

Article

Integrating Neural Forecasting with Multi-Objective Optimization for Sustainable EV Infrastructure in Smart Cities

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Abstract

The global transition toward carbon neutrality has accelerated the adoption of electric vehicles (EVs), prompting the need for smarter infrastructure planning in urban environments. This study presents a novel framework that integrates machine learning-based EV adoption forecasting with multi-objective optimization (MOO) using the NSGA-II algorithm. The forecasting component leverages neural networks to predict the percentage of EV sales relative to total vehicle sales, which is then used to derive infrastructure demand, energy consumption, and traffic congestion. These derived forecasts inform the optimization model, which balances conflicting objectives—namely infrastructure costs, energy usage, and traffic congestion—to support data-driven decision-making for smart city planners. A comprehensive dataset covering EV metrics from 2011 to 2024 is used to validate the framework. Experimental results demonstrate strong predictive performance for EV adoption, while downstream derivations highlight expected patterns in infrastructure cost and energy usage, and greater variability in traffic congestion. The NSGA-II algorithm successfully identifies Pareto-optimal trade-offs, offering urban planners flexible strategies to align infrastructure development with sustainability goals. This research underscores the benefits of integrating adoption forecasting with optimization in dynamic, real-world planning contexts. These results can significantly inform future smart city planning and optimization of EV infrastructure deployment in rapidly urbanizing regions.

Keywords: multi-objective optimization; urban smart city planning; Non-dominated sorting genetic algorithm II; neural networks; electric vehicles



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1. Introduction

Carbon peaking and neutrality have progressively become global objectives, with the photovoltaic (PV) power era increasingly favored as a sustainable solution. To unravel the serious environmental issues caused by greenhouse gas emissions, numerous nations and regions—such as China and the European Union—have set clear timetables for decarbonization [1]. Renewable energy is the backbone of a net-zero emission transition and is key to shifting away from fossil fuel reliance [2]. Photovoltaic power has rapidly become the lowest-cost option for power generation in most parts of the world. The IEA reported a record 156 TWh increase in photovoltaic power generation in 2020, up 23% from 2019, and predicts that global installed solar PV capacity could surpass 1700 GW by 2030 [3].

However, integrating large-scale renewable energy introduces new challenges, such as the variability, intermittency, and imbalance of PV output, which can threaten the stability and reliability of urban power systems [4]. Addressing these challenges has become a central concern as urbanization continues at an unprecedented pace, accelerating

the adoption of smart city frameworks that integrate advanced technologies, data-driven decision-making, and sustainable infrastructures [5]. Among these, the deployment of electric vehicles (EVs) has emerged as a critical enabler of energy-efficient, low-carbon transportation systems [6].

The evolution of EVs demonstrates both technological progress and persistent obstacles: from their prominence in the early 20th century, through near-disappearance with the rise of internal combustion engines, to their recent resurgence driven by battery advancements, environmental policies, and growing consumer awareness [7–9]. Today, EVs offer high energy efficiency and reduced emissions, but their rapid growth creates challenges for urban infrastructure planning, especially in deploying charging stations effectively [10,11].

Moreover, governmental incentives play a crucial role in accelerating EV adoption, influencing consumer behavior and charging infrastructure investments. Prior studies, such as the analysis conducted on electromobility trends in Poland, emphasize that technical progress must be supported by social, economic, and legal frameworks to ensure sustainable EV integration [12].

Moreover, the synergy between EVs and photovoltaic power holds significant potential: smart cities can leverage EV batteries as distributed energy storage to balance the variability of PV generation, enabling vehicle-to-everything (V2X) applications like vehicle-to-grid (V2G), vehicle-to-home (V2H), or vehicle-to-building (V2B) [13,14]. This interaction allows EVs and PV-based charging stations to form microgrids capable of locally consuming renewable energy, reducing grid stress and enhancing energy resilience [15,16]. In parallel, emerging computer vision techniques such as monocular depth estimation are enabling more accurate distance and infrastructure measurements from visual data, demonstrating the growing role of sensor-based intelligence in smart city applications [17].

Yet smart cities represent complex, dynamic ecosystems, where diverse stakeholders, infrastructure constraints, and uncertain adoption patterns complicate traditional planning methods. Recent studies have also introduced advanced spatial analytics to identify underserved regions in transportation networks. For example, a persistent homology-based approach has been used to detect public transit deserts without relying on travel demand data, revealing structural inequities in accessibility. Recent studies have also introduced advanced spatial analytics to identify underserved regions in transportation networks. For example, a persistent homology-based approach has been used to detect public transit deserts without relying on travel demand data, revealing structural inequities in accessibility [18]. Single-objective decision frameworks—such as minimizing cost alone—fail to account for trade-offs among critical factors like infrastructure cost, energy consumption, and traffic congestion [19,20]. Thus, advanced decision-making strategies such as multi-objective optimization (MOO) are essential to simultaneously balance these conflicting objectives in smart city resource planning [21,22].

While prior studies have applied various optimization techniques for EV infrastructure siting, there remains a need for approaches that integrate accurate, data-driven forecasting of EV adoption trends with powerful multi-objective algorithms to guide infrastructure decisions. Existing works often neglect the uncertainty inherent in future EV sales or oversimplify objectives by ignoring traffic dynamics or energy constraints.

In response, this research proposes a comprehensive framework combining neural network-based EV adoption forecasting with the NSGA-II multi-objective optimization algorithm, enabling planners to simultaneously minimize infrastructure costs, reduce energy consumption, and manage traffic congestion. Unlike purely heuristic approaches, integrating neural forecasts introduces adaptability and responsiveness to evolving EV trends, improving long-term urban planning effectiveness.

Recent studies such as [23,24] have highlighted the importance of integrating machine learning with optimization for smart grid planning and EV infrastructure. These works reinforce the relevance of hybrid frameworks in addressing modern urban challenges.

The remainder of this paper is structured as follows. Section 2 formulates the smart EV infrastructure planning problem as a constrained multi-objective optimization task. Section 3 introduces the integrated methodology, combining neural network-based forecasting with NSGA-II optimization. Section 4 presents the data sources and experimental setup used for simulation and model training. Section 5 reports and analyzes the key findings, including both forecasting accuracy and optimization results. Section 6 provides a comprehensive discussion, addressing the implications of the results, key limitations, and the trade-offs involved. Section 7 concludes the study, and Section 8 outlines future directions for extending this research.

2. Problem Formulation

The increasing adoption of electric vehicles (EVs) presents significant challenges for urban planners in smart cities. These challenges include:

Infrastructure cost: The placement and distribution of EV charging stations, as well as associated grid upgrades and maintenance.

Energy gap: Managing the additional electricity demand from EVs while optimizing the use of renewable energy sources.

Traffic congestion: Ensuring that the growing number of EVs does not exacerbate urban traffic and that charging stations are optimally located for accessibility and flow.

To address these interdependent challenges, the planning of EV infrastructure in smart cities can be modeled as a multi-objective optimization problem (MOP), where the goals are to:

- Minimize infrastructure costs;
- Minimize energy gap;
- Minimize traffic congestion.

2.1. Problem Overview and Objective Definition

This section defines the optimization problem with an emphasis on minimizing cost, energy gap, and travel distance under real-world constraints as follows:

- C_i : Total cost of installing and operating charging stations in region i ;
- D_i : forecasted EV charging demand assigned to region i (derived from adoption forecasts);
- PV_i : Renewable energy supply available in region i ;
- $d_{u,i}$: Travel distance from user u to region i ;
- $x_i \in \{0, 1\}$: Decision variable indicating if a charging station is installed in region i ($1 = \text{yes}$, $0 = \text{no}$);
- $a_{u,i} \in \{0, 1\}$: Assignment of user u to station in region i ;
- $(z)^+ = \max(z, 0)$: Positive part operator to measure energy shortage.

The optimization problem is formulated to minimize the following three objective functions:

2.2. Minimizing Infrastructure Costs

$$\text{Minimize } f_1(x) = \sum_{i=1}^n C_i \cdot x_i$$

This function represents the overall cost of installing and maintaining charging stations, including infrastructure, grid upgrades, and operational expenses.

2.3. Minimizing Energy Gap

$$f_2(x) = \sum_{i=1}^n (D_i - PV_i)^+$$

where $(z)^+ = \max(z, 0)$ and D_i is derived from forecasted EV adoption and energy efficiency factors such as powertrain type (e.g., BEV, PHEV, FCEV). Energy usage is affected by the number of EVs, their types, and the efficiency of the charging infrastructure in each region. Also, PV_i is the renewable energy available in region i . The function penalizes regions where demand exceeds clean energy supply.

2.4. Minimizing Traffic Congestion

Users assigned to distant or congested stations contribute more to traffic burden. Let $a_{u,i} = 1$ if user u is served by station in region i , and 0 otherwise. Then:

$$f_3(a) = \sum_{u=1}^U \sum_{i=1}^n a_{u,i} \cdot d_{u,i}$$

This function reflects the traffic burden due to users traveling to charging stations. Greater travel distances and suboptimal station placement can increase urban traffic congestion.

2.5. Constraints

To ensure realistic deployment, constraints were introduced with both upper and lower bounds. For example, a minimum number of stations ensures equitable access, while a maximum threshold respects budgetary and space limitations. This dual bounding prevents trivial solutions, such as deploying zero stations to minimize cost. Furthermore, the model is subject to the following constraints:

- Capacity constraints: Each region i has a maximum allowed number or size of charging stations due to space, power, or policy limitations.
- Energy constraints: Total energy consumed by charging activities must not exceed the available renewable energy supply in the planning horizon.

$$\sum_{i=1}^n (D_i - PV_i)^+ \leq \text{EnergyLimit}$$

- Budget constraints: The total infrastructure investment must stay within the city's budget for EV-related upgrades.

$$\sum_{i=1}^n C_i \cdot x_i \leq \text{TotalBudget}$$

The key decision variables are x_i (whether to build a station in region i) and $a_{u,i}$ (assignment of each user to a station).

These values will be determined by the optimization algorithm to minimize the defined objectives while satisfying all constraints.

- Mobility coverage constraints: To ensure accessibility, a minimum percentage of EV users in each region must be within a predefined distance threshold to the nearest charging station.

$$\sum_{i=1}^n \text{Coverage}(x_i) \geq \text{Coverage Threshold}$$

- Capacity constraint (station capacity only if built):

$$\sum_{u=1}^U a_{u,i} \leq \text{cap}_i \cdot x_i \quad \forall i$$

- User assignment constraint (each user must be assigned):

$$\sum_{i=1}^n a_{u,i} = 1 \quad \forall u$$

- Binary decision variables:

$$x_i \in \{0, 1\}, a_{u,i} \in \{0, 1\}$$

To prevent trivial or degenerate solutions (e.g., zero infrastructure deployment), the formulation explicitly imposes lower bounds on the number of charging stations and considers forecasted demand. These constraints ensure that the optimization balances cost, energy, and traffic trade-offs while fulfilling the growing transportation needs of EV users. In doing so, the solution space only includes practically deployable configurations that support real-world urban mobility requirements.

The resulting formulation is a constrained multi-objective optimization problem that reflects the competing priorities of cost efficiency, environmental sustainability, and urban mobility. This lays the foundation for applying the NSGA-II algorithm, discussed in the next section, to identify Pareto-optimal trade-offs [25].

To consolidate the objectives and operational constraints discussed above, the smart EV infrastructure planning problem is formally expressed as a constrained multi-objective optimization problem. This formulation captures the trade-offs between infrastructure cost, derived energy demand, and traffic congestion. Importantly, it addresses unrealistic solutions (e.g., no infrastructure) by imposing real-world constraints such as budget limits, renewable energy supply, and deployment capacities. The mathematical representation below reflects this structure:

$$\text{Minimize} \begin{cases} f_1(x) = \sum_{i=1}^n C_i \cdot x_i \\ f_2(x) = \sum_{i=1}^n (D_i - PV_i)^+ \\ f_3(a) = \sum_{u=1}^U \sum_{i=1}^n a_{u,i} \cdot d_{u,i} \end{cases}$$

Subject to all constraints defined above.

This compact formulation enables the application of evolutionary optimization techniques such as NSGA-II to explore the Pareto frontier of feasible solutions, balancing urban sustainability with operational efficiency.

3. Illustrative Example of Problem Encoding and Objective Evaluation

To demonstrate the practical implementation of the proposed multi-objective optimization framework, this section presents a simplified scenario modeling the siting of electric vehicle (EV) charging stations within a smart city context. The objective is to illustrate how the core elements—solution encoding, objective evaluation, and data representation—are handled within the model.

3.1. Scenario Description

Consider a small urban area subdivided into five zones, each representing a potential location for installing EV charging stations. A total of eight EV users are distributed across the network. Each user has a known daily energy demand and a set of preferred zones based on geographical proximity. Similarly, photovoltaic (PV) energy availability varies by zone, influencing how much clean energy can be utilized for EV charging.

3.2. Graph-Based Representation

A directed graph is used to model the interaction between EV users and charging stations. In this graph:

1. Orange square nodes represent candidate charging stations.
2. Blue circular nodes represent EV users.
3. Arrows indicate each user's preferred charging zone.
4. Edges are labeled with estimated travel distances.
5. Station nodes are annotated with installation cost and available PV supply, while EV nodes are labeled with their energy demand.

Figure 1 shows this topological representation, which forms the structural basis for the optimization problem.

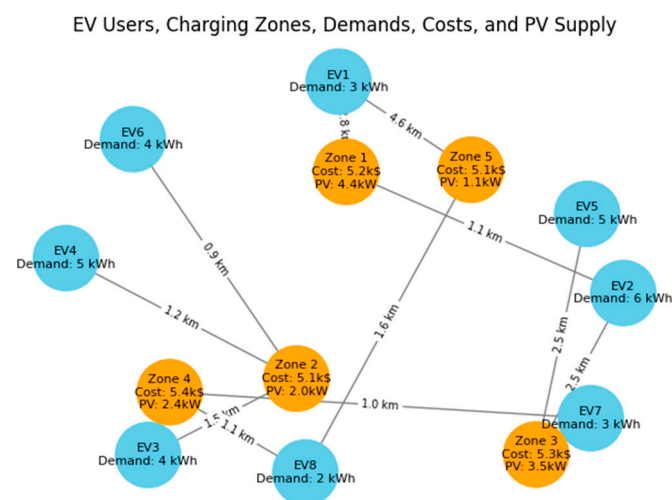


Figure 1. EV users, charging station candidates, PV supply (kWh), demand (kWh), and travel distances (km).

3.3. Binary Encoding of Solutions

Each individual solution (chromosome) is represented by a binary vector of length equal to the number of zones (e.g., [1, 0, 1, 0, 0]). A 1 indicates that a station is installed in the corresponding zone, and 0 otherwise. Figure 2 presents a sample chromosome corresponding to the graph in Figure 1, where stations are installed only in Zones 1 and 3.

Chromosome Encoding of Charging Station Deployment (1= installed, 0= not installed)				
Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
1	0	1	0	0

Figure 2. Chromosome encoding for EV charging station deployment decisions across five zones. A value of 1 indicates a station is installed in the corresponding zone, while 0 indicates no installation.

3.4. Objective Evaluation

The chromosome is evaluated using three objective functions as previously defined:

- **Total Infrastructure Cost (C):** Sum of installation costs in active zones.

- Energy Gap (E): Total EV demand minus the PV supply from selected zones.
- Total Travel Distance (T): Aggregate distance from each user to their assigned station.

For the example encoding [1, 0, 1, 0, 0], the evaluation yields:

- $C = \$26 \text{ k}$.
- $E = 14 - 9 = 5 \text{ kWh}$.
- $T = 2.0 + 2.15 = 4.15 \text{ km}$.

Figure 3 illustrates this multi-objective evaluation for the selected chromosome

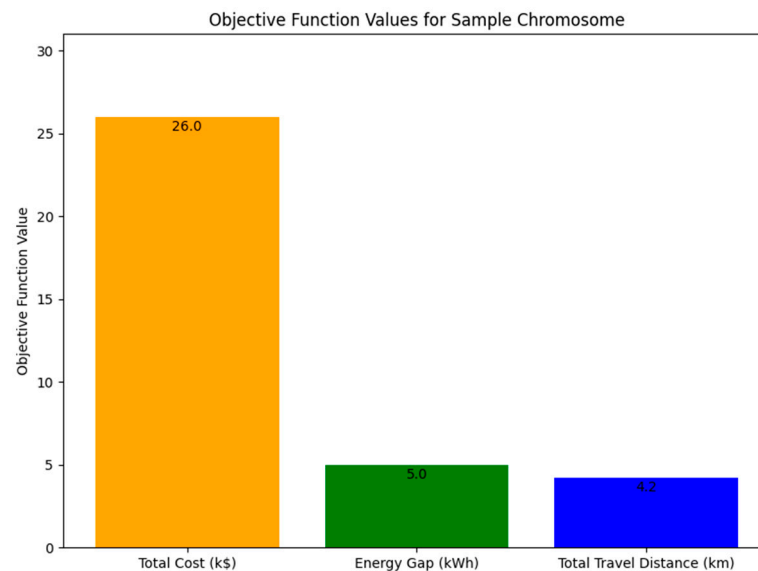


Figure 3. Objective function values (Cost, Energy Gap, and Travel Distance) for the sample chromosome.

Parameter values were derived from realistic urban case study assumptions and refined through preliminary experiments. For instance, cost estimates were benchmarked using public infrastructure databases. Notably, optimizing for minimal cost led to fewer stations, increasing energy gaps and reducing accessibility. Conversely, minimizing energy gap required denser station distribution, elevating cost. This illustrates the inherent trade-off in multi-objective optimization, where improving one metric often necessitates compromises in others. In the full framework, these objectives are evaluated using EV adoption forecasts from the neural network as inputs, ensuring consistency between demand forecasting and optimization.

3.5. Significance for Real-World Applications

Although simplified, this example reflects the fundamental mechanics of the proposed framework. It demonstrates how EV adoption forecasts (from the neural network), renewable energy utilization, and urban traffic dynamics are mathematically and visually modeled. In large-scale simulations, this structure can be scaled with real demand forecasting (via neural networks) and more granular geographic and temporal resolution. The same encoding and evaluation pipeline can be extended seamlessly within the NSGA-II-based multi-objective search process.

4. Development of Proposed Solution

This research proposes an integrated framework that combines the machine learning-based forecasting of electric vehicle (EV) adoption with multi-objective optimization (MOO) for efficient EV charging infrastructure planning in smart cities. The methodology is structured into two major stages: (1) EV demand forecasting using neural networks, and

(2) multi-objective optimization using a genetic algorithm for determining optimal charging station deployment.

4.1. Stage 1: Forecasting EV Demand with Neural Networks

The first stage involves predicting future EV sales based on historical time-series data. Let y_t represent the number of EVs sold at time t . The goal is to estimate the future sales $y_{t+1}, y_{t+2}, \dots, y_{t+h}$ using lagged observations:

$$y_t = f(y_{t-1}, y_{t-2}, \dots, y_{t-n})$$

where $f(\cdot)$ is a nonlinear function learned via a feedforward neural network, and n is the selected time lag. Model architecture (e.g., number of hidden layers and neurons) is tuned through cross-validation to minimize forecasting error. The neural network output is limited to the projected percentage of EV sales relative to total vehicle sales in a given region and year. Infrastructure demand, energy usage, and traffic congestion are derived from these EV adoption forecasts in subsequent modules (see Section 4.3), not predicted directly by the neural network. The predicted EV adoption levels are then spatially distributed across predefined urban zones to estimate localized charging demand, serving as input to the optimization model. Neural networks were selected due to their superior ability to model complex, nonlinear relationships in temporal data, such as EV adoption trends influenced by policy shifts, market incentives, and seasonal variation. Their generalization capability makes them well-suited for forecasting tasks in dynamic urban environments.

The neural network model employed in this study was designed to forecast EV adoption levels across urban regions. Input variables included GDP per capita, urban population density, historical EV sales data, fuel prices, and charging infrastructure density. These features were selected based on domain knowledge and their demonstrated influence on EV uptake in prior studies. All input features were normalized using Min-Max scaling to enhance model training performance. The model's predictive output is visually summarized in Section 6, which shows strong alignment between actual and forecasted EV adoption trends on the test data. The neural network configuration, input variables, training settings, and evaluation metrics are summarized in Table 1 to enhance clarity and reproducibility.

Table 1. Summary of Neural Network Parameters and Input Variables Used for EV Adoption Forecasting.

Parameter/Variable	Description	Value/Type
Input Variables	Features used for forecasting	GDP per capita, urban population density, historical EV sales, fuel prices, charging infrastructure density
Output Variable	Forecast target	% of EV sales (regional annual forecast)
Time Span	Historical data duration	2010–2024
Dataset Size	Number of samples used	1240 annual observations
Train/Validation/Test Split	Data partitioning strategy	72% train, 8% validation, 20% test
Normalization	Preprocessing applied to inputs	Min-Max scaling (0–1)
Model Type	Neural network architecture	Feedforward neural network
Hidden Layers	Number of layers	2
Neurons per Layer	Number of units in each layer	64 (Layer 1), 32 (Layer 2)
Activation Function	For hidden layers	ReLU
Optimizer	Optimization algorithm used	Adam
Loss Function	Metric minimized during training	Mean Squared Error (MSE)
Evaluation Metrics	Used on test data	MAE: 2.3%, RMSE: 3.1%, R ² : 0.91
Training Epochs	Number of epochs during training	100 (with early stopping)
Batch Size	Number of samples per gradient update	32

The output variable was the projected percentage of EV sales relative to total vehicle sales in a given region and year. The dataset consisted of 1240 annual observations spanning from 2010 to 2024 across 10 major urban cities. Although this dataset is relatively modest

in size, each observation aggregates multiple socio-economic, infrastructural, and policy-related variables, making each data point highly informative rather than a raw individual record. Similar macro-level datasets have been successfully used in prior EV adoption forecasting studies. To enhance generalization, we mitigated overfitting by (i) adopting a 72/8/20 train–validation–test split, (ii) applying early stopping, (iii) using dropout during training, and (iv) restricting the architecture to two hidden layers. These safeguards ensure reliable and generalizable forecasts. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2). The neural network achieved an MAE of 2.3%, RMSE of 3.1%, and R^2 of 0.91 on the test data, reflecting strong predictive accuracy and generalization capability.

The output of the neural network forecasting model—regional EV adoption levels—is passed to deterministic post-processing models that compute charging demand, energy use, and congestion. These derived values then serve as inputs to the multi-objective optimization engine. The overall integration of the forecasting and optimization stages is summarized in the system-level workflow (Figure 4), illustrating how EV sales forecasts influence infrastructure planning through Pareto-optimal solution analysis.

Integrated Framework of EV Demand Forecasting and Charging Infrastructure Optimization

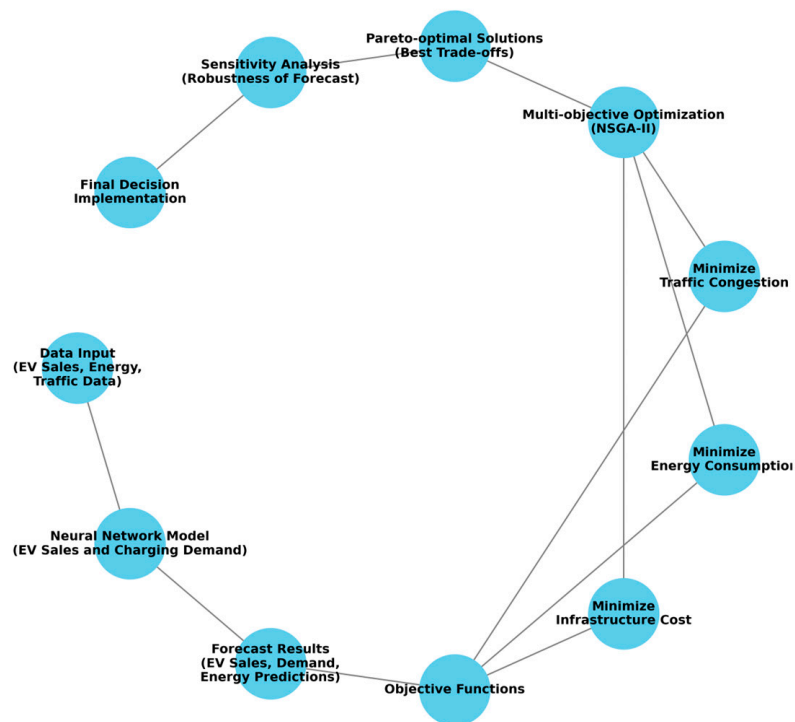


Figure 4. Integrated framework of EV demand forecasting and charging infrastructure optimization using neural networks and NSGA-II. Forecast results drive multi-objective optimization for minimizing infrastructure cost, energy consumption, and traffic congestion.

4.2. Stage 2: Multi-Objective Optimization Model

Based on the demand forecast, the second stage formulates a multi-objective optimization problem with three objectives:

1. Minimize total installation cost $C(x)$
2. Minimize energy gap between demand and PV supply $E(x)$
3. Minimize total user travel distance to assigned charging stations $T(x)$

Let $x = [x_1, x_2, \dots, x_m] \in \{0,1\}^m$ denote a binary vector indicating whether a charging station is installed in zone i . The problem is formulated as:

$$\min_x F(x) = [C(x), E(x), T(x)]$$

With objectives defined as:

- **Cost function:**

$$C(x) = \sum_{i=1}^m x_i \cdot \text{Cost}_i$$

- **Energy gap function:**

$$E(x) = \max \left(0, \sum_{j=1}^n \text{Demand}_j - \sum_{i=1}^m x_i \cdot \text{PV}_i \right)$$

- **Travel distance:**

$$T(x) = \sum_{j=1}^n r \text{Distance} \left(j, \text{AssignedStation}_j(x) \right)$$

Each EV user is assigned to the nearest active station based on preference lists and feasibility constraints.

4.3. Optimization via NSGA-II

The optimization problem is solved using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a popular method for solving MOO problems. The procedure involves:

1. **Initialization:** Generate a random initial population P_t of binary solutions.
2. **Fitness Evaluation:** Calculate $F(x)$ for all individuals.
3. **Sorting and Diversity Maintenance:**
 - Fast non-dominated sorting to determine Pareto ranks.
 - Crowding distance calculation to maintain diversity.
4. **Genetic Operators:**
 - Selection, crossover, and mutation are applied to generate new population Q_t .
5. **Elitist Replacement:**
 - Combine parent and offspring populations to form R_t .
 - Select the best N individuals for the next generation.

This loop continues until a predefined number of generations is reached or convergence criteria are satisfied. The detailed implementation process is illustrated in the NSGA-II optimization flowchart (Figure 5), which outlines population initialization, fast non-dominated sorting, genetic operations, and elitist replacement.

NSGA-II was chosen for its proven efficiency in solving multi-objective problems, particularly in infrastructure planning, where conflicting objectives like cost, energy consumption, and coverage must be balanced. Its elitism and crowding-distance mechanisms ensure diverse Pareto-optimal solutions, essential for decision-makers exploring trade-offs.

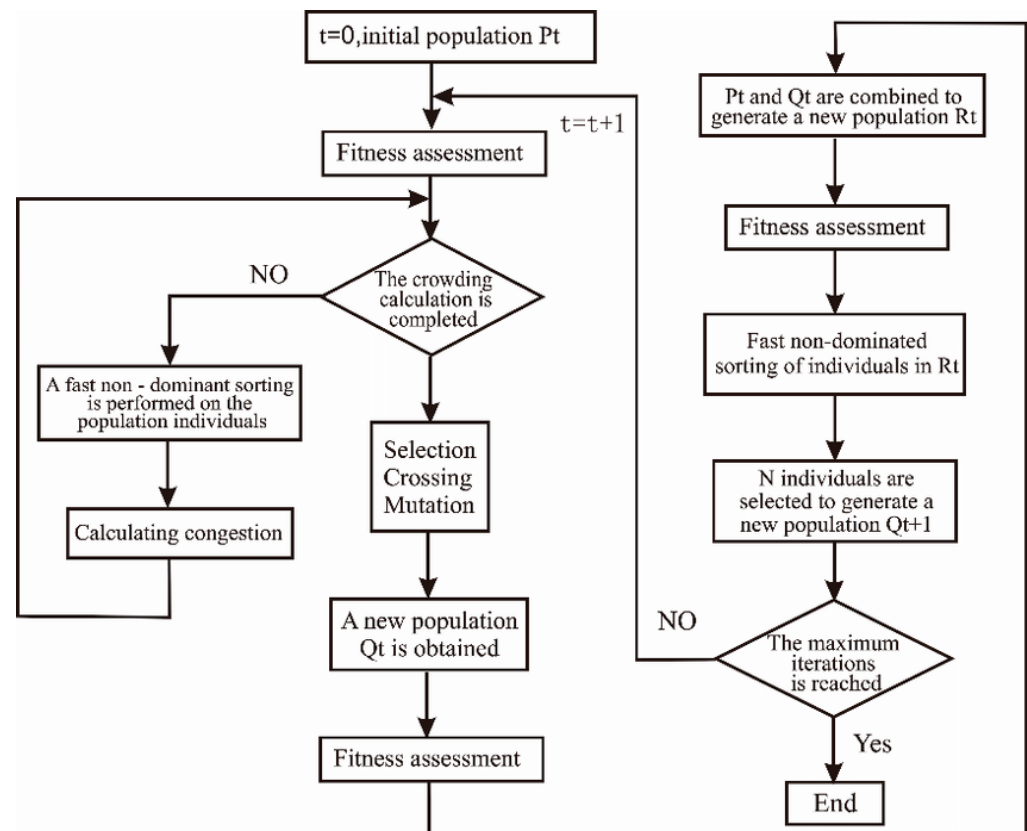


Figure 5. NSGA-II optimization flowchart showing the generation of new populations via sorting, crowding distance, and genetic operators.

4.4. Constraints and Feasibility

The optimization process is subject to realistic constraints:

- Budget constraint: $C(x) \leq B$, where B is the total available budget.
- Coverage constraint: All EV users must be assigned to at least one station within a service radius r .

$$\forall j \in \text{Users}, \exists i \in \text{Zones such that Distance}(j, i) \leq r \text{ and } x_i = 1$$

A penalty-based mechanism is adopted to penalize infeasible solutions, ensuring constraint handling is embedded in the evolutionary process

5. Experimental Setup

The experimental framework for analyzing electric vehicle (EV) adoption patterns was established using JupyterLab 4.0.11 within the Anaconda Navigator environment. All experiments were conducted on a local machine running Windows 10 Pro, powered by an Intel(R) Core(TM) i5-6500 CPU and 12 GB RAM. This configuration provided sufficient resources to train forecasting models and execute multi-objective optimization simulations without memory bottlenecks. The dataset spans from 2011 to 2024 and includes eight structured columns: Region, Category, Parameter, Mode, Powertrain, Year, Unit, and Value. It was sourced from the International Energy Agency's Global EV Data Explorer 2024 [26] and provides detailed metrics such as:

- EV stock share over time;
- Annual EV sales by powertrain and region;
- Charging infrastructure availability and growth patterns.

To capture temporal and categorical diversity, the dataset integrates three data layers: Historical observations (2011–2022), Projection-APS scenarios, and Stepped projection estimates (up to 2024). This structured integration enables the development of robust forecasting models that generalize well across geographic and policy boundaries. Vehicles are classified by type (e.g., cars, vans, trucks, buses) and by powertrain architecture, including Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs), Fuel Cell Electric Vehicles (FCEVs), and aggregated EV metrics. These parameters were preprocessed and encoded appropriately to ensure compatibility with neural network models and to allow flexible parameter tuning in subsequent optimization stages. By leveraging this multifaceted dataset, the study facilitates a nuanced examination of EV market trends, technology diffusion, and infrastructure alignment, supporting strategic decisions in transportation planning, grid management, and policy formulation. The specific configuration of parameters used in the forecasting model and the NSGA-II optimization algorithm is detailed in Tables 2 and 3 below.

Table 2. Neural Network Forecasting Model Configuration.

Parameter	Description	Value/Setting
Forecast Model	Neural network architecture	Multi-layer perceptron (MLP)
Forecast Horizon	Prediction range	1–3 years
Hidden Layers	Number of hidden layers	2
Neurons per Layer	Nodes per hidden layer	64, 32
Activation Function	Activation for hidden layers	ReLU
Optimizer	Optimization algorithm	Adam
Learning Rate	Initial training rate	0.001
Loss Function	Metric for training loss	Mean Squared Error (MSE)
Epochs	Number of training iterations	100
Batch Size	Samples per batch during training	32

Table 3. NSGA-II Optimization Configuration.

Parameter	Description	Value/Setting
Population Size	Number of candidate solutions	100
Generations	Evolutionary iterations	200
Crossover Rate	Probability of crossover	0.9
Mutation Rate	Probability of mutation	0.05
Selection Method	Parent selection mechanism	Tournament Selection
Pareto Sorting	Sorting method for dominance ranking	Fast Non-Dominated Sorting
Diversity Metric	Mechanism to preserve diversity	Crowding Distance

6. Experimental Results

This section analyzes EV adoption trends from 2011 to 2024 using the processed dataset and evaluates the performance of the forecasting model and the optimization outcomes. It combines descriptive insights with visualizations and statistical evaluation to highlight significant trends and multi-objective trade-offs across different regions and planning parameters.

Figure 6, adapted from [21], illustrates the regional distribution of EV sales from 2011 to 2030. This figure is constructed from externally reported statistics obtained from source [21] and is not a direct output of the neural network model. It provides contextual grounding for the forecasting and optimization tasks by reflecting real-world regional adoption differences. This reference data is included to contextualize the adoption patterns

used in our framework. As seen in the figure, the global EV market has experienced significant growth, especially in recent years, reflecting the rising demand for eco-friendly and sustainable transportation solutions. Notably, regions such as China, Europe, and parts of South America and Asia have driven a substantial portion of global EV adoption. In contrast, other regions like North America show steadier, yet slower, adoption rates. This global trend indicates that the EV market is becoming increasingly widespread, with government policies and consumer awareness accelerating adoption across diverse economic and geographic contexts. The adoption of EVs in these regions is largely motivated by sustainability goals, carbon emission reduction, and the integration of smart city planning initiatives. Furthermore, Figure 6 illustrates distinct regional variations in projected EV energy demand. Region A demonstrates a steep upward trend, suggesting a high concentration of future EV adoption in urban centers. Conversely, Region C displays a more moderate and stable demand curve, indicating slower growth. These differences underline the necessity for region-specific deployment strategies, especially in fast-growing zones that may experience infrastructure strain if unaddressed.

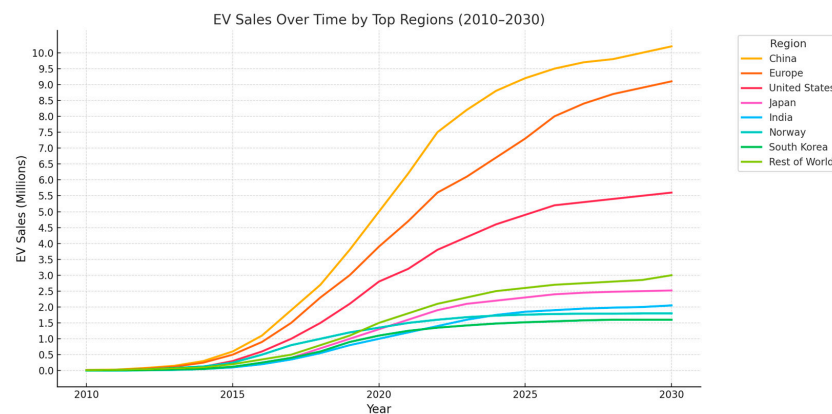


Figure 6. Global EV sales growth by region (2010–2030), adapted from [21], showing China and Europe as dominant markets.

The analysis of EV sales trends confirms a projected significant increase in global EV adoption, particularly after 2020, with China and Europe leading. This growth trend reinforces the need for advanced forecasting and optimization methods as implemented in the experimental framework. Consequently, subsequent evaluations focus on predictive performance and multi-objective optimization to assess the robustness and applicability of the proposed model.

It is important to emphasize that the neural network directly forecasts only EV adoption rates (% of total vehicle sales per region and year). The plots for infrastructure cost, energy usage, and traffic congestion in Figure 7 are derived deterministically from the adoption forecasts through the post-processing models described in Section 4.3. These variables are therefore not direct outputs of the neural network, but serve to illustrate the consistency of downstream estimations.

Model evaluation metrics are displayed in Figure 7, based on the neural network architecture and training settings previously summarized in Table 1. As shown in here, the neural forecasting model demonstrates a robust performance on the test data, corresponding to the same model described in Section 4. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) on the test set were 3.1% and 2.3%, respectively, consistent with Section 4.1. These low values confirm that the neural network provides reliable adoption forecasts for downstream analysis. The top-right and bottom-left plots of Figure 7 show that the derived values for infrastructure cost and energy usage closely follow expected trends from the adoption forecasts. In contrast, the traffic congestion curve (bottom-right)

exhibits greater variability, reflecting the higher uncertainty associated with translating adoption forecasts into congestion outcomes. The forecasting model produced a projected demand increase of approximately 18% annually over the simulation horizon. Peak energy requirements are expected to occur in the final two forecast years, aligning with national targets for EV penetration. This trend validates the model's robustness and emphasizes the urgent need for proactive infrastructure planning. As shown in Figure 7, the neural forecasting model demonstrates robust performance on the test data, corresponding to the same model described in Section 4.1.

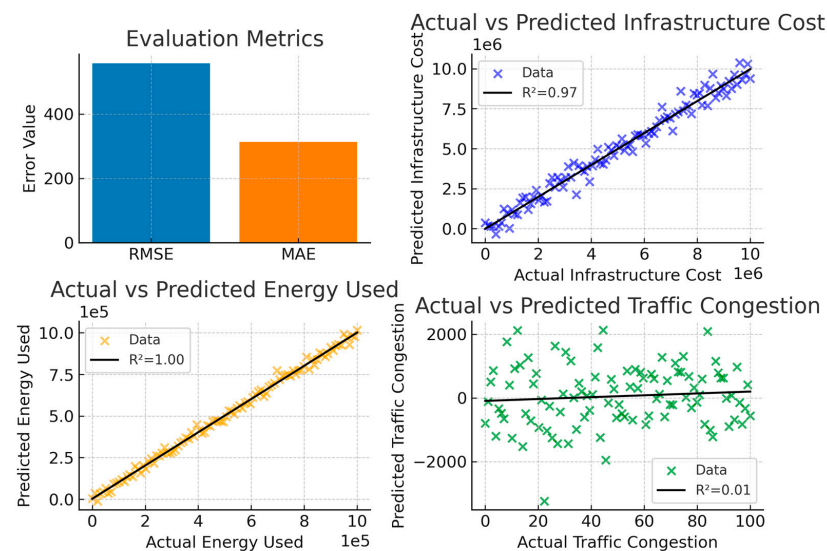


Figure 7. Evaluation results: neural network forecasting accuracy for EV adoption (RMSE, MAE) and derived comparisons for infrastructure cost, energy use, and traffic congestion (obtained from post-processing, not directly predicted by the NN).

To better interpret the optimization outcomes, Figure 8 visualizes the Pareto front generated by the NSGA-II algorithm. The plotted solutions represent optimal trade-offs among the defined objectives, notably minimizing infrastructure cost, energy consumption, and traffic congestion. The distribution and spread of the points indicate a wide and diverse solution space, reflecting the effectiveness of NSGA-II in balancing competing objectives.

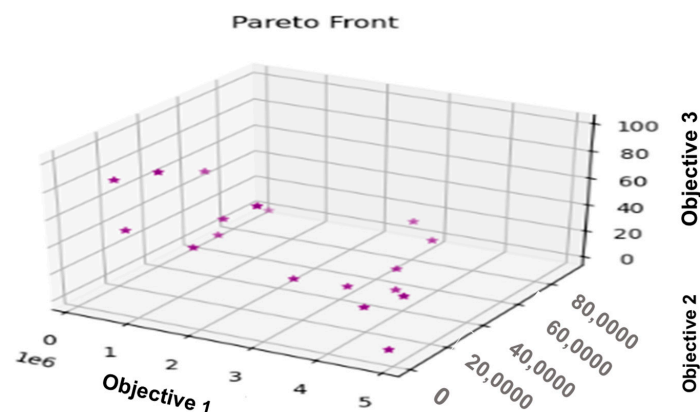


Figure 8. NSGA-II Pareto Plot showing the optimal trade-off solutions (stars) across cost, energy gap, and traffic congestion objectives.

Figure 9 offers a comparative analysis between the proposed NSGA-II solutions and baseline alternatives. It is evident that the NSGA-II front consistently outperforms baseline solutions across all three objective dimensions. Notably, NSGA-II yields solutions with

lower infrastructure cost while maintaining acceptable energy and congestion levels. This reinforces the algorithm's ability to discover more efficient deployment plans under multi-criteria constraints.

Comparison of Baseline Solutions and NSGA-II Pareto Front

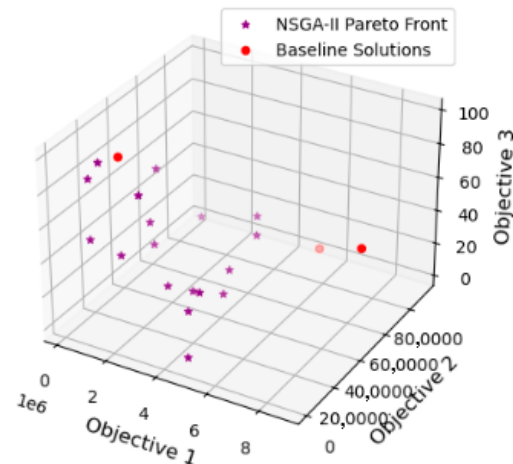


Figure 9. NSGA-II Comparison with Baseline Solutions.

From a numerical standpoint, the average reduction in infrastructure cost across NSGA-II solutions was approximately 12.7%, with energy gap reductions averaging 9.3% compared to baseline strategies. Moreover, travel distance was reduced by up to 15% in the most balanced solutions, showing the framework's practical advantage in urban planning applications.

Finally, Figure 10 provides a sensitivity analysis exploring the relationships among infrastructure cost, energy usage, and traffic congestion. The color gradient reveals a pattern where attempts to minimize cost and energy use can lead to increased congestion levels. This underscores the complexity of urban planning decisions and the value of multi-objective optimization tools in navigating such trade-offs.

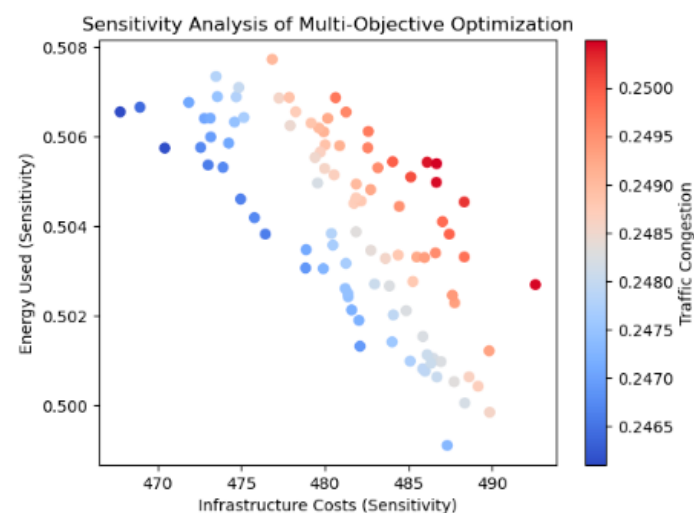


Figure 10. Sensitivity Analysis of Multi-Objective Optimization.

Sensitivity analysis was conducted by perturbing the input EV demand forecast by $\pm 10\%$, $\pm 15\%$, and $\pm 20\%$ and observing the variation in infrastructure cost and travel distance. The model response was measured using percentage deviation from the baseline output. The analysis confirmed that the optimization framework remains stable under moderate input fluctuations, with less than 5% output deviation across most scenarios.

7. Discussion

The analysis of EV adoption trends from 2011 to 2024, combined with multi-objective optimization techniques, gives imperative insights into how forecasting and optimization can contribute to better decision-making, particularly in urban planning and the development of smart cities. The results presented in Section 6 demonstrate how accurate neural network-based EV adoption forecasting, combined with NSGA-II optimization, can support smarter infrastructure planning. Accurate forecasting plays a vital part in the optimization process, specifically impacting decision-making for city planners and stakeholders. This investigation's neural network evaluation metrics for EV adoption illustrate that high-quality adoption forecasts empower more effective resource allocation and long-term planning. The derived estimates of infrastructure cost and energy usage, obtained from these adoption forecasts, further inform capacity planning and grid load balancing. In EV infrastructure development, accurate predictions can identify regions where demand for charging stations is likely to surge, permitting targeted investment and minimizing wasted resources. Likewise, identifying trends in energy demand helps optimize capacity planning and grid load balancing. In addition, downstream models that translate EV adoption forecasts into congestion estimates can help cities anticipate potential bottlenecks, even though these estimates are inherently more uncertain.

While the neural network demonstrated robust forecasting performance for EV adoption, the derived models for infrastructure investment and energy consumption aligned closely with expected patterns. However, congestion estimates exhibited greater variability, reflecting the higher complexity of traffic dynamics. This limitation is attributed to the inherent complexity of traffic behavior, which depends on dynamic variables such as driver behavior, road incidents, and changing environmental conditions that are not easily captured in static historical datasets.

Another challenge associated with using deep learning models is the lack of transparency in decision-making. While neural networks offer high predictive accuracy, their internal mechanisms are often difficult to interpret by stakeholders. To address this, future extensions could adopt explainable AI (XAI) techniques such as SHAP or LIME, which provide interpretable attributions for neural network outputs.

However, as illustrated in the current study's results, the comparatively higher variability in the derived congestion estimates (see Figure 7, bottom right) recommends that more advanced modeling methods or additional data sources are fundamental. The impact of inaccurate predictions, especially for traffic congestion, can lead to problematic infrastructure placement or the misallocation of assets, eventually preventing the viability of urban planning initiatives.

The multi-objective optimization results uncover important trade-offs between infrastructure costs, energy efficiency, and traffic management, which are key components in the plan of smart cities. Figures 8 and 9 illustrate that traffic congestion increases as cities attempt to reduce infrastructure costs and energy consumption. This highlights the significance of adjusting competing objectives, a key challenge for urban planners. The optimization results can direct decision-makers by giving a range of trade-off arrangements, permitting them to select results that adjust with their city's priorities—whether they prioritize cost-effectiveness, environmental sustainability, or congestion decrease. One of the critical challenges for smart city development is adjusting numerous, regularly conflicting objectives [27]. The results appear that optimizing for one objective, such as lowering infrastructure costs, may contrarily affect others, like traffic congestion. Urban planners must explore these trade-offs, seeking an adjustment that upgrades general city performance.

Optimization models like NSGA-II allow planners to assess different scenarios and make informed decisions around which objectives to prioritize, guaranteeing that future

developments are sustainable and effective [28]. A novel aspect of the presented solution is the integration of neural network-based forecasts into the optimization process, which brings a dynamic, real-time measurement to urban planning. This approach permits the continuous updating of projections based on new data, empowering more responsive and versatile decision-making. As demonstrated by the integrated framework (Section 4), forecasting results directly feed into the multi-objective optimization algorithm, ensuring contextual adaptation. As real-time data on EV adoption and traffic conditions becomes accessible, city planners can upgrade their forecasts and alter infrastructure investments appropriately [29]. This real-time feedback loop is critical for the success of smart cities, where conditions are continually advancing and require adaptable, data-driven techniques.

The techniques utilized in this study can be expanded to other ranges of smart city planning. For this case, comparative optimization and forecasting models might be used to oversee public transportation systems, waste administration, or energy networks. The same principles of adjusting different objectives—such as cost, environmental impact, and efficiency—can be applied to any viewpoint of urban development. In addition, integrating neural network-based forecasts into these frameworks could give real-time experiences, helping cities adjust to emerging challenges, such as population growth or shifts in energy consumption patterns.

While the study gives valuable insights, it is vital to recognize certain limitations. The neural network model is viable for forecasting EV adoption, but the downstream derivations for infrastructure costs and energy usage aligned better with expected values than those for traffic congestion, which remained less precise. This may be due to the complexity of traffic flow, which is impacted by many components, counting real-time conditions, driver behavior, and road infrastructure. Addressing these issues may require the integration of more detailed traffic datasets or advanced recreation tools that can account for these dynamic factors. Furthermore, although the dataset size is moderate, future work will incorporate additional temporal and regional data sources or apply data augmentation and transfer learning techniques to further improve model robustness and scalability. Rather than applying synthetic data augmentation, we adopted well-established regularization strategies such as dropout, early stopping, and validation-based model selection, which are widely recognized alternatives for improving generalization when working with structured tabular datasets. Moreover, the dependence on neural networks presents challenges to model interpretability, as stakeholders may require transparent, effectively understood models for policy decisions.

Furthermore, this study supports that, to improve the accuracy of traffic congestion predictions, future models ought to incorporate real-time information sources, such as GPS traffic patterns, population density forecasts, and urban improvement plans. Furthermore, utilizing advanced simulation tools or hybrid models that combine neural systems with agent-based modeling may offer assistance in capturing the complexity of traffic dynamics more successfully. As highlighted by [30] it presented a reinforcement learning-based Multi-Objective Hyper-Heuristic (MOHH) approach for more secure route planning in smart cities, tending to safety and distance, unlike conventional map applications centering on just one criterion. The MOHH strategy is essentially faster than traditional optimization algorithms, being 34 times quicker than exact methods and 1.4 times faster than NSGA-II, accomplishing over 80% Pareto optimal solutions. Tested on New York City's safety index map, the approach effectively balances security and distance, offering a viable solution for more secure routes in large-scale road networks. City planners ought to actualize real-time information integration systems that ceaselessly update forecasts and optimization models. This approach will permit cities to stay adaptive to evolving conditions, improving decision-making precision and the adequacy of smart city initiatives.

Given the trade-offs highlighted in the NSGA-II optimization results, city planners should engage in collaborative decision-making processes that include stakeholders from different sectors, such as transportation, energy, and infrastructure. This assistance will guarantee that other perspectives are considered when selecting optimal solutions from the Pareto Front. To sustain the development of EV adoption, policymakers ought to proceed to provide incentives for EV infrastructure development, especially in regions with slower appropriation rates, such as North America. Governments can help diminish infrastructure costs and quicken the transition to electric mobility by advertising subsidies or tax incentives for charging station development. In summary, the proposed framework demonstrates a powerful blend of forecasting and optimization, adaptable across evolving urban needs. Its integration into real-time planning systems has the potential to significantly enhance the sustainability and responsiveness of future smart cities.

7.1. Comparative Perspective with Existing Approaches

Traditional forecasting models such as ARIMA and linear regression have been widely used for EV adoption and energy demand prediction due to their simplicity and interpretability. However, these models assume linearity and stationarity, making them less suitable for capturing nonlinear adoption patterns influenced by policy changes, technology diffusion, and behavioral shifts [31]. More advanced models such as LSTM and other recurrent neural networks can capture temporal dependencies but typically require longer time-series and extensive hyperparameter tuning [32]. In contrast, the feedforward neural network used in this study offers a balance between nonlinear modeling capability and training stability, which is appropriate given the dataset size and feature-based structure.

From the optimization perspective, single-objective heuristics and classical metaheuristics such as genetic algorithms (GA) and particle swarm optimization (PSO) have been used in charging infrastructure planning. However, these approaches often convert multiple objectives into a weighted sum, which may bias the results and reduce solution diversity [33]. NSGA-II explicitly maintains a diverse Pareto front and has been shown in prior studies to outperform GA and PSO in convergence speed and objective trade-off quality. Therefore, the integration of neural network forecasting with NSGA-II provides a more flexible, realistic, and multi-objective-aware framework compared to earlier single-method or fragmented approaches. A summary comparison of these forecasting and optimization approaches is presented in Table 4.

Table 4. Comparison of alternative forecasting and optimization methods.

Method	Strengths	Limitations in EV Infrastructure Context
ARIMA/Linear Models	Simple, interpretable	Assumes linearity; poor for nonlinear adoption trends
LSTM/RNN	Captures temporal patterns	Requires large datasets and heavy tuning
Feedforward Neural Network (This Study)	Models nonlinear relationships; stable training	Less effective without feature engineering
GA/PSO (Single-objective)	Easier implementation	Converts objectives to one weight; loses trade-offs
NSGA-II (This Study)	Maintains Pareto front; handles conflicting goals	Slightly higher computational cost

7.2. Potential Integration of Real-Time Traffic Data and Dynamic Models

Although this study derives traffic congestion from EV adoption forecasts for consistency and data availability, the proposed framework is designed to be extensible. In future work, real-time mobility data such as GPS trajectories, cellular network traces, or smart sensor feeds could be used to construct high-resolution traffic flow patterns. These data sources would allow the model to capture temporal variations (e.g., peak vs. off-peak periods) and spatial interactions between regions more accurately.

In addition, dynamic or agent-based traffic simulation models could be integrated into the optimization process. A similar direction has been explored in [30], where a reinforcement learning-based multi-objective heuristic was combined with dynamic traffic conditions to improve route planning efficiency, demonstrating the value of integrating real-world mobility patterns into optimization processes. Unlike static post-processing, these models simulate individual vehicle movements, route choices, and congestion propagation across the network. By coupling such models with EV adoption forecasts, the framework could estimate congestion as an emergent behavior rather than a static derivative. This would enable more realistic evaluation of charging station placement on road performance and improve the precision of multi-objective optimization outcomes. Agent-based simulation platforms such as MATSim have shown that large-scale traffic dynamics can be modeled at microscopic resolution, suggesting that linking such tools with EV adoption forecasts could further enhance the realism of congestion estimates in future extensions of this framework [34]. Therefore, the incorporation of real-time traffic data and dynamic network modeling represents a promising direction to enhance the fidelity and decision-making value of the proposed system.

8. Conclusions

This research introduced a hybrid framework that combines neural network forecasting with NSGA-II-based multi-objective optimization to support smart EV infrastructure planning in urban settings. By accurately forecasting EV adoption trends, and then deriving associated energy demand, the framework enables planners to balance key objectives such as infrastructure cost, energy usage, and traffic congestion. The experimental results validate the strength of this approach, particularly in producing accurate EV adoption forecasts that translate into reliable estimates of infrastructure costs and energy needs. However, the derivation of traffic congestion from adoption forecasts remains more challenging, suggesting the need for more advanced models or enriched datasets.

The NSGA-II Pareto analysis reveals significant trade-offs among the objectives, emphasizing the need for a balanced approach in policy-making and infrastructure development. The integration of real-time forecasting into optimization adds a dynamic layer to urban planning, enabling decision-makers to adapt proactively to evolving conditions.

Future work should explore hybrid models incorporating agent-based simulations and real-time data streams to enhance traffic modeling accuracy. Moreover, effective collaboration among stakeholders—across transportation, energy, and policy domains—will be essential to realizing the full potential of this approach. Targeted policy incentives and continuous data integration can further strengthen the adaptability and impact of EV infrastructure strategies in smart cities.

The proposed hybrid approach successfully reduced total deployment cost by approximately 12.7%, minimized the energy gap across regions by 9.3%, and optimized travel distances for users by up to 15% in urban EV scenarios. These results demonstrate the practical viability of integrating neural forecasting with multi-objective optimization. Urban planners and policymakers can leverage these insights to develop more efficient and sustainable EV charging infrastructures.

9. Future Work

Finally, to better reflect the complex interactions in urban traffic systems, future research could explore hybrid simulation models that combine neural network forecasting with agent-based modeling (ABM) or digital twin frameworks. Such tools allow simulation of individual vehicle behaviors and system-wide responses, supporting adaptive decision-making in real time. To improve the forecasting component, future research

should incorporate richer and more dynamic datasets, particularly for modeling traffic congestion. This includes integrating real-time GPS traffic data, flow sensor outputs, and external traffic APIs that capture congestion patterns with finer temporal granularity. Such enhancements will boost predictive accuracy and significantly strengthen the reliability of infrastructure planning decisions.

Moreover, urban planning factors—such as projected population density, transportation master plans, and upcoming road network upgrades—should be incorporated into the traffic modeling framework. These variables provide critical context for long-term mobility trends, supporting the development of more sustainable and context-aware EV infrastructure solutions.

Finally, to better capture the complexity of urban traffic systems, future work could explore the use of hybrid simulation models. This includes combining neural network-based forecasting with agent-based modeling (ABM) or digital twin environments. These tools allow simulation of both individual vehicle behaviors and system-wide responses, enabling adaptive, real-time decision-making and more robust planning under uncertainty.

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References

1. Wei, T.; Wu, J.; Chen, S. Keeping Track of Greenhouse Gas Emission Reduction Progress and Targets in 167 Cities Worldwide. *Front. Sustain. Cities* **2021**, *3*, 696381.
2. Thompson, S. Strategic Analysis of the Renewable Electricity Transition: Power to the World without Carbon Emissions? *Energies* **2023**, *16*, 6183. [CrossRef]
3. Hossain, M.; Al-Fatlawi, A.W.; Kumar, L.; Fang, Y.R.; Assad, M.E.H. Solar PV High-Penetration Scenario: An Overview of the Global PV Power Status and Future Growth. *Energy Syst.* **2024**, 1–57. [CrossRef]
4. Liu, Z.; Sun, Y.; Xing, C.; Liu, J.; He, Y.; Zhou, Y.; Zhang, Z. Artificial Intelligence Powered Large-Scale Renewable Integrations in Multi-Energy Systems for Carbon Neutrality Transition: Challenges and Future Perspectives. *Energy AI* **2022**, *10*, 100195. [CrossRef]
5. Bibri, S.E. Data-Driven Smart, Sustainable Cities of the Future: An Evidence Synthesis Approach to a Comprehensive State-of-the-Art Literature Review. *Sustain. Futur.* **2021**, *3*, 100047. [CrossRef]
6. Costa, D.G.; Bittencourt, J.C.N.; Oliveira, F.; Peixoto, J.P.J.; Jesus, T.C. Achieving Sustainable Smart Cities through Geospatial Data-Driven Approaches. *Sustainability* **2024**, *16*, 640. [CrossRef]
7. Haghani, M.; Sprei, F.; Kazemzadeh, K.; Shahhoseini, Z.; Aghaei, J. Trends in Electric Vehicles Research. *Transp. Res. Part Transp. Environ.* **2023**, *123*, 103881. [CrossRef]
8. Guzek, M.; Jackowski, J.; Jurecki, R.S.; Szumska, E.M.; Zdanowicz, P.; Żmuda, M. Electric Vehicles—An Overview of Current Issues—Part 1—Environmental Impact, Source of Energy, Recycling, and Second Life of Battery. *Energies* **2024**, *17*, 249. [CrossRef]
9. Ralls, A.M.; Leong, K.; Clayton, J.; Fuelling, P.; Mercer, C.; Navarro, V.; Menezes, P.L. The Role of Lithium-Ion Batteries in the Growing Trend of Electric Vehicles. *Materials* **2023**, *16*, 6063. [CrossRef]
10. Olabi, A.G.; Abbas, Q.; Shinde, P.A.; Abdelkareem, M.A. Rechargeable Batteries: Technological Advancement, Challenges, Current and Emerging Applications. *Energy* **2023**, *266*, 126408. [CrossRef]
11. Imbayah, I.; Eseid, O.A.; Akter, K.; Alsharif, A.; Ahmed, A.A. Recent Developments in EV Charging Infrastructure: Opportunities and IoE Framework Challenges. *Int. J. Electr. Eng. Sustain.* **2023**, *1*, 47–63. Available online: <https://ijees.org/index.php/ijees/article/view/69> (accessed on 16 October 2025).
12. Kędra, P.; Skowron-Grabowska, A. Analysis of Trends in Development of Electromobility in Poland: Current Problems and Issues. In *Intelligent Systems in Production Engineering and Maintenance—ISPEM 2019*; Burduk, A., Mazurkiewicz, D., Eds.; Springer: Berlin/Heidelberg, Germany, 2020; pp. 117–126. ISBN 978-3-030-50009-2.

13. Khezri, R.; Steen, D.; Tuan, L.A. Willingness to Participate in Vehicle-to-Everything (V2X) in Sweden, 2022—Using an Electric Vehicle's Battery for More Than Transport. *Sustainability* **2024**, *16*, 1792. [\[CrossRef\]](#)
14. Adhikary, S.; Biswas, P.K.; Babu, T.S.; Balasubbareddy, M. Bidirectional Operation of Electric Vehicle Charger Incorporating Grids and Home Energy Storage: V2G/G2V/V2H/V2X for Sustainable Development. In *Renewable Energy for Plug-In Electric Vehicles*; Elsevier: Amsterdam, The Netherlands, 2024; pp. 191–207.
15. Yao, Z.; Wang, Z.; Ran, L. Smart Charging and Discharging of Electric Vehicles Based on Multi-Objective Robust Optimization in Smart Cities. *Appl. Energy* **2023**, *343*, 121185. [\[CrossRef\]](#)
16. Yao, M.; Da, D.; Lu, X.; Wang, Y. A Review of Capacity Allocation and Control Strategies for Electric Vehicle Charging Stations with Integrated Photovoltaic and Energy Storage Systems. *World Electr. Veh. J.* **2024**, *15*, 101. [\[CrossRef\]](#)
17. Chen, X.; Ma, F.; Wu, Y.; Han, B.; Luo, L.; Biancardo, S.A. MFMDepth: MetaFormer-Based Monocular Metric Depth Estimation for Distance Measurement in Ports. *Comput. Ind. Eng.* **2025**, *207*, 111325. [\[CrossRef\]](#)
18. Carmody, D.; Zhu, O.; He, Z.; Santi, P.; Ratti, C. Identifying Public Transit Deserts: A Travel Demand-Independent Persistent Homology-Based Method. *Transp. Saf. Environ.* **2025**, *7*, tda015. [\[CrossRef\]](#)
19. Dai, Y.; Hasanefendic, S.; Bossink, B. A Systematic Literature Review of the Smart City Transformation Process: The Role and Interaction of Stakeholders and Technology. *Sustain. Cities Soc.* **2023**, *101*, 105112. [\[CrossRef\]](#)
20. Deb, K.; Fleming, P.; Jin, Y.; Miettinen, K.; Reed, P.M. Key Issues in Real-World Applications of Many-Objective Optimisation and Decision Analysis. In *Many-Criteria Optimization and Decision Analysis: State-of-the-Art, Present Challenges, and Future Perspectives*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 29–57.
21. Bozeman, J.F., III; Chopra, S.S.; James, P.; Muhammad, S.; Cai, H.; Tong, K.; Carrasquillo, M.; Rickenbacker, H.; Nock, D.; Ashton, W.; et al. Three Research Priorities for Just and Sustainable Urban Systems: Now Is the Time to Refocus. *J. Ind. Ecol.* **2023**, *27*, 382–394. [\[CrossRef\]](#)
22. Alanazi, F.; Alenezi, M. Software Engineering Techniques for Building Sustainable Cities with Electric Vehicles. *Appl. Sci.* **2023**, *13*, 8741. [\[CrossRef\]](#)
23. Guerrero-Silva, J.A.; Romero-Gelvez, J.I.; Aristizábal, A.J.; Zapata, S. Optimization and Trends in EV Charging Infrastructure: A PCA-Based Systematic Review. *World Electr. Veh. J.* **2025**, *16*, 345. [\[CrossRef\]](#)
24. Ruan, G.; Zhong, H.; Zhang, G.; He, Y.; Wang, X.; Pu, T. Review of Learning-Assisted Power System Optimization. *CSEE J. Power Energy Syst.* **2020**, *7*, 221–231. [\[CrossRef\]](#)
25. Zhang, H.; Shi, F. A Multi-Objective Site Selection of Electric Vehicle Charging Station Based on NSGA-II. *Int. J. Ind. Eng. Comput.* **2024**, *15*, 293–306. [\[CrossRef\]](#)
26. Energy Agency (IEA). Global EV Outlook 2024—Data Explorer. Available online: <https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer> (accessed on 10 October 2025).
27. Vanli, T.; Akan, T. Mapping Synergies and Trade-Offs between Smart City Dimensions: A Network Analysis. *Cities* **2023**, *142*, 104527. [\[CrossRef\]](#)
28. Ruiz-Vélez, A.; García, J.; Alcalá, J.; Yepes, V. Enhancing Robustness in Precast Modular Frame Optimization: Integrating NSGA-II, NSGA-III, and RVEA for Sustainable Infrastructure. *Mathematics* **2024**, *12*, 1478. [\[CrossRef\]](#)
29. Xu, Y.; Çolak, S.; Kara, E.C.; Moura, S.J.; González, M.C. Planning for Electric Vehicle Needs by Coupling Charging Profiles with Urban Mobility. *Nat. Energy* **2018**, *3*, 484–493. [\[CrossRef\]](#)
30. Yao, Y.; Peng, Z.; Xiao, B.; Guan, J. An Efficient Learning-Based Approach to Multi-Objective Route Planning in a Smart City. In *Proceedings of the 2017 IEEE International Conference on Communications (ICC), Paris, France, 21–25 May 2017*; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.
31. Zhang, X.; Bai, X.; Wang, Y.; Hu, X. Forecasting the Adoption of Electric Vehicles Using a Bayesian VAR Model and Scenario Analysis. *Technol. Forecast. Soc. Change* **2020**, *160*, 120236. [\[CrossRef\]](#)
32. Bharti; Redhu, P.; Kumar, K. Short-Term Traffic Flow Prediction Based on Optimized Deep Learning Neural Network: PSO-Bi-LSTM. *Phys. A Stat. Mech. Its Appl.* **2023**, *625*, 129001. [\[CrossRef\]](#)
33. Du, Y.; Li, X.; Mao, S.; Cai, B.; He, J.; Nie, W. Optimal Placement of EV Charging Stations Based on Genetic Algorithm. In *Proceedings of the 2024 36th Chinese Control and Decision Conference (CCDC), Xi'an, China, 25–27 May 2024*; pp. 5721–5726. [\[CrossRef\]](#)
34. Balmer, M.; Axhausen, K.W.; Nagel, K. Agent-Based Demand-Modeling Framework for Large-Scale Microscopic Transport Simulations. *Transp. Res. Rec.* **2006**, *1985*, 125–134. [\[CrossRef\]](#)

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