftarrow k + 1$ and the vehicle is marked to skip discharge the next day. When $k \geq 3$, the model forces the vehicle to use fly-wire charging, drawing power directly from its building. The number of charging steps is calculated in the same way as above. Upon successful completion of charging (whether station or fly-wire), the hunger count is reset to zero and the skip-discharge flag is cleared.

3.3.5. Load Calculation and Energy Statistics

At each time step t , the total power drawn by all charging stations is:

$$P_{station}(t) = \sum_{s=1}^{N_s} \sum_{j \in Q_s(t)} P_{i(j)} \quad (9)$$

where $Q_s(t)$ is the set of vehicles charging at station s at time t . The three-phase fly-wire power is:

Daily accumulated energy: $E_{\text{day}} = \Delta t / 60 \cdot \sum_i P(t)$ (kWh). Daily peak power: $P_{\text{max}} = \max_i P(t)$ (kW). The model outputs global peak values and summary statistics, and produces the overall statistics.

The simulation integrates energy dynamics, behavioral randomness, facility competition, and emergency fly-wire charging, providing a reproducible numerical tool for assessing E2W charging loads on the distribution network.

3.4. Parameter Selection and Sensitivity Analysis

Fly-wire charging poses severe threats to power system operation and public safety. It will lead to abnormal power load, aggravate three-phase imbalance of the distribution network, and significantly raise the probability of electrical fires. The fly-wire charging can quantitatively reflect the scale of risky charging activities, so it is used as a key indicator to evaluate safety risks in this research. A 7-day E2W charging survey in the substation area recorded 194 events, which extrapolates to an expected 832 events over a 30-day simulation period. This value serves as the calibration target for the simulation parameters. To determine the optimal combination of key parameters that minimizes the deviation between the simulated fly-wire charging frequency and a preset target, this study adopts Bayesian optimization for parameter calibration. The loss function is defined as the absolute difference between the simulated fly charging frequency and the target value. Eight parameters (maximum walking distance threshold D_a , low-SOC threshold 1 S_{low1} , low-SOC threshold 2 S_{low2} , weekend factor γ_{weekend} , rainy factor γ_{rain} , rainfall probability, energy consumption fluctuation coefficient ε , and base energy consumption E_0) are treated as optimization variables with reasonable search ranges. Bayesian optimization constructs a Gaussian process surrogate model under parallel computing, performing 2000 objective function evaluations, each averaged over 20 repeated simulations to mitigate stochastic noise, and finally obtains the optimal parameter set that minimizes the loss function. As shown in Figure 11, the algorithm uses the surrogate model to “guess” which parameter combination is most promising, evaluates that guess through actual simulation, updates its model with the result, and repeats this cycle until the search converges to the optimal configuration.

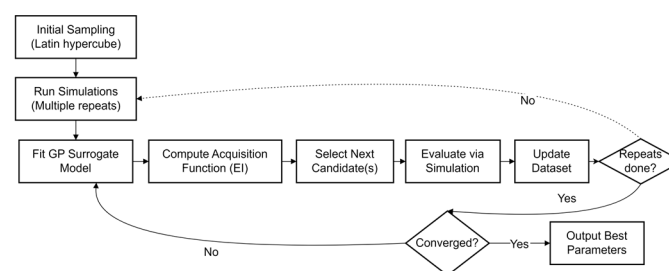


Figure 11. Bayesian optimization procedure for parameter calibration.

As shown in Table 1, based on the Bayesian optimization results, O1–O10 represent the top ten groups with the optimal observed outcomes in sequence.

Table 1. Bayesian optimization for parameter calibration.

Group	D_a	soc low1	soc low2	Weekend Factor	Rainy Factor	Rainfall Probability	Energy Variation	Base Energy
O1	83.537	0.498	0.064	0.885	0.604	0.083	0.273	0.126
O2	90.380	0.486	0.062	0.742	0.636	0.256	0.206	0.125
O3	84.142	0.481	0.055	0.877	0.614	0.102	0.506	0.125
O4	24.784	0.328	0.052	0.891	0.789	0.103	0.254	0.101

O5	82.453	0.207	0.108	0.737	0.782	0.295	0.570	0.122
O6	74.602	0.499	0.073	0.881	0.615	0.096	0.458	0.124
O7	27.446	0.210	0.123	0.724	0.730	0.216	0.642	0.100
O8	68.633	0.480	0.086	0.718	0.609	0.120	0.367	0.122
O9	85.395	0.448	0.101	0.601	0.719	0.051	0.426	0.121
O10	24.256	0.278	0.059	0.627	0.707	0.189	0.526	0.102

On this basis, a global sensitivity analysis is conducted using the trained Gaussian process model. The method fixes all other parameters at their optimal values, varies the target parameter uniformly across its entire search range, and predicts the corresponding loss function values via the Gaussian process model. The range (maximum minus minimum) of the predicted loss is taken as the sensitivity metric for that parameter. A larger range indicates a stronger influence of that parameter on the fly charging frequency. The analysis yields a quantitative ranking of parameter sensitivities, identifies the key driving factors affecting charging demand, and provides a theoretical foundation for model simplification and focused parameter monitoring.

As shown in Figure 12, the normalized results of sensitivity analysis clearly indicate that the daily basic electricity consumption exerts the most significant impact, while the low-SOC thresholds, energy variation and maximum acceptable walking distance also have considerable influences.

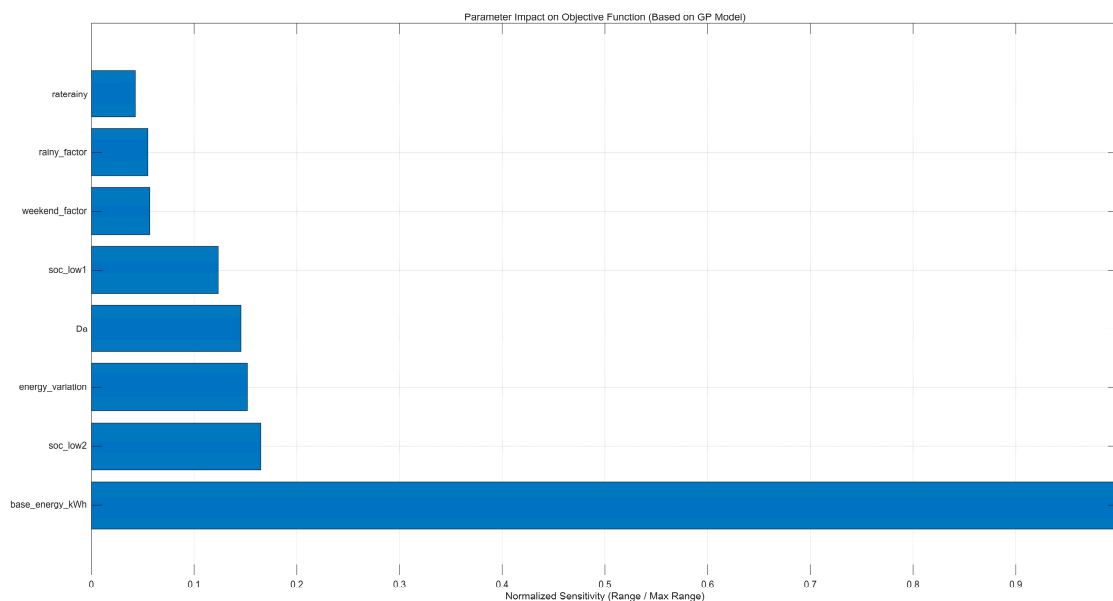


Figure 12. Sensitivity analysis of parameters.

3.5. Simulation Workflow and Operational Logic

As shown in Figure 13, the model follows a two-tier temporal hierarchy. The outer loop iterates over days, while the inner loop advances in discrete time intervals. Each day begins with an energy consumption phase, followed by demand generation. At each time step, the simulation sequentially: (i) advances all ongoing charging processes; (ii) handles newly arriving users—attempting station assignment and, for repeatedly failed mandatory demands, activating forced fly-wire charging; and (iii) computes instantaneous station and three-phase fly-wire loads. Daily energy and peak power statistics are accumulated, and at simulation completion, all results are exported for subsequent analysis.

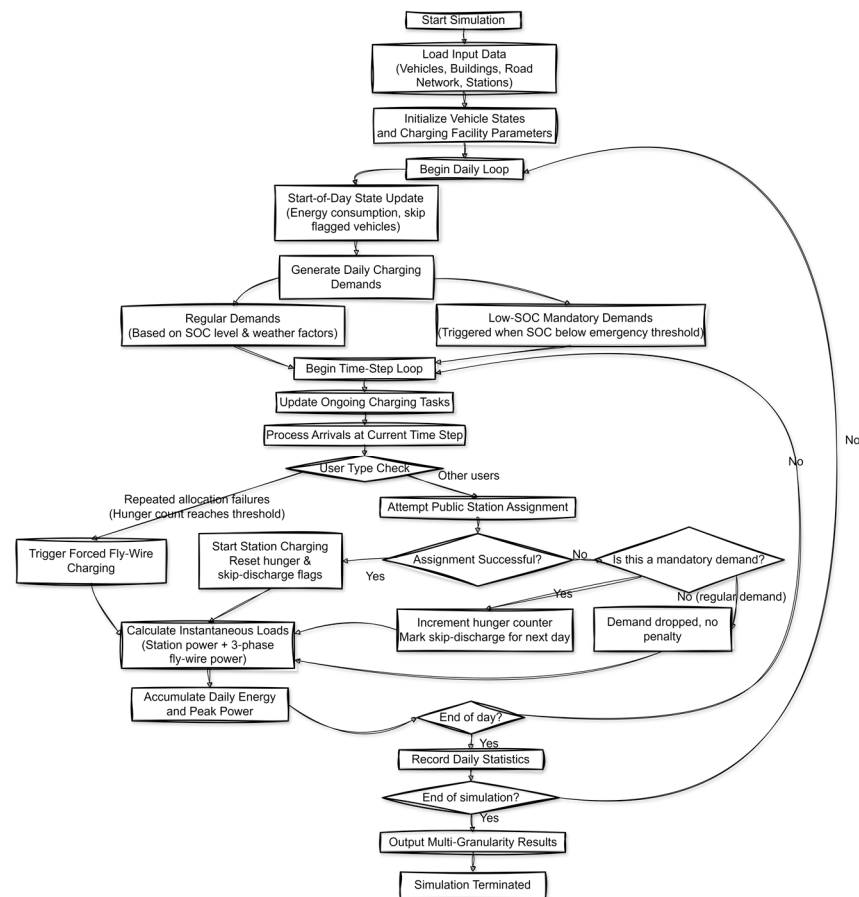


Figure 13. Flowchart of the E2W charging simulation process.

4. Results and Discussion

4.1. Results of the Digital Sandbox Simulation

In Figure 14, the time-series load profiles reveal that station charging power peaks at 9.11 kW, while fly-wire charging exhibits phase-specific peaks: 6.80 kW on phase A, 4.25 kW on phase B, and 6.84 kW on phase C. Both station and fly-wire activities coincide with the residential evening peak. This temporal coincidence exacerbates the existing peak demand on low-voltage feeders.

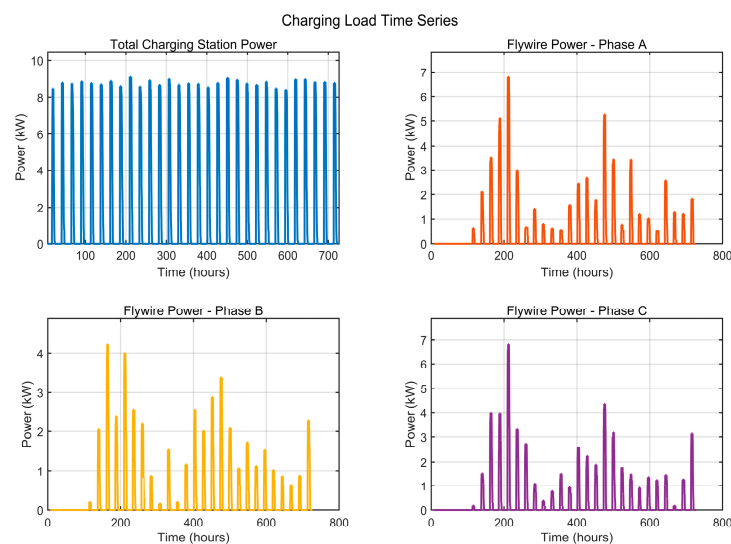


Figure 14. Charging Load Time Series.

Over the 30-day simulation, daily charging demands average 257.7 (maximum 399). Figure 15 shows that successful station assignments average 70.4 per day (maximum 133), while fly-wire completions average 26.4 (maximum 89). The average SOC at the start of each day ranges from 25.0% to 50.8%, with a mean of 37.7%. The SOC decline in the first week and subsequent stabilisation (after forced fly-wire activation) highlight how insufficient public infrastructure pushes users toward unmanaged fly-wire, increasing grid stress.

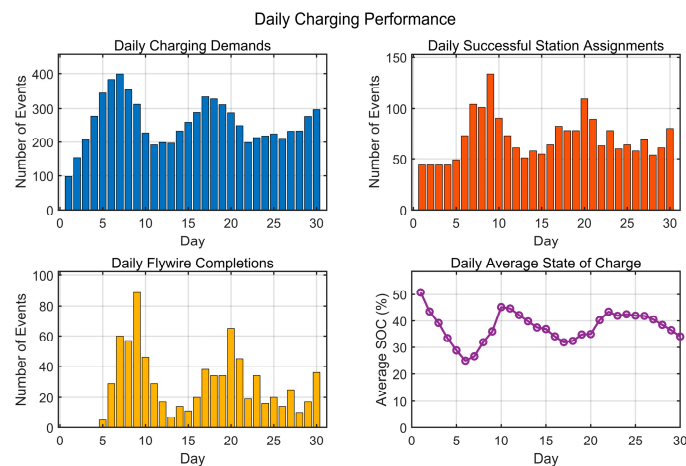


Figure 15. Daily Charging Performance.

As shown in Figure 16, the global peak station power is 9.11 kW (daily average 8.79 kW). The peak fly-wire power reaches 17.64 kW (daily average 5.21 kW). Total station energy is 1342.4 kWh (daily average 44.7 kWh), and total fly-wire energy is 853.0 kWh (daily average 28.4 kWh, max daily 95.9 kWh). Fly-wire accounts for 38.9% of total charging energy. The significantly higher fly-wire peaks imply that uncoordinated fly-wire charging imposes sudden, large load steps on low-voltage feeders, risking voltage drops and transformer overloading.

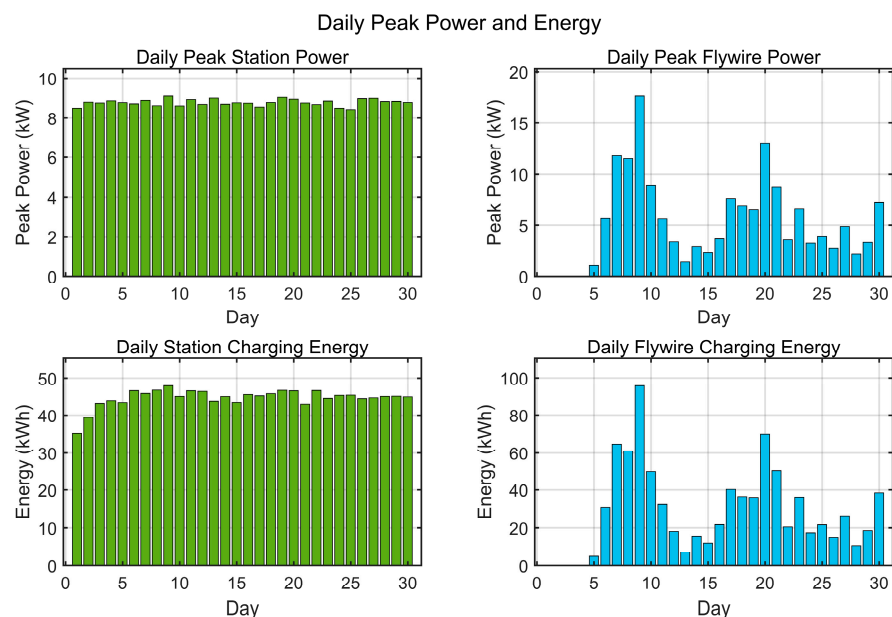


Figure 16. Daily Peak Power and Energy.

As depicted in Figure 17, fly-wire usage is highly concentrated: the building with the most fly-wire events recorded 57 completions, and the top 10 buildings account for 280

out of 791 total fly-wire completions (35.4%). Such spatial concentration means that a few building-level transformers may experience repeated high stress, making them priority targets for network reinforcement or demand-side management.

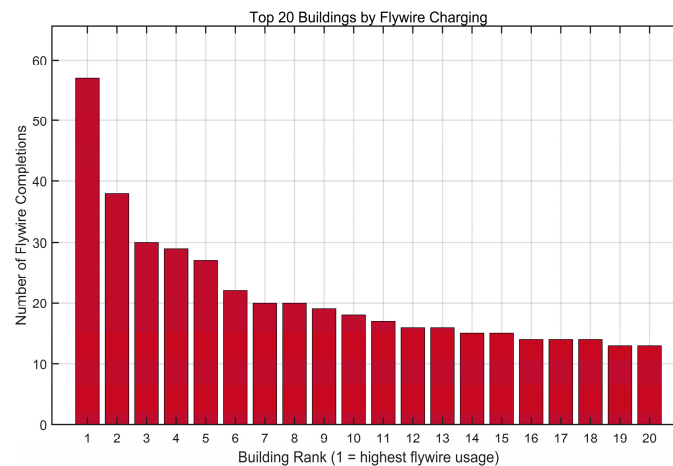


Figure 17. Top 20 Buildings by Fly-wire Charging.

Figure 18 compares charging durations. Overall mean duration is 5.33 h (median 5.25 h). Station charging is slightly shorter (mean 5.19 h, median 5.00 h) than fly-wire (mean 5.57 h, median 5.50 h). Longer fly-wire sessions, often starting from very low SOC, increase the probability of overlapping fly-wire events, amplifying the already high phase-wise peaks and prolonging grid stress periods.

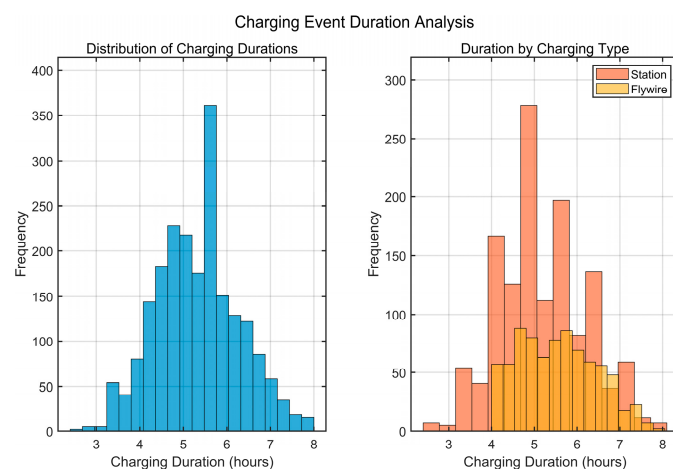


Figure 18. Charging Duration Analysis.

Figure 19 summarises the overall metrics. Total charging demands: 7,731; successful station charges: 2,111 (27.3%); fly-wire completions: 791 (10.2%); unserved demands: 4,829 (62.5%). Peak station load: 9.11 kW; peak fly-wire load: 17.64 kW (more than double the station peak). The combination of a high unserved demand share, a fly-wire peak that far exceeds the station peak, and phase imbalance (seen in Figure 15) poses a serious threat to low-voltage network reliability and power quality. Immediate measures such as station capacity expansion, phase-aware fly-wire management, and building-level peak limiting are recommended.

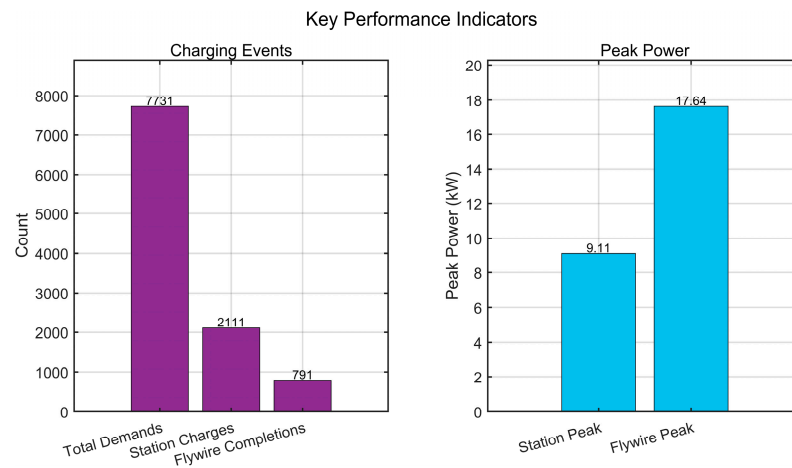


Figure 19. Key Performance Indicators.

In general, the simulation outputs both comprehensive indicators and detailed spatio-temporal data, which conventional top-down load forecasting cannot easily provide. By mapping individual vehicle activities to building and phase loads, the model supports decision-making for power distribution staff and urban planners. Before launching any physical projects, users can apply it to find network weak links, analyse the influence of fly-wire charging on transformer deterioration, and optimise the site selection and capacity of public charging stations.

4.2. Discussion Based on the Simulation Results

4.2.1. Peak Coincidence and the Fly-Wire Amplification Effect

The simulation results (Figure 14) reveal that both station and fly-wire charging activities are strongly concentrated during the residential evening peak. This temporal coincidence is not incidental; it arises from the large-scale return of users to their residences in the evening, where charging demand synchronously materializes [3,24]. The more critical finding is the amplification effect introduced by fly-wire charging: while the station peak reaches only 9.11 kW, the aggregate fly-wire peak attains 17.64 kW, and single-phase fly-wire peaks are comparable to or even exceed the station peak. Because fly-wire connections are predominantly single-phase and stochastically distributed, such loads inherently aggravate three-phase imbalance in the low-voltage network, a phenomenon well documented in studies of single-phase charger integration into three-phase systems [25]. For distribution transformers already operating near their thermal limits during evening hours, this compounded stress further degrades operating conditions and elevates the risk of protection maloperation [6,7].

4.2.2. Infrastructure Scarcity as a Driver of Unmanaged Load

The supply–demand gap exposed in Figure 15—daily average of 257.7 charging demands versus only 70.4 successful station assignments—underscores the severity of formal charging infrastructure insufficiency. Even with fly-wire charging activated once the battery hunger threshold is crossed, 62.5% of total demand remains unserved over the 30-day period (Figure 19). The decline and subsequent stabilization of the average initial state of charge indicates that a substantial fraction of batteries persistently operate near critically low levels, which constitutes an immediate safety hazard. Prior research has identified indoor and fly-wire charging of E2Ws as significant contributors to electrical fires [26]. Moreover, because fly-wire events leave no trace in station order records, analyses relying solely on charging station operational data will systematically underestimate the actual load and associated risk [15,17]. The 791 fly-wire completions captured in the simulation

thus represent only the visible portion of informal charging; the true extent of unsafe practices under severe scarcity is likely higher.

4.2.3. Spatial Concentration and Phase Imbalance as Entry Points for Targeted Intervention

Fly-wire charging is highly concentrated in space: the top ten buildings account for 35.4% of all fly-wire events (Figure 17), implying that the service transformers or distribution panels in a small number of buildings experience repeated high stress. Combined with the phase-specific power profiles (Figure 14), the model enables precise identification of vulnerable buildings and phases. Such granular output addresses the insufficient treatment of spatial heterogeneity in current charging load studies [3,17]. The phase-disaggregated dynamic loads provided by the sandbox constitute a necessary basis for the coordinated charging or phase-balancing strategies advocated in the literature [8,9].

4.2.4. Charging Duration and Overlap: The Hidden Dimension of Transformer Stress

The mean fly-wire charging duration (5.57 h) is slightly longer than that of station charging (5.19 h, Figure 18), and multiple fly-wire events initiating from low states of charge overlap substantially during nighttime hours, subjecting transformers to sustained elevated load rather than a short-lived peak. Prolonged thermal stress accelerates insulation aging and has been shown to significantly reduce distribution transformer lifetime [27]. In the present case, the superposition of sustained fly-wire load onto the already high evening peak renders the daily load profile more likely to exceed the transformer's cyclic rating. Hence, infrastructure planning that considers only peak magnitude is insufficient; load duration and concurrency must also be taken into account—dimensions that existing station planning methods [18] tend to overlook.

4.2.5. Implications for Low-Voltage Network Planning

In dense urban settlements, conventional planning practice tends to treat E2W charging as uniformly distributed after-diversity demand or simply extrapolates from electric vehicle charging characteristics. Our findings demonstrate that fly-wire load is an endogenously generated adaptive behavior arising from infrastructure scarcity and short walking thresholds. Its load signature—higher peaks, longer duration, and phase selectivity—differs markedly from that of formal station charging. Fly-wire charging accounts for 38.9% of total charging energy (Figure 16); ignoring this component leads to a comparably severe underestimation of total transformer loading. Moreover, the high share of unserved demand implies substantial hidden demand that will materialize once additional formal infrastructure is deployed, potentially creating new local overloads [12]. Because the emergence of fly-wire load is a dynamic response to scarcity that conventional planning tools cannot capture, a simulation-based approach is needed to test “what-if” expansion scenarios. By simulating counterfactual scenarios, the sandbox enables observation of the emergent rebalancing between station and fly-wire shares, providing evidence-based support for distribution network upgrades and charging facility siting, and thereby helping to avoid misinformed investment decisions.

4.2.6. Paradigmatic Divergence from Electric Vehicle Research

The findings reveal fundamental distinctions between the E2W charging problem and the established electric vehicle (EV) research paradigm. Conventional EV charging models are predominantly built upon macro-level traffic corridors, centralized charging stations, and data-driven methods for load forecasting and infrastructure planning [21,23,28]. E2W charging, in contrast, is highly dispersed at residential endpoints, and users are constrained by extremely short walking tolerance distances [29]. When nearby

charging berths are unavailable, users do not travel to an alternative station as EV drivers would; instead, they immediately resort to non-compliant fly-wire behavior. Furthermore, EV charging points are typically engineered as balanced three-phase connections, whereas the massive number of single-phase E2Ws constitutes a principal source of three-phase imbalance in low-voltage networks [25]. The centralized, data-driven paradigm suitable for EVs therefore cannot be directly transplanted to such settings. The hyper-granular agent-based modeling adopted by the digital sandbox represents a deliberate response to this paradigmatic gap [22].

4.2.7. Model Calibration and Credibility

The spatial distribution of E2Ws across buildings is initialized from strict statistical data. Behavioral parameters, which cannot be directly observed at the individual level in this setting, were calibrated using the aggregate fly-wire charging frequency obtained from field surveys as the macroscopic anchor. A Bayesian optimization procedure identified the parameter set that best reproduces this observed aggregate outcome. Consequently, the model matches the known macroscopic charging statistics while resolving the microscopic spatiotemporal dynamics that generate them.

The emergent patterns from the simulation align qualitatively with independent findings in the literature: the concentration of station and fly-wire charging loads during the residential evening peak with resulting feeder-level load superposition, the pronounced phase imbalance in fly-wire charging, and the marked spatial clustering of fly-wire events with overlapping extended-duration charging sessions are all consistent with reports that E2W charging demand exhibits morning and evening twin peaks, that the evening peak tends to coincide with residential electricity consumption causing voltage fluctuations at distribution nodes, and that uneven spatiotemporal load distributions characterize such settings [3,24]. This qualitative consistency supports the sandbox as a credible exploratory tool for evaluating infrastructure scenarios, while the fidelity of individual-level behavioral trajectories remains contingent on the calibration assumptions.

4.2.8. Limitations and Future Work

Several limitations should be acknowledged. First, the 30-day simulation employs fixed weekly behavioral patterns and does not incorporate seasonal variations or extreme weather effects. Second, the behavioral heuristics, although calibrated, remain a simplification of complex socio-psychological processes. Third, the current electrical model aggregates load at the building and phase level, without performing full power-flow calculations to precisely evaluate voltage profiles and equipment thermal states [6,9]. Fourth, fly-wire loads are treated as homogeneous, whereas real-world wiring resistance, connection quality, and protection arrangements vary considerably and affect risk levels. Future work should integrate real-time meter data to strengthen empirical validation, incorporate economic signals such as time-of-use tariffs, and extend the sandbox toward co-simulation of transformer thermal aging [27], thereby forming a more comprehensive evaluation framework.

5. Conclusions

This study introduced a GIS-integrated digital sandbox framework to simulate the spatiotemporal evolution of electric two-wheeler charging behavior in ultra-dense urban villages, explicitly capturing the coupling between infrastructure scarcity, user adaptive decisions, and low-voltage grid stress. The 30-day simulation at individual-vehicle resolution yielded three principal findings:

- ① Peak amplification and phase imbalance: Unmanaged fly-wire charging produced an aggregate peak of 17.64 kW, nearly double the public station peak of 9.11 kW. Its stochastic single-phase connection pattern inherently aggravated three-phase imbalance, threatening transformer operational reliability.
- ② Scarcity-driven unsafe load: With 62.5% of total charging demand unserved, fly-wire charging contributed 38.9% of total energy, revealing a precarious equilibrium in which infrastructure scarcity systematically pushes users toward hazardous and grid-damaging charging practices.
- ③ Spatial targeting enabled: Fly-wire events were highly concentrated, with the top ten buildings accounting for 35.4% of all occurrences. This spatial concentration, combined with phase-specific load profiles, enables precise identification of vulnerable transformers and phases for priority reinforcement.

The sandbox transforms static spatial survey data into a dynamic decision-support platform. Distribution network operators can use its building- and phase-level outputs to identify weak links, prioritize capacity upgrades, and test counterfactual interventions before committing capital. Urban planners can evaluate the safety and reliability implications of alternative charging infrastructure configurations under high spatial and electrical constraints.

The model is calibrated for high-density urban villages in southern China; its applicability to other regions requires recalibration with local field data. The current version employs simplified rule-based behavioral heuristics and does not yet incorporate economic cost factors or time-of-use pricing signals. As a foundational framework, however, the digital sandbox establishes a rigorous bottom-up coupling of GIS road networks, building nodes, individual vehicle attributes, and phase loading. This open, scalable architecture provides a standard blueprint for risk-informed charging infrastructure planning, enabling future extensions such as dynamic tariff response layers, machine learning modules for user preference modeling, and direct coupling with real-time transformer health diagnostics. By shifting E2W infrastructure planning from empirical estimation toward particle-level digital twin simulation, this work offers a critical methodological advancement for governing complex, data-scarce urban environments.

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Abbreviations

The following abbreviations are used in this manuscript:

E2W	Electric Two-Wheeler
V2G	Vehicle-to-Grid
GIS	Geographic Information System
SOC	State of Charge

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