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Hierarchical framework for demand prediction and iterative optimization of EV charging network infrastructure under uncertainty with cost and quality-of-service consideration

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A R T I C L E I N F O

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A B S T R A C T

As electric vehicles (EVs) continue to grow in popularity, the demand for efficient and effective EV charging infrastructure is rapidly increasing. However, the design and deployment of such infrastructure faces numerous challenges, some of which include demand uncertainty, EV network layout, maintenance cost, and quality of service (QoS), and have proven to be particularly challenging in cases where all objectives need to be addressed simultaneously. To address these challenges, this study proposes a hierarchical iterative optimization approach that aims to minimize the demand–supply mismatch at a higher level and considers both cost and QoS under uncertainty at a lower level in a dynamic EV charging network. Specifically, the proposed approach uses a time-series linear regression ensemble to accurately predict future demand at demand points, which is then used to match demand at demand points with supply at supply points. We then model the infrastructure allocation problem as a knapsack problem and use an allocation algorithm to determine the optimal number of charging stations at each supply point. The infrastructure is allocated to minimize total cost and maximize QoS. A framework for EV infrastructure optimization is designed and can be applied to any type of network. The effectiveness of our proposed approach is demonstrated through extensive experimentation on various datasets by comparing with existing state-of-the-art approaches. Simulation results show that the proposed approach is robust to different EV networks, handles uncertainty well, can effectively address the challenges associated with EV infrastructure optimization, and can provide policy makers and infrastructure planners with a practical and efficient tool for designing and deploying charging infrastructure. This study contributes to the field of EV infrastructure network optimization by modeling QoS and proposing a hierarchical optimization framework that effectively addresses the challenges associated with the design and deployment of charging infrastructure.

1. Introduction

The push by policymakers and the widespread adoption of Electric Vehicles (EVs) have become crucial in reducing greenhouse gas emissions and achieving sustainable mobility (Singh & Singh, 2022). The adoption of fully electric mobility among alternative fuel vehicles is considered a promising solution to reduce environmental pollution and energy consumption caused by transportation systems (Das & Bhat, 2022). However, the availability and cost of public charging resources are important factors that can affect the large-scale adoption of EVs. An effective solution is to find a cost-effective allocation of charging facilities to serve public charging demand in any given national, regional, urban, or rural transportation network.

Improving EV charging infrastructure is a crucial factor that will encourage more people to adopt EVs by effectively managing the balance between demand and supply (Singh & Singh, 2022). To achieve this, it is essential to establish a reliable and efficient charging network. This network should have sufficient charging capacity, maintain a high quality of service (QoS), and minimize the overall cost of infrastructure development and operation.

As the adoption of EVs increases, it becomes even more important to manage the charging of these vehicles across different locations and time periods. Properly balancing the demand and supply of charging facilities can help prevent additional peak loads during specific times of the day. For example, home charging attempts during evenings and

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end-of-day charging of EV fleets can create unnecessary strain on the system and negatively impact QoS.

To overcome such problems, a well-designed charging infrastructure should be in place to ensure a smooth and convenient charging experience for EV owners. By addressing these challenges, we can make the transition to electric vehicles more attractive and sustainable for everyone.

Time series analysis, gradient boosting and neural networks methods are usually used to help forecast charging demand across locations and time (Arias, Kim, & Bae, 2017). Accurate demand prediction informs infrastructure planning and allocation. Due to changes in urban landscape design, varying infrastructure networks, existing methods often fail to account for spatial relationships and interactions between charging locations.

Aware of charging demand, modeling approaches for infrastructure allocation using mathematical optimization techniques like linear programming, game theory, and metaheuristic algorithms are then utilized to meet the objectives of the system (Narasipuram & Mopidevi, 2021). These methods rely heavily on demand forecasts and usually struggle complex networks.

Hybrid and hierarchical techniques attempt to get the best of both worlds. The aim is to integrate spatial modeling, robust forecasting, and optimization algorithms (Wu et al., 2022). For example, a model could spatially cluster charging locations at one level and then optimize infrastructure allocation within each cluster. Such integrated approaches show promise in tackling the challenges of EV infrastructure planning. However, more research is needed to develop flexible and scalable solutions. Overall, accurately predicting demand and then efficiently allocating charging infrastructure remains an open challenge (Narasipuram & Mopidevi, 2021).

This study aims to improve EV charging by addressing complex challenges, driven by the goal of creating a sustainable mobility future. Focused on creating an efficient and reliable EV charging network, we aim to develop a robust optimization algorithm that considers factors such as where to place charging stations, how to managing their capacity and understanding changing EV demand distribution in a given network. All of these efforts are aimed at reducing costs while maintaining a high QoS. Through these efforts, the study aims not only to overcome the complexities of EV charging optimization, but also to pave the way for a future of sustainability, improved user experience, and widespread EV adoption. We propose a novel hierarchical model for optimizing electric vehicle (EV) charging infrastructure deployment. The key innovation is using an ensemble time series forecasting approach at the upper level to accurately predict future charging demand across locations. This addresses a major gap in existing work — poor demand forecasts lead to inefficient infrastructure planning. At the lower level, an iterative matching and optimization algorithm allocates chargers across supply points to minimize costs and maximize quality of service. Each supply point is modeled as a knapsack problem with demand capacity as the constraint. The charger allocation takes into account installation and maintenance costs, wait times, and charging times to find the optimal solution. A key benefit is the model's robustness in balancing demand, quality of service and infrastructure costs. The hierarchical approach allows for customization of the prediction and optimization models used at each level.

A hypothetical network from the shell.ai 2022 EV network optimization challenge for sustainable and affordable energy (Shell, 2022) and an augmentation of the network to other real-world scenarios is adopted. Through numerical results and analysis, we demonstrate that our algorithm performance is robust achieving a balance between demand and QoS. Moreover, we analyze the relationship between QoS and infrastructure cost and examine the trade-offs that the algorithm presents in this regard.

Thus, this study contributes to the field of EV infrastructure network optimization in several ways:

1. Formulate a mathematical model for quantifying QoS based on driving distance, waiting time, and charging time with a tunable threshold parameter, allowing for adaptable and customizable adjustments.
2. Propose a hierarchical framework for demand prediction and iterative optimization that considers cost and QoS, which are essential factors in designing an efficient and effective EV charging infrastructure.
3. Develop a robust model for infrastructure allocation, treating it as a knapsack problem. Iterate the process by continually reestimating supply point demand to dynamically accommodate uncertainty in demand prediction. By reallocating infrastructure resources accordingly, this approach ensures an optimal allocation that remains resilient and adaptive to changing conditions.
4. Demonstrate the effectiveness of our proposed approach through extensive experimentation, comparing its performance with existing state-of-the-art approaches, and showing its ability to achieve superior results in terms of both cost and quality of service.

The structure of this paper is outlined as follows: In Section 2, we present a brief review of the literature. Section 3 introduces the mathematical formulation of the optimization objectives. Section 4 details the optimization solution framework to achieve these objectives. In Section 5, we present the simulated experiment and its results. Finally, in Section 6, we conclude the study and discuss potential avenues for future research.

2. Literature review

EV infrastructure network optimization has been extensively studied in recent years. These studies can be categorized on the basis of their focus and methodology as follows:

There are studies that focus on classical location models for recharging EVs, considering revisiting charging facilities and the concept of range limitation. Noteworthy studies in this category include (Afolabi & Farzaneh, 2023; Fadda, Manerba, Cabodi, Camurati, & Tadei, 2021; Fontaine, Minner, & Schiffer, 2023; Huang, Kanaroglou, & Zhang, 2016; Hwang, Jang, Ko, & Lee, 2017; Mirheli & Hajibabai, 2021). In Fadda et al. (2021), they evaluated optimal charging station location for EVs in an Italian case-study. Hwang et al. (2017) optimized a system for dynamic wireless charging EVs operating in a multiple-route environment. Mirheli and Hajibabai (2021) focused on the hierarchical optimization of EV charging infrastructure design and facility logistics while (Fontaine et al., 2023) discussed the design, consolidation, and regulation of smart and sustainable city logistics, which includes EV charging infrastructure. Additionally, Afolabi and Farzaneh (2023) presented an optimal design and operation of an off-grid hybrid renewable energy system in Nigeria's rural residential area, which utilizes EV charging infrastructure. However, these studies do not consider uncertainty and dynamic changes in EV demand and infrastructure availability.

Some studies focus on understanding the impact of demand uncertainty and presents robust optimization models to address this issue. Some notable studies in this category are (Pourgholamali et al., 2023; Quddus, Yavuz, Usher, & Marufuzzaman, 2019; Sarker, Pandžić, & Ortega-Vazquez, 2014; Xie, Wei, Khodayar, Wang, & Mei, 2018). These studies propose robust optimization models capable of effectively handling uncertain EV demand, aiming to minimize the overall infrastructure cost across various scenarios. However, it is important to note that these studies may not fully account for real-time dynamic changes in both demand and infrastructure availability.

Furthermore, there are data-driven approaches that leverages machine learning and data analytics techniques to predict EV demand and optimize the allocation of charging infrastructure. Noteworthy studies in this category are (Almaghrebi, Aljuheshi, Rafaie, James, &

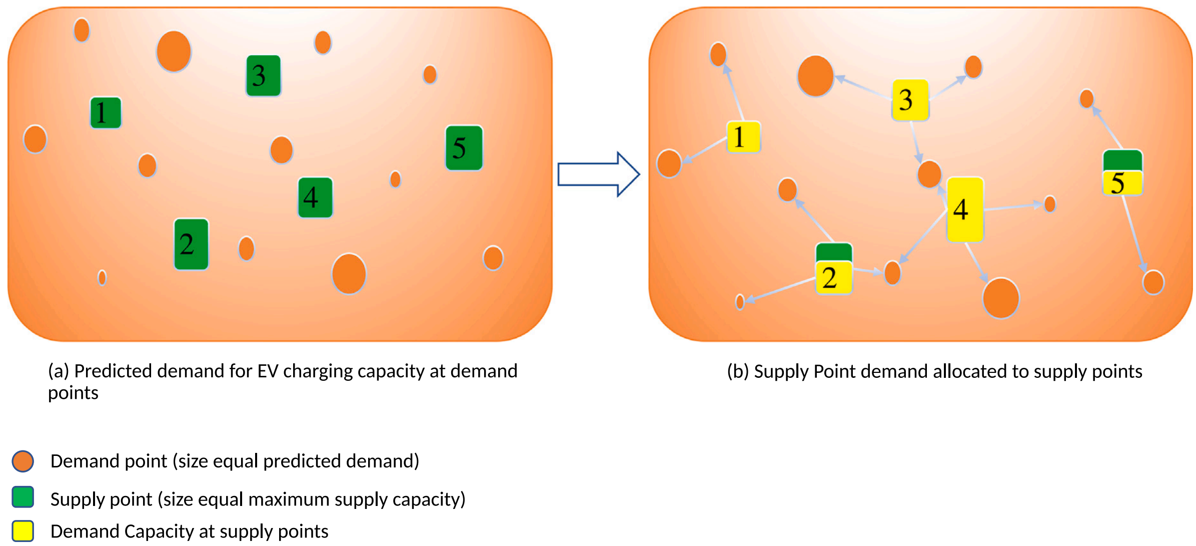

Fig. 1. An illustration of an EV network infrastructure with demand points and five supply points. The first step is to predict the future demand at each demand point as shown in (a). This prediction is then used to determine the expected demand capacity at each supply point, taking into account the distance between each demand point and supply point, as shown in (b).

Alahmad, 2020; Hafeez, Alammari, & Iqbal, 2023; Jiang, Ortmeyer, Fan, & Ai, 2022; Tao, Qiu, Lai, Sun, & Zhao, 2022). These studies have achieved remarkable accuracy in forecasting EV demand and efficiently allocating charging infrastructure. However, it is important to acknowledge that they may encounter scalability issues and might demand substantial data and computational resources.

Understanding the influence of various stakeholders, such as EV users, charging station owners, and power grid operators, on the optimization of EV infrastructure networks is an areas of research. Notable studies in this category are (Battapothula, Yammani, & Maheswarapu, 2019; Huang, Fang, & Deng, 2020; Mahato, Aharwal, & Sinha, 2023). These studies propose multi-objective optimization models that take into account the diverse and sometimes conflicting objectives of different stakeholders, aiming to strike a balance between their interests. However, it is worth noting that achieving this balance requires the use of complex negotiation mechanisms.

Finally, there are also review papers that provide a comprehensive overview of the research on EV infrastructure network optimization, such as the studies by Reddy and Narayana (2022), and Solanke, Khatua, Ramachandaramurthy, Yong, and Tan (2021). These review papers summarize the main findings and contributions of the previous studies and highlight the future research directions in the field.

Studies on EV infrastructure network optimization have made significant contributions to the design and deployment of charging infrastructure. However, there is still room for improvement, particularly in dealing with uncertainty and dynamic changes in demand and infrastructure availability with cost reduction and QoS consideration (Mirheli & Hajibabai, 2022).

This work plays a critical role in bridging the gap between prediction and optimization. It introduces a hierarchical framework for demand forecasting and infrastructure allocation that takes into account demand uncertainty and the QoS requirements of EV owners. Furthermore, the study proposes a quantitative model for QoS with a flexible threshold that allows for adaptive and customizable adjustments.

3. Problem formulation

The primary objective of this study is twofold. First, it aims to develop a robust prediction model for EV charging demand with the goal of minimizing demand mismatch. Second, the study seeks to find an optimal allocation strategy for future EV charging infrastructure. This optimization process takes into account multiple objectives: reducing infrastructure costs and ensuring a high QoS for EV owners. This section presents the mathematical formulation of the hierarchical demand forecasting and optimization problem.

Nomenclature

D_i^{year}: EV charging demand at demand point i in a given year
SCS_j: Number of slow charging stations at jth supply point
FCS_j: Number of fast charging stations at jth supply point
RCS_j: Number of rapid charging stations at jth supply point
$N_{\text{SCS},j}$: Number of SCS at supply point j
$N_{\text{FCS},j}$: Number of FCS at supply point j
$N_{\text{RCS},j}$: Number of RCS at supply point j
PS_j: Total parking slots at jth supply point
Cap_{SCS}: Charging capacity of a slow charging station = 200
Cap_{FCS}: Charging capacity of a fast charging station = 400
Cap_{RCS}: Charging capacity of a rapid charging station = 800
$Smax_j$: Maximum Supply at jth supply point = $(Cap_{\text{SCS}} \times \text{SCS}_j) + (Cap_{\text{FCS}} \times \text{FCS}_j) + (Cap_{\text{RCS}} \times \text{RCS}_j)$
$Dist_{i,j}$: Distance between ith supply point and jth demand point
$DS_{i,j}$: Demand–Supply matrix with how much demand at demand point i is satisfied by supply point j

3.1. Demand prediction

In a region with a demand map and demand locations as shown in Fig. 1, we are given a time series of EV charging demand for the region, broken down for each demand point, and we need to forecast future demand. Our forecasting objective here is to minimize the error in the demand forecast for each demand location, as shown in Eq. (1), and for the region as a whole, as shown in Eq. (2), for a given year.

$$D_{\text{error},i}^{\text{year}} = \left| D_{\text{forecast},i}^{\text{year}} - D_{\text{true},i}^{\text{year}} \right| \tag{1}$$

$$D_{\text{error}}^{\text{year}} = \sum_i \left| D_{\text{forecast},i}^{\text{year}} - D_{\text{true},i}^{\text{year}} \right| \tag{2}$$

$D_{\text{forecast},i}^{\text{year}}$ and $D_{\text{true},i}^{\text{year}}$ represent the predicted and true demand for demand point i in a given year, respectively. Note that the objective function here is not necessarily a loss function used to train a forecasting model, but a function used to judge the quality of a forecast or the mismatch of the demand.

3.2. Infrastructure cost for demand balancing

Infrastructure cost is modeled as the operating, maintenance, and amortized capital cost of owning an EV infrastructure. This takes into account the different costs of operating and maintaining the slow, fast, and rapid chargers. The infrastructure cost is formulated as shown in Eq. (3), which is the infrastructure cost of maintaining and operating the stations at a single supply location. $\text{Cost}^{j}_{\text{IF}}$ represents the infrastructure cost at supply point j. It is calculated as the sum of the number of SCS_j and the weighted sum of FCS_j and RCS_j. Eq. (4) formulates the total infrastructure cost for the entire region. It is calculated as the sum over all supply points j of the sum of the number of slow charging stations SCS_j, the weighted sum of the number of fast charging stations FCS_j, and the weighted sum of the number of rapid charging stations. The cost of operating and maintaining a SCS, FCS, and a RCS are all different and weighted by a ratio relative to the cost of infrastructure for a SCS as given in Shell (2022). The cost of maintaining a RCS is higher than the cost of maintaining a FCS, and that of a FCS is higher than that of a SCS.

$$\text{Cost}^{j}_{\text{IF}} = \text{SCS}_j + (r_1 \cdot \text{FCS}_j) + (r_2 \cdot \text{RCS}_j) \tag{3}$$

$$\text{Cost}_{\text{IF}} = \sum_{j} \left(\text{SCS}_j + (r_1 \cdot \text{FCS}_j) + (r_2 \cdot \text{RCS}_j)\right) \tag{4}$$

In Eqs. (3) and (4), the ratios r_1 and r_2 represent the maintenance cost ratios of FCS to SCS and RCS to SCS, respectively. Therefore, the SCS term in the equations is multiplied by one, while the other costs are computed relative to it. In our case, $r_1 = 1.5$ and $r_2 = 2.0$. In addition to ensuring that our infrastructure costs are reasonable, we must also ensure that it meets projected demand. To evaluate how well our infrastructure meets demand and how robust it is, we compute the demand–supply balance cost, which is modeled as the travel distance from a demand point to a supply point based on the distribution of demand across supply points. This metric measures how well the supply points can meet the projected demand in the network, as shown in Eq. (5).

$$\text{Cost}^{\text{forecast}}_{\text{DS}} = \sum_{i,j} \text{Dist}_{i,j} * \text{DS}^{\text{forecast}}_{i,j} \tag{5}$$

Using the true demand, we also compute the true cost of demand supply balancing using Eq. (6).

$$\text{Cost}^{\text{true}}_{\text{DS}} = \sum_{i,j} \text{Dist}_{i,j} \cdot \text{DS}^{\text{true}}_{i,j} \tag{6}$$

With the forecasted and true demand–supply cost, we compute the cost error, as the absolute value of the difference between the forecasted and true demand–supply cost outlined in Eq. (7). This formulation helps to determine how well an allocation algorithm is performing.

$$\text{Cost}^{\text{error}}_{\text{DS}} = \sum_{i,j} \left|\text{Dist}_{(i,j)} \cdot \text{DS}^{\text{forecast}}_{i,j} - \text{Dist}_{i,j} \cdot \text{DS}^{\text{true}}_{i,j}\right| \tag{7}$$

The matrix $\text{DS}_{(i,j)}$ represents the quantity of demand from demand point i handled by supply point j. This matrix is sparse, as most demand points have their demand met by 1 to 3 nearest supply points.

In cases where the true demand is unknown, i.e. when we want to determine the infrastructure to be built for the future, we can simply minimize the predicted demand–supply balance cost as our objective function.

The Demand Supply Balancing Cost is designed to address the range anxiety problem for EV drivers and to assess the robustness and effectiveness of the built infrastructure in meeting demand without requiring customers to travel long distances to charge. It ensures that the infrastructure can adequately meet the demand.

We optimize EV infrastructure and balance supply and demand under the following constraints:

- **Constraint 1:** $\text{DS}_{i,j} \geq 0$
- **Constraint 2:** $\text{SCS}_j \geq 0$, $\text{FCS}_j \geq 0$, $\text{RCS}_j \geq 0$
- **Constraint 3:** $\text{SCS}_j + \text{FCS}_j + \text{RCS}_j \leq \text{PS}_j$
- **Constraint 4:** $\text{SCS}^{\text{year}}_j \geq \text{SCS}^{\text{year-1}}_j$, $\text{FCS}j^{\text{year}} \geq \text{FCS}j^{\text{year-1}}$, $\text{RCS}j^{\text{year}} \geq \text{RCS}j^{\text{year-1}}$
- **Constraint 5:** $\sum_i \text{DS}(i,j) \leq \text{Smax}j$
- **Constraint 6:** $\sum_i \text{DS}^{\text{forecast}}_{i,j} = D_{\text{forecast},i}$, $\sum_i \text{DS}^{\text{true}}_{i,j} = D_{\text{true},i}$

Table 1
Charging time using different types of chargers for different battery models.

Vehicle information Battery	Charger information Pod point confidence range	Slow (hours)	Fast (hours)	Rapid (hours)
13.8 kWh	24 miles	4	4	0.6
40 kWh	143 miles	11	6	1
75 kWh	238 miles	21	6	1

Constraint 1 ensures that all values in the demand–supply matrix are non-negative, since we cannot have negative supply for a given demand–supply point. Constraint 2 ensures that the number of chargers in a supply point is non-negative. Constraint 3 restricts the total number of chargers at a supply point to within the available parking spaces. Constraint 4 ensures that the number of chargers at a delivery point should always increase or remain the same from one year to the next. Constraint 5 ensures that the demand satisfied by each delivery point must be less than or equal to the maximum supply determined by the infrastructure. Constraint 6 ensures that the forecast demand at each demand point is exactly satisfied and distributed to the supply points in the network. These constraints, especially constraints 5 and 6, are designed to ensure a fair evaluation of the cost of balancing demand and supply by guaranteeing that the forecasted demand is exactly distributed to supply points without exceeding the maximum supply capacity of the optimized infrastructure.

3.3. Quality of service

Once the infrastructure is built and ready for use, it is important to quantify its impact and evaluate how well it serves its purpose. To do this, we formulate a QoS model based on charging time, travel time, and waiting time, which are widely used in the EV transportation domain Davidov and Pantoš (2017). Travel time measures how easy it is for an EV driver to find a charging station from the time he needs one. Charging time, on the other hand, tells us how long it takes a driver to charge an EV, while wait time measures how long a driver waits in line before charging during peak demand periods. These three metrics give us a measure of the convenience EV drivers experience given the infrastructure in the network. In the following section, we outline the modeling of each of these metrics.

3.3.1. Charging time

For an EV, the charging time at a supply point depends on a number of factors include 1. The vehicle's battery type 2. The battery state of Charge (SoC) and 3. The type of charger used to charge the vehicle. The relationship between the charger type and battery on the charging time is shown in Table 1. On the other hand, the charging time of a car at a supply point depends on the number and type of chargers at the supply point. With this information we model the charging time of a car at a station as follows.

To compute the charging time of a car at a supply point, we first compute the probability of the car being charged at any of the charging stations SCS, FCS, or RCS as P_{Fcs}, P_{Scs}, and P_{Rcs} respectively using Eq. (8).

$$P^{j}_{i} = \begin{cases} P^{j}_{\text{FCS},i} = \dfrac{N^{\text{free}}_{\text{FCS},j}}{N^{\text{free}}_{\text{FC},j}}, & \text{if } i = \text{FCS} \quad \text{(a)} \\ P^{j}_{\text{SCS},i} = \dfrac{N^{\text{free}}_{\text{SCS},j}}{N_{\text{FC},j}}, & \text{if } i = \text{SCS} \quad \text{(b)} \\ P^{j}_{\text{RCS},i} = \dfrac{N^{\text{free}}_{\text{RCS},j}}{N_{\text{FC},j}}, & \text{if } i = \text{RCS} \quad \text{(c)} \end{cases} \tag{8}$$

where $P^j_{\mathrm{SCS},i}$, $P^j_{\mathrm{FCS},i}$, and $P^j_{\mathrm{RCS},i}$ represent the probability of charging car i at an SCS, FCS, and RCS, respectively, at station j. NFC_j represents the number of free charging stations at station j, while $N^{\mathrm{free}}_{\mathrm{SCS},j}$, $N^{\mathrm{free}}_{\mathrm{FCS},j}$, and $N^{\mathrm{free}}_{\mathrm{RCS},j}$ represent the number of free SCS, FCS, and RCS, respectively, at station j at the time when car i is chooses which station to use. Eq. (8) expresses the likelihood of a car being charged at a specific charging station when it arrives at a supply point. This information helps us approximate the average charging time a car will take at a station, considering the available options at the time of arrival. This estimation is outlined in Eq. (9), which represents the charging time of car i at supply point j.

$$\mathrm{CT}^j_i = \sum_{k=1}^{\mathrm{NFC}_j} \frac{F_{BL} * \mathrm{CT}^{k,l}_i}{\mathrm{NFC}_j} \tag{9}$$

where F_{BL} is a parameter that adjusts the charging time to account for battery level and can fall in the range [0.7, 0.9], and $\mathrm{CT}^{k,l}_i$ is the charging time using the selected charging station l for car i with battery type k at supply point j (provided in Table 1). CT^j_i is the estimated charging time of car i at supply point j. The average charging time at supply point j is formulated as expressed in Eq. (10), which is the sum of the time spent by every car that visited the station divided by the number of cars that visited the station. This information is useful for EV drivers and can be used to inform them about how long, on average, they should expect to spend charging their car at any given supply location.

$$\mathrm{CT}^j_{\mathrm{avg}} = \frac{\sum_{i=1}^{n^j_c} \mathrm{CT}^j_i}{n^j_c} \tag{10}$$

where n^j_c is the number of cars that visited the supply point.

To evaluate the efficiency of our charging network, we compute the average charging time in the entire network, which is simply the sum of the average charging times at every charging location divided by the total number of supply points in the network as shown in Eq. (11).

$$\mathrm{NCT}^{avg} = \frac{\sum_j \mathrm{CT}^j_{avg}}{\mathrm{NSP}} \tag{11}$$

NCT^{avg} is the average network charging time and NSP is the number of supply points in the network. The total charging time in the network (NCT) is as shown in Eq. (12).

$$\mathrm{NCT} = \sum_j \mathrm{CT}^j_{avg} \tag{12}$$

The metric for charging time can inform us on the efficiency of our charging network and of each individual supply point in the network. The lower the values the better it is as a measure for our quality of service.

3.3.2. Travel time

The travel time is an important metric that expresses the range anxiety of EV drivers in a network. The shorter the distance for a driver to get to a charging station from the time he needs charge, the better they feel and the better the service quality. Travel time quantifies the overall anxiety of EV drivers in the network to evaluate how well the service is in terms of the ease of finding a new charger.

The travel time of car to a charging station for charging depends on 1. Demand location of the car when it requests for charging, 2. The state of occupancy of charging stations in the network 3. The recommendation given to the car for which charging station to use (Supply point recommended) and 4. The day of week and time of day in which the car requires charging. The travel time of the car to the charging station is computed using Eq. (13)

$$TT^{i,j}_{t,d} = \frac{CD_{i,j}}{U(0.7,1) * TS_{t,d}} \tag{13}$$

The travel time of a car from its location i to the supply point j (recommended by the recommender algorithm) at time of day d is denoted as $TT^{i,j}_t$. It is calculated using the following Eq. (13). $CD_{i,j}$ represents the car distance from location i to supply point j, $TS_{t,d}$ is the travel speed of the car at time of day t and day of week d. $U(0.7,1)$ is a random number in the range $(0.7, 1)$ that accounts for the stochasticity in travel speed of a driver. The total network travel time on a specific day and time is denoted as $\mathrm{NTT}_{t,d}$ and is computed by summing the travel times $TT^{i,j}_{t,d}$ for all cars in the network as shown in Eq. (14):

$$\mathrm{NTT}_{t,d} = \sum_{t,d} TT^{i,j}_{t,d} \tag{14}$$

The total network travel time on a specific day is denoted as NTT_d is obtained using in Eq. (15) by summing the travel times for all time periods t on that day:

$$\mathrm{NTT}_d = \sum_d \sum_t TT^{i,j}_{t,d} \tag{15}$$

The total network travel time across all days is denoted as NTT, and it is computed using Eq. (16) by summing the travel times for all days:

$$\mathrm{NTT} = \sum_d \sum_t TT^{i,j}_{t,d}, \quad \forall d \tag{16}$$

The average network travel time NTT^{avg} is computed by dividing the total network travel time by the number of cars in the network N_c as shown in Eq. (17):

$$\mathrm{NTT}^{avg} = \frac{\sum_d \sum_t TT^{i,j}_{t,d}}{N_c}, \quad \forall d \tag{17}$$

These Travel time metrics measure the anxiety of EV drivers at different times of day in built infrastructure on different days and times of day and the performance of entire network.

3.3.3. Waiting time

The waiting time is the time a car spends at a supply point waiting for a charging station to be available after arrival. This metric evaluates the performance of the optimized infrastructure during peak demand times. The waiting time depends on the occupancy of the charging network and the recommended station for the car. To compute the waiting time, we first calculate the maximum waiting time at a supply point, denoted as $WT^j_{\max}$. This time is influenced by the type and number of charging stations at the supply point. The average waiting time, denoted as $\bar{WT}$, is computed using Eq. (18). To calculate $\bar{WT}$, we determine the maximum charging time for each battery on all charging stations at a supply point. It is important to note that the charging time at a station is equivalent to the waiting time of a car waiting to charge, as the car will only charge when a station becomes available after being freed up or when another car finishes charging. Thus, the waiting time of a car at a supply point is modeled according to Eq. (18).

$$WT^j_{\max} = \frac{\sum_k \left(\sum_1^l CT^l_{\max,k}\right)}{k * N^j_{\mathrm{CS}}} \tag{18}$$

$CT^l_{\max,i}$ is the maximum charge time of a car with battery type k using charging station l (information is referenced from Table 1) at supply point j. N^j_{CS} is the number of charging stations in supply point j. k is the number of unique charger types in a supply point. The waiting time of a car at supply point j where it is to charge, is computed as modeled in Eq. (19) which depends on the position of the car in a queue (it's Qrank). Mean while, the average waiting time at the station is given by Eq. (19) and is dependent on the number of charging stations in the network and the number of cars served.

$$WT^j = \begin{cases} 0 & \text{if Qrank} = 0 \\ \sum_1^{\mathrm{Qrank}} LP_{\mathrm{Qrank}} * WT^j_{\max} & \text{otherwise} \end{cases} \tag{19}$$

$$WT^j = \frac{\sum_c \begin{cases} 0 & \text{if Qrank} = 0 \\ \sum_1^{\mathrm{Qrank}} LP_{\mathrm{Qrank}} \cdot WT^j_{\max} & \text{otherwise} \end{cases}}{N^j_c} \tag{20}$$

$\mathrm{LP}_{\mathrm{Qrank}}$ is a parameter that defines the leaving probability of a car from a charging spot and falls in the range [0, 1]. It models how often a car leaves the station. N_c^j is the number of cars that visited supply point j. For a car that arrives at the station when a charging station was available (i.e., if its $Qrank$ is 0), the waiting time for that car is 0.

Now that we have modeled the waiting time at a station, we can now model the waiting time at a given time of the day and day of the week. This can help reduce anxiety for drivers and enhance their planning as they will know ahead of time what to expect at any charging station. The waiting time at a given station on a given day and time is expressed in Eqs. (21) and (22).

$$\mathrm{WT}^j_{(t,d)} = \frac{\sum_c \begin{cases} 0 & \text{if Qrank} = 0 \\ \sum_1^{\mathrm{Qrank}} LP_{\mathrm{Qrank}} \cdot \mathrm{WT}^j_{\max} & \text{otherwise} \end{cases}}{N_c^j} \quad \forall c \in t, d \tag{21}$$

$$\mathrm{WT}^j_{d} = \frac{\sum_c \begin{cases} 0 & \text{if Qrank} = 0 \\ \sum_1^{\mathrm{Qrank}} LP_{\mathrm{Qrank}} \cdot \mathrm{WT}^j_{\max} & \text{otherwise} \end{cases}}{N_c^j} \quad \forall c \in d \tag{22}$$

Evaluating the waiting time of our built infrastructure on the entire network, we compute the average waiting time of a car in the network as shown in Eq. (22). We also compute the average waiting time in the network for a given time and day as shown in Eqs. (23) and (24).

$$\mathrm{NWT}_{\mathrm{avg}} = \frac{\sum_j \mathrm{WT}^j_{(t,d)}}{\mathrm{NSP}} \tag{23}$$

$$\mathrm{NWT}^{\mathrm{avg}}_d = \frac{\sum_j \mathrm{WT}^j_{d}}{\mathrm{NSP}} \tag{24}$$

$$\mathrm{NWT}^{\mathrm{avg}}_{(t,d)} = \frac{\sum_j \mathrm{WT}^j_{(t,d)}}{\mathrm{NSP}} \tag{25}$$

To put it all together, we evaluate the QoS on all metrics by taking the sum of charging time, travel time and waiting time. This metric captures the time spent in completing a service from the time of demand to charge completion. The QoS metric is computed as expressed in Eq. (26). Eqs. (27) and (28) express the QoS on a given day and on a given day and hour. Unlike NTT and NWT that vary with time day and time, NCT is independent of day and time as the charging speed of a charger does not change and therefore, we use NCT for computing the QoS for a given time, day and time of day.

$$\mathrm{QoS} = \mathrm{NCT}^{\mathrm{avg}} + \mathrm{NTT}^{\mathrm{avg}} + \mathrm{NWT}^{\mathrm{avg}} \tag{26}$$

$$\mathrm{QoS}_d = \mathrm{NCT}^{\mathrm{avg}} + \mathrm{NTT}^{\mathrm{avg}}_d + \mathrm{NWT}^{\mathrm{avg}}_d \tag{27}$$

$$\mathrm{QoS}_{t,d} = \mathrm{NCT}^{\mathrm{avg}} + \mathrm{NTT}^{\mathrm{avg}}_{t,d} + \mathrm{NWT}^{\mathrm{avg}}_{t,d} \tag{28}$$

4. Solution methodology

The problem we set out to solve is to predict future demand at various demand points and optimizing infrastructure at supply points to meet demand while considering cost and quality of service. This prediction and optimization problem can be formulated and solved in two ways: predict then optimize (Elmachtoub & Grigas, 2022) or predict and optimize (Mandi, Stuckey, Guns, et al., 2020). Choosing between these approaches depends on factors such as problem analysis, complexity, and differentiability (Vanderschueren, Verdonck, Baesens, & Verbeke, 2022). Our solution adopts the predict then optimize approach due to the intricate details and complexities in our optimization layer. The prediction problem is a time series forecasting task, where we estimate future demand in a given year at demand points, and then use this information to optimize for infrastructure at various supply points. We have outlined our solution framework in Fig. 2, which includes an input layer, a demand prediction layer, an infrastructure optimization layer, and a built infrastructure layer.

The input data layer contains data on past demand at demand points (demand data) and the EV infrastructure already built and in use in the region or network (infrastructure data). In our first task, the demand data is fed to the demand prediction layer from which future estimates of demand are determined using a carefully designed time series linear regression ensemble. Note that demand data only contains historical data of demand points as explained in detail in Section 5.1.1.

After future demand has been estimated, it is used as input in the optimization layer to find the optimal number of charging stations needed in each demand point in the charging network. We first approximate supply point demand from input of demand predictions at demand points and the infrastructure data, based off the network layout. We then use the supply point demand and the current infrastructure to estimate the charging capacity needed at each supply point. This capacity is what we then use to allocate infrastructure to be built at any supply point in the network using an allocation algorithm. After allocation, we evaluate the objective function and if the stopping criteria has not been met, we return to recompute our supply point and repeat the optimization cycle until we converge to a desired solution as shown in Fig. 2. The newly determined infrastructure is built and the infrastructure data is updated. We update the infrastructure data because we want to plan future infrastructure two years ahead and therefore should be aware of previous infrastructure. The details for the Demand Prediction (in Section 4.1) and Infrastructure Optimization (in Section 4.2) layer will be covered next.

4.1. Demand prediction

In this section we explain the machine learning approach we adopt for our time series prediction problem. We estimate future demand at demand points using a linear regression ensemble in order to capture the nonlinear trends in the time series data which cannot be captured by a simple linear model and in which neural networks and gradient boosting methods are less efficient. This approach is used due to the nature of our data, its simplicity and its ability to capture trends in short time series data.

4.1.1. Linear regression primer

Linear regression (Hyndman & Athanasopoulos, 2018) is a common statistical technique used to make predictions based on the relationship between a response variable and predictor variables. In this approach, the goal is to model the relationship between a response variable and one or more predictor variables by fitting a linear equation to the observed data. This relationship is represented by a linear equation, as shown in Eq. (29), which is fitted to the observed data, and the resulting model can be used to make predictions.

To begin, assume y is our response variable, and let $x_1, x_2, \dots, x_n$ be the predictor variables. The relationship between y and the predictors is modeled using the following equation:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + e \tag{29}$$

where $(\beta_0, \beta_1, \dots, \beta_n)$ are the coefficients that are learned based on the observed data, and e is the error term, representing the difference between the predicted value and the actual observed value of y. It accounts for the part of y that is not explained by the independent variables. The coefficients represent the strength and influence of each predictor $(x_1, x_2, \dots, x_n)$ on the response variable y, as well as the direction of the relationship between each predictor and the response. $beta_0$ represents the intercept term, also known as the y-intercept. It is the value of y when all the independent variables $(x_1, x_2, \dots, x_n)$ are equal to zero. In other words, it represents the expected or average value of y when all the independent variables have no effect on the dependent variable.

With good coefficients estimates, the learned model is used to make predictions for new input data points or future time points. To make a prediction for a new time point, we simply plug in the values for the predictor variables and use the estimated coefficients to calculate the predicted response.

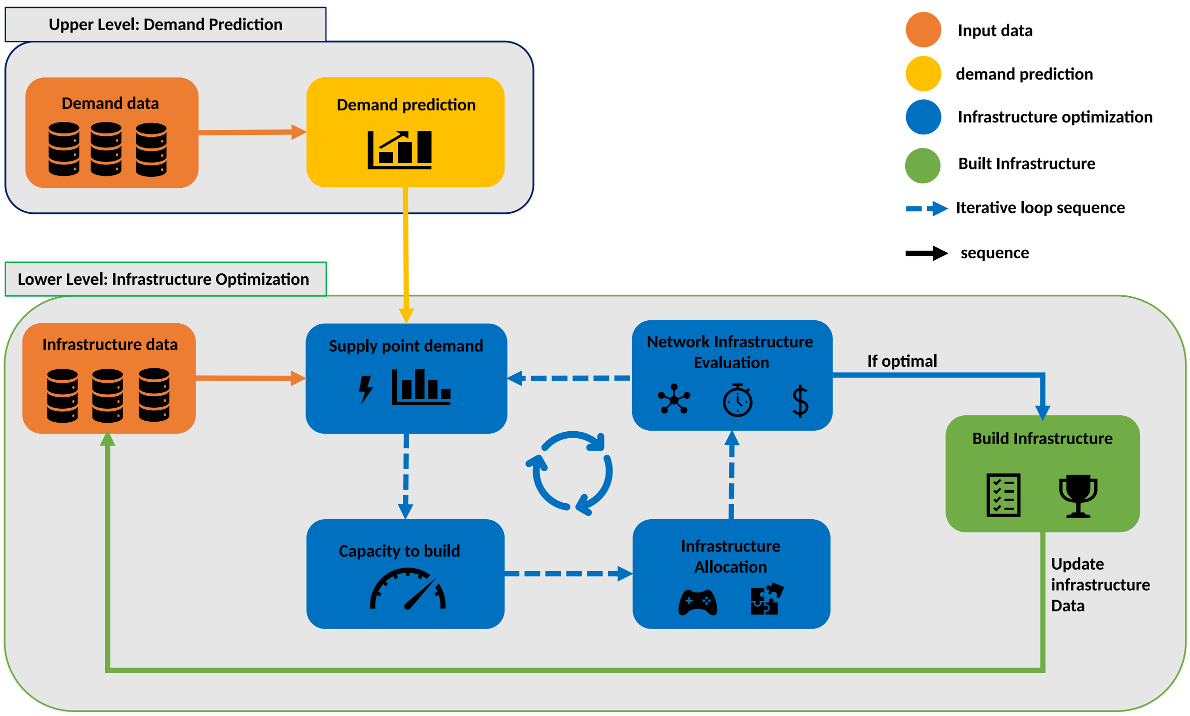

Fig. 2. Hierarchical framework for Demand prediction and optimization for EV charging network infrastructure.

Linear regression is a powerful tool for time series prediction, and has been successfully applied in a wide range of research studies (Hyndman & Athanasopoulos, 2018). However, it is important to keep in mind that the linear relationship assumption may not hold in all cases, and more complex models may be needed to accurately capture the underlying patterns in the data. In the time series case, the model coefficients and response variables are modeled to fit a trend in the data. A combination of domain knowledge and exploratory data analysis can help with knowing how to go about the linear regression approach to try out. Next, we explain how we use these for our solution.

4.1.2. Our approach

Our approach is designed specifically based on the nature of our dataset as explained in detail in Section 5. In the demand data, we are given the demand for EV charging at every demand point D for every year over a period of n years. So, for a demand point D_i we have the demand for year $1, 2, 3, \dots, n$ and we want to learn a linear model to predict the demand in year $n+1$ and $n+2$ at point D_i. We predict for two years ahead because we want to plan infrastructure for those years.

A straightforward way using linear regression will be to find a linear model or estimate a demand growth curve over the years but this will be inefficient because the demand at different demand points is highly variable and a simple linear fit on the entire data will not capture the influence of the regional or network layout. Another alternative approach will be to learn a linear model for every demand location. This approach performs better than the general linear model for all demand locations but falls short in capturing the influence of its location in the dataset. This information can be captured using a decision tree regressor or gradient boosting method but it requires some form of feature engineering for location data which we avoid because of the simplistic nature of the data and the tendency for overfitting. Linear regression can easily capture the time series growth trend over the years for every demand point but the challenge is to incorporate the location information which will reduce the error of our model. Intuitively, we know that demand points near each other will have similar demand trends as drivers will seek to charge their cars in nearby areas but the challenge is to find the best way to incorporate this information in our model to have a more accurate prediction of future demand.

In our approach, we first learn the best linear regression model for each individual demand point, using as input features only the demand in previous years. For each demand point, we focus on reducing the prediction error for that individual demand point, which translates into reducing the error in predicting demand for the entire region. Therefore, for each demand point there is a linear regression model $D_i^{ForecastModel}$. The type of models we search for the demand points include a simple linear regression model and a regression model with exponential features. The forecast model search for each demand point is as described in the Algorithm 1. The model with the lowest error for a demand point is selected for the given demand point. This works well because demand grows exponentially at some points, while it grows linearly or follows some other function at others. By searching for the best model for each demand point, we solve the problem of variable demand across different demand points.

To further improve the accuracy of a demand point model, we define a neighborhood radius N_r for demand points and develop an ensemble model that uses the prediction models of the neighbors (demand point) within this radius on the demand point with weights as shown in Eq. (30) and applied in Algorithm 2 for demand prediction.

$$
\begin{aligned}
D_i^{EnsembleModel} = {} & \alpha_0 D_i^{ForecastModel} + \\
& \alpha_1 D_{i+1}^{ForecastModel} + \\
& \cdots + \\
& \alpha_n D_n^{ForecastModel}
\end{aligned}
\tag{30}
$$

The weights α for each model determine their influence on the final forecast and are learned using a search algorithm. These values are chosen to minimize the error or improve the future demand forecast for the demand point D_i. By applying a search algorithm for each demand point, we minimize the demand prediction error across the entire network. We limit the number of neighboring models to the five nearest demand points, as empirical results show that including more neighbors does not significantly improve the performance. This limitation reduces the complexity of the ensemble and search dimension for the weight parameters. It is important to note that the restriction to five neighbors is applied only when there are more than five neighbors within the defined neighborhood radius. Based on empirical results, this methodology significantly improves the performance of our forecasting algorithm.

The other forecast models, such as $D_{i+1}^{ForecastModel}$ in Eq. (30), are used to predict the future demand for demand point D_i using input data from its neighboring demand points. The final model used to forecast demand point D_i is outlined in Algorithm 2.

To find a good forecasting model for demand point D_i, we incorporate the neighboring models along with the model for that demand point and determine the weighted influence of each model using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) algorithm. CMA-ES is a state-of-the-art parameter search method for continuous black-box optimization. Our objective is to minimize the prediction error at that demand point. This approach significantly improves the quality of our forecasting model and reduces the overall error $D_{\text{error}}^{\text{year}}$ in the network, which is our primary objective function. Accurate predictions are crucial as they inform infrastructure allocation decisions for each year.

Algorithm 1 Demand Point Linear Regression Model Search

Require: Demand data D for all demand points, number of years n, number of regression models to search k
Ensure: Best demand prediction model M for each demand point
Initialize an empty set M to store the best demand prediction model for each demand point
for each demand point D_i **do**
    Select the demand data for that demand point over n years
    Initialize an empty set E to store the prediction errors of regression models
    for j from 1 to k **do**
        Train the jth regression model on the demand data using input features of demand in previous years only using Eq. (29)
        Compute the prediction error of the model using (1)
        Add the prediction error to set E
    end for
    Select the model with the lowest prediction error as the best demand prediction model for demand point D_i
    Store the best demand prediction model for demand point D_i in set M
end for
return M

Algorithm 2 Demand Prediction using Ensemble Model

Require: Demand data D for all demand points, set of best demand prediction models M for each demand point, neighborhood radius Nr, number of neighbors to consider k
Ensure: Demand predictions Y for all demand points
Initialize an empty list Y to store the demand predictions for all demand points
for each demand point D_i **do**
    Find the k nearest neighbors of D_i within the neighborhood radius Nr
    Compute the weights α of each model using the CMA-ES algorithm to minimize the prediction error of the ensemble model on D_i
    Compute the demand prediction for D_i using the weighted average of the demand predictions of the best regression models of D_i and its k nearest neighbors
    Append the demand prediction of D_i to Y
end for
return Y

4.2. Infrastructure optimization

In this section, we outline our iterative design approach to find the optimal infrastructure for any given year in a charging network. Using the future demand estimated from our forecast algorithm at demand locations, we start by approximating supply point demand, then the capacity needed to be built to meet demand and finally we allocate the infrastructure based on the determined capacity to build. It is clear that the infrastructure allocation is influenced by the determined capacity to build which in turn is influenced by the supply point demand. Therefore, after evaluating our built infrastructure, we iteratively return to recompute a new supply point demand estimate, then capacity to build and then final allocation. We do so until we find an optimal allocation or a stopping criterion is met. In the following section we present the methodologies we use to determine the supply point demand, capacity to build and the allocation algorithm.

4.2.1. Supply point demand

Supply point demand is the charging demand at a supply point and in our case depends on the supply point location. Intuitively we know that if a supply point is located close to demand points with high demand, the supply point will definitely incur a high charging demand and vice versa. We also have to keep in mind that a supply point will be able to supply multiple demand points and how we allocate those demands to supply points will influence our downstream infrastructure allocation. For this reason, we iteratively re-estimate supply point demand to deal with uncertainty. For a supply point to cater for any demand at a demand point, its distance from the demand point should be close enough, we set a supply distance threshold to deal with this situation.

Supply distance threshold: The supply distance threshold represents the minimum distance, denoted as $D_{\text{threshold}}$, between a supply point and a demand point for the supply point to be considered eligible to provide charging service to the demand point. It is important to determine this threshold because EV drivers prefer charging stations that are close to their location to minimize inconvenience. If the distance between a supply point and a demand point is greater than the supply distance threshold, then the supply point is not eligible to serve the demand point. We note that in our network, every supply point must serve at least one demand point. This serves as the basis for finding the supply distance threshold.

To find a potential supply distance threshold, we compute the distance from every demand point to its nearest supply point. We then calculate the following statistics: minimum distance (D_{min}), mean distance (D_{mean}), maximum distance (D_{max}), and standard deviation (D_{std}). Based on these statistics, we consider the following potential supply point thresholds:

- Minimum distance: D_{min}
- Minimum distance plus standard deviation: $D_{\text{min}} + D_{\text{std}}$
- Mean distance minus standard deviation: $D_{\text{mean}} - D_{\text{std}}$
- Mean distance: D_{mean}
- Mean distance plus standard deviation: $D_{\text{mean}} + D_{\text{std}}$
- Maximum distance minus standard deviation: $D_{\text{max}} - D_{\text{std}}$
- Maximum distance: D_{max}

Determining the best supply threshold distance for a given network is achieved through optimization. By considering these different options, we narrow down the search space during optimization, ensuring that we explore potential threshold values that are more likely to be optimal. This approach helps in avoiding nonoptimal values that could arise from an unrestricted search space.

Once a supply-distance threshold is determined, we can identify the supply points that are potentially capable of providing charging service when there is a demand request from each demand point. However, it is important to note that at this stage, this estimate is only used to estimate the demand at the supply point and does not consider other factors such as charging capacity or infrastructure constraints.

Potential supply points for demand point: These are the supply points within the supply distance threshold from a demand point. Using the Supply point threshold, we can determine which demand points for which a supply point will be a potential supplier. We do so by simply matching demand points to supply points that are within the supply-point threshold. With the Potential Supply Points for Demand Points determined, we now have all the ingredients to compute the total charging demand at a supply point. We compute the demand at a supply point by summing the predicted demand for the demand points to be supplied by that demand point and dividing by the number of supply points it will supply, as shown in Eq. (31). Empirically, this formulation yielded the best results.

$$D_j^{\text{year}} = \frac{1}{n}\sum_{i=1}^{n} D_{\text{forecast},i}^{\text{year}} \tag{31}$$

where n is the number of demand points that supply point j (D_j^{year}) can supply, and $\sum_1^n D_{\text{forecast},i}^{\text{year}}$ represents the sum of the forecasted demands for the given year from those demand points. This equation allows us to determine the demand for every supply point.

4.2.2. Supply point capacity to build

With the demand known for each supply point, we can now determine the capacity needed to meet that demand. Each supply point must build infrastructure that can accommodate its charging demand capacity. Supply Point Capacity to Build: The capacity to build is determined by the existing infrastructure and the demand at a supply point. It represents the additional capacity needed to meet the estimated demand at that supply point. For each supply point, we have information about the existing infrastructure, including the number of SCS, FCS, and RCS that are already in operation, as well as the number of parking slots available. New charging infrastructure can only be built at parking slots without charging stations, and each parking slot can accommodate only one charging station. The capacity of an SCS is 200, an FCS is 400, and an RCS is 800. To determine the capacity to build, we can compute the existing capacity as the sum of the capacities of the already built charging stations, as outlined in Eq. (31). Meanwhile, the demand capacity for the supply point is given by Eq. (32).

$$\begin{aligned} CapSP_j^{\text{year}} = Cap_{\text{SCS}} \times \sum \text{SCS}_j + \\ Cap_{\text{FCS}} \times \sum_{\text{FCS}_j} + \\ Cap_{\text{RCS}} \times \sum \text{RCS}_j \end{aligned} \tag{32}$$

The maximum capacity a supply point can hold is the existing capacity plus the capacity if we built an RCS (because it has the largest capacity) in all remaining charging slots. We compute the maximum capacity of a charging station as shown in Eq. (33). Which is the existing capacity plus the capacity if all remaining slots are filled with RCS.

$$MaxCapSP_j^{\text{year}} = CapSP_j^{\text{year}} + (Cap_{\text{RCS}} \times FreeSlots_j^{\text{year}}) \tag{33}$$

Now we want to determine whether the demand at a supply point in the year we want to build our infrastructure already meets the demand or new charging stations are needed or the charging stations are not enough.

In the first situation, where the current charging capacity can meet the current demand, i.e., $CapSP_j^{\text{year}} - D_j^{\text{year}}$ is negative, no new capacity needs to be built at that supply point as the current capacity is enough to meet demand. In the second case, where the demand exceeds the current capacity, i.e., $CapSP_j^{\text{year}} - D_j^{\text{year}}$ is positive, we determine that new infrastructure needs to be built and the capacity to build is the amount of exceeded capacity ($CapSP_j^{\text{year}} - D_j^{\text{year}}$).

For supply points where new charging infrastructure is to be built, we check to see if the current demand exceeds the maximum capacity of the supply point, i.e., if $D_j^{\text{year}} > MaxCapSP_j^{\text{year}}$, and if so, the capacity to build at that demand point will be $MaxCapSP_j^{\text{year}}$. When $D_j^{\text{year}} > MaxCapSP_j^{\text{year}}$, we have an overcapacity situation, and we devise a means to deal with such a situation.

Handling Overcapacity: Overcapacity occurs when the charging capacity demand for a supply station exceeds its maximum supply capacity. The intuition behind our approach to handle this is that when there are no free charging spots at a charging station, we can either wait for an available charging spot or go to the nearest supply point to find a charging station. With this in mind, when there is overcapacity, we share the capacity to the nearest supply locations.

This exceeded capacity is the total capacity that cannot be met by the supply point. The quantity of demand to share is shown in Eq. (34), which we refer to as the demand to share.

$$D_j^{\text{year,share}} = D_j^{\text{year}} - \text{MaxCapSP}_j^{\text{year}} \tag{34}$$

The demand to share for a supply point is shared to its neighbors beginning from its nearest until there is no more demand to be shared. For a neighbor to receive a portion of shared demand we need to check if it has not itself exceeded its maximum capacity. To receive shared demand, we check by computing the demand it can take using Eq. (35).

$$D_j^{\text{year,take}} = \text{MaxCapSP}_j^{\text{year}} - (\text{Cap2Build}_j^{\text{year}} + \text{CapSP}_j^{\text{year}}) \tag{35}$$

$Cap2Build_j^{year}$ represents the capacity that has been determined to be built at the supply point in that year. Now, we determine if $D_j^{(year,take)} \geq D_j^{(year,share)}$. If this condition is true, we update the capacity to build for the neighbor using Eq. (36).

$$\begin{aligned} Cap2Build_j^{year} = Cap2Build_j^{year} + \\ (D_j^{year,take} \times Proportion2Take) \end{aligned} \tag{36}$$

$Proportion2Take$ is a parameter in the range [0, 0.5] which ensures we do not add too much capacity to the neighbor. We also ensure added capacity to a supply point only happens once to avoid overloading capacity at any supply point. Also, the capacity to share is only shared with the first available neighbor that can receive a shared capacity. The algorithm to determine the capacity to build and for handling overcapacity is outlined in Algorithm 2.

4.2.3. Infrastructure allocation

In this section, we describe how we allocate infrastructure to be built in a given year. At every supply point, we have to decide how many new SCS, FCS, and RCS need to be added. The new allocation is dependent on the supply point demand and the computed capacity to build, which gives us an upper bound to the capacity we should build in the supply station. Additionally, we ensure that the built infrastructure does not cost too much to maintain and provides a good QoS to EV drivers.

To solve this problem, we model every supply point as a knapsack problem (Salkin & De Kluyver, 1975) with items being SCS, FCS, and RCS, and the capacity of the knapsack being the $Cap2Build_j^{year}$. The only remaining ingredients are the values and weights of each item. The weight of a charging station is the capacity the charging station provides, and therefore the weights for SCS, FCS, and RCS are 200, 400, and 800, respectively.

Determining the value of the charging stations is the challenging part of the problem design. The value assigned to a given charging station ultimately decides which stations are built at a supply point and, therefore, is very important. Because we aim to build infrastructure with a low cost of maintenance, which is one of our optimization objectives, we use the maintenance cost as a proxy of a charging station to model its value. We know from our data that the maintenance cost for FCS is 1.5 and for RCS is 2.0 relative to the SCS. Therefore, we assign the relative cost of maintenance as the value for a charging station, which makes sense because RCS provide more charging capacity and cost relatively less compared to the capacity it provides and, therefore, should have more value.

The knapsack problem is a traditional optimization problem where many state-of-the-art methods and solvers have been proposed for the different variants of the problem. We use the open-source Google OR-Tools solver (Google, 2023b) to model and solve the problems with the parameters described above. The solution to the knapsack problem for any given charging station gives us the infrastructure that needs to be built for that supply point.

In summary, we solve the knapsack problem to build infrastructure at every supply point in the following manner:

1. For a supply point, we take the $Cap2Build_j^{year}$ as the knapsack capacity.
2. The number of items, i.e., SCS, FCS, and RCS, is equal to the number of slots without charging stations $FreeSlots_j$ in the supply point, i.e., we have a total of $FreeSlots_j \times 3$ items.
3. The value of each SCS, FCS, and RCS is 1, 1.5, and 2.0, respectively.
4. The weight of each SCS, FCS, and RCS is 200, 400, and 800, respectively.
5. We allocate charging stations to be built at a supply point and compute the maintenance cost.
6. We repeat steps 1 to 5 for all supply points.
7. After every station has been built, we compute the infrastructure cost of the entire network.

4.2.4. Network infrastructure evaluation

We evaluate our network infrastructure hierarchically on two metrics: (1). Cost, which includes infrastructure cost and demand–supply balance cost. (2). Quality of Service (QoS), which includes the charging time, travel time, and waiting time of an EV in the network.

The cost metric is weighted for infrastructure cost and demand–supply balance cost and summed using Eq. (37), which is determined analytically depending on the structure of the data. One approach that would be more efficient would be to employ a multi-objective optimization, but this is not suitable in our hierarchical design.

$$\text{Cost} = (a * \text{Cost}_{IF}) + (b * \text{Cost}_{DS}^{error}) \tag{37}$$

Here, a and b are the weights of the infrastructure cost and demand–supply balancing cost. After evaluating for cost, we evaluate for QoS using Eq. (26). We set a QoS threshold, below which solutions are considered to be violating the service agreement. Therefore, we only keep a record of solutions that meet the QoS standard. To construct our final infrastructure, we need to select a solution that meets the QoS and has a reasonable cost. We select a solution in which the QoS to Cost ratio is highest.

To optimize the final infrastructure to build, we iteratively improve the quality of our infrastructure by looping back to determine the demand at supply points using different threshold distances, determining the capacity to build for every supply point, then allocating and evaluating the built infrastructure. We repeat this process until we converge to an optimal solution or there is no improvement in our solution quality. Then, we build the infrastructure that was found to be the best according to our evaluation metric. For infrastructure two years ahead, we follow the same optimization process outlined above with the assumption that the infrastructure one year ahead is already built. This means we update the infrastructure data and use time series prediction for two years ahead, iteratively optimizing to find the optimal infrastructure to build.

5. Simulations and experiments

Our aim in these experiments is to determine the ideal number and placement of EV charging stations in order to provide the best QoS within a charging network. The data used for this study includes network infrastructure and demand information from the 2022 Shell EV Charging Network Challenge for sustainable and affordable energy (Shell, 2022), as well as a synthesized dataset. Furthermore, we simulate daily demand for EV charging to quantify the quality of service of the built infrastructure. Findings are compared to both a baseline which we design and state-of-the-art algorithms designed specifically for optimizing EV infrastructure. In the following sections, we will delve into the specifics of our experimental setup, covering aspects from data, evaluation metric design, algorithm performance and analysis.

5.1. Data

5.1.1. Demand data

The data utilized in this experiment includes yearly EV charging demand across a specified region (this is the same dataset used in the 2022 shell.ai EV Charging Network Optimization Challenge). The region is divided into 4096 equi-spaced demand points with unique x and y coordinates that form a square grid. This data set provides a comprehensive demand history covering the years 2010 to 2018. In order to account for uncertainty and increase the transferability of our algorithm to other charging networks, as is often the case in real-world scenarios, we augment the dataset by adding noise to the demand location data, randomly shifting the location by some random units. Additionally, this augmentation allows us to assess the adaptability of our algorithm in changing conditions, further enhancing its practicality and potential for real-world applications. By incorporating uncertainty into our dataset, we are able to evaluate the robustness of our algorithm and ensure that it can be effectively applied in a variety of scenarios.

To add uncertainty to the dataset, we multiply each demand point coordinate and demand by a random uniform variable within the range [0.9, 1.1]. This range was selected carefully to ensure that the distances between the points are not uniform but not so far away from the original that the demand data becomes meaningless. By adding this level of noise, we aim to make the dataset more realistic as demand points in the real world are not always uniform or equi-distanced, unlike the original data set, which was designed to evaluate algorithms and methodologies for EV infrastructure optimization.

Our choice to add noise to the dataset makes it more representative of real-world scenarios, as algorithms must be able to function effectively in non-deterministic environments (Jain, Gupta, Rai, & Kumar, 2021). The result of this augmentation is two demand datasets, the original "Demand" dataset and an "Augmented Demand" dataset.

It is important to note that the original data set is synthetic and designed to test algorithms and methodologies for EV infrastructure optimization. Our augmentation provides an additional layer of realism, as algorithms must be able to handle changes in mobility and user behavior in a region. By testing our algorithm on both the original and augmented demand datasets, we can assess the robustness and stability in the face of uncertainty.

5.1.2. Infrastructure data

The infrastructure data consists of information on existing 100 supply stations in the year 2018, including their x and y location coordinates. Unlike the demand points, the supply points are not equi-spaced and no augmentation has been made to them. Information is provided about the number of parking slots, SCS, and FCS at each location. However, infrastructure data from 2010 to 2017 is not available.

Given that the test data covers the years 2017 and 2018, we assume that the true infrastructure data for these years is that provided. This assumption takes into account the fact that in many regions, infrastructure built in 2015 may still be the same in 2018 if no optimizations are made to enhance the service. Additionally, the years prior to the optimization period do not have RCS which we introduce as a new charger type that can be built in a supply location.

This approach and the assumptions in the dataset provide a baseline for the infrastructure and allow us to evaluate the influence of introducing RCS, which is realistic given that new battery technologies are rapidly evolving. In the 2017 and 2018 optimization periods, we consider two scenarios: one where no RCS are available and another where RCS are included among the infrastructure we can build.

Our experiments make use of four datasets, which are:

1. **DnI − RCS:** Demand and Infrastructure Data without Rapid Charging Stations
2. **DnI + RCS:** Demand and Infrastructure Data with Rapid Charging Stations
3. **ADnI − RCS:** Augmented Demand and Infrastructure Data without Rapid Charging Stations
4. **ADnI + RCS:** Augmented Demand and Infrastructure Data with Rapid Charging Stations

By leveraging these demand and infrastructure datasets, we aim to predict demand and optimize the EV infrastructure for the years 2017 and 2018, subject to practical constraints as described in the problem modeling section.

5.1.3. Daily EV charging demand simulation

We use a simulation approach to model the EV driving and charging behavior in the region based on the driving behavior in the network and the demand at each demand location. In the simulation, the charging speed of a car is based on the factors listed in Table 1 as provided in the study (U.S. Department of Transportation, 2023) and the distribution of demand at different times of the day as shown in Fig. 1. The driving behavior in the network is such that there are peak-demand periods, and this is modeled based on the normal distribution of traffic. For each demand point, demand at every given time of day is drawn from a normal distribution with the mean is calculated as 2 times the demand and a standard deviation of demand/10 as shown. The demand and peak-times for weekdays and weekends are different and are simulated to reflect the study (Dizon & Pranggono, 2022). Therefore, at each hour of the day, the demand for charging at each charging station is sampled and used to compute and after 24 h, we can compute the QoS for that day. In our experiments we run 100 simulations to compute the QoS for the entire network. Details for the simulation are explained in the metric design section.

5.2. Evaluation

The objectives of this study are threefold, including demand prediction, infrastructure cost and QoS optimization. The evaluation of these objectives is performed using the objective functions described in Section 2. In order to determine the effectiveness of our proposed method, a comparison with other existing prediction and optimization methods is carried out. This comparison is conducted to identify the strengths and weaknesses of our methodology compared to state-of-the-art solutions.

5.2.1. Demand prediction evaluation

Demand predicted is evaluated on three metrics, which include R-squared (R2), root mean squared error (RMSE), and demand prediction error (D_{error}^{year}) outlined in Eq. (2). R^2 is important because it provides an indication of how well the historical demand data can explain or predict future demand. RMSE, on the other hand, is a commonly used metric for regression problems that evaluates the performance of a model by calculating the square root of the average of the squared differences between the predicted and actual values. (D_{error}^{year}) quantifies the error of the network and gives us an understanding of the potential amount of demand that may be missed using our model. This is crucial in dealing with uncertainty in demand.

The goal of our prediction model is to inform our optimization model. However, it is important to note that a good prediction model does not always lead to a good optimization objective. How we handle uncertainty in the predictions is critical, and $D_{error,i}^{year}$, along with D_{error}^{year}, provides us with valuable information in this regard.

We compare our proposed method with three variants of linear regression (Hyndman & Athanasopoulos, 2018), Random Forest regressor (Tyralis & Papacharalampous, 2017), XGBoost (Almaghrebi et al., 2020), and Recurrent Neural Network (RNN) (Shanmuganathan, Victoire, Balraj, & Victoire, 2022). The models and their training methodologies are listed as follows:

1. **Linear Regression (LR-All):** The model is trained with all data points in the network.
2. **Linear Regression (LR-DP):** The model is trained only for every individual demand point in the network, meaning each demand point has its own prediction model.
3. **Linear Regression (LRE):** The model uses exponential features and is trained for every individual demand point in the network.
4. **Random Forest (RF):** This algorithm is chosen for its ability to handle large datasets, robustness to outliers, and capability to handle non-linear relationships between variables. The RF model is trained using all the demand data points in the network, taking into account the location features which the linear regression method struggles with.
5. **XGBoost:** This algorithm is a sequential decision tree ensemble, where each tree is trained to correct the errors made by the previous tree (Chen & Guestrin, 2016). The XGBoost Regressor a state-of-the-art machine learning algorithm. However, for our case, we made specific considerations and carried out preprocessing steps that were necessary when working with time series data. The model was trained using all demand data points in the network, similar to the Random Forest model.
6. **Recurrent Neural Networks (RNN):** This neural network model is specifically designed to handle sequential data, making it the best choice for our dataset given its short length and sequential nature. The RNN model was trained individually for each demand point in the network.

5.2.2. EV network infrastructure evaluation

Cost: This is evaluated using the infrastructure cost ($Cost_{IF}$), demand supply balancing cost ($Cost_{DS}^{forecast}$) or simply ($Cost_{DS}$), and demand supply balancing cost error ($Cost_{DS}^{error}$) outlined in Eqs. (4), (5) and (7). $Cost_{IF}$ represents the maintenance cost of the infrastructure built in the network, and $Cost_{DS}^{error}$ is the cost of the built infrastructure matching the demand. A combination of the infrastructure and demand supply balancing cost is used to compute a cost which reflects the efficiency of the infrastructure on the demand.

Cost evaluation is performed using three metrics, namely the infrastructure cost ($Cost_{IF}$), demand supply balancing cost ($Cost_{DS}^{forecast}$) or simply $Cost_{DS}$, and demand–supply balancing cost error ($Cost_{DS}^{error}$), as outlined in Eqs. (4), (5) and (7). The infrastructure cost ($Cost_{IF}$) represents the maintenance cost of the infrastructure in the network. On the other hand, the demand–supply balancing cost error ($Cost_{DS}^{error}$) quantifies the cost of ensuring that the built infrastructure matches the demand. Finally, a combination of the infrastructure cost and demand–supply balancing cost is used to calculate an overall cost that reflects the efficiency of the infrastructure in meeting the demand. The cost is the weighted sum in the ratio of 1:24 of $Cost_{IF}$ and $Cost_{DS}$, respectively, as provided in Singh and Singh (2022).

Quality of Service: QoS of the built infrastructure in the charging network is computed as the sum of the average network charging time ($\mathrm{NCT}^{\mathrm{avg}}$), average network travel time ($\mathrm{NTT}^{\mathrm{avg}}$), and the average waiting time ($\mathrm{NWT}^{\mathrm{avg}}$) as modeled in Eq. (26) using a daily simulation of demand for EV charging. This metric tells us how convenient it is for a driver to find and charge an EV when in need. In this computation, we see that a higher value for quality of service means poor quality. To make it more interpretable, we use a parameter which we called QoS

Table 2
Demand prediction results.

	Dataset											
	DnI			ADnI			DnI			ADnI		
	R2	RMSE	$D^{2017}_{error}(10^5)$	R2	RMSE	$D^{2017}_{error}(10^5)$	R2	RMSE	$D^{2018}_{error}(10^5)$	R2	RMSE	$D^{2018}_{erroo}(10^5)$
LR-All	0.90	82.53	3.31	0.85	89.22	3.70	0.90	29.05	1.20	0.90	33.60	1.30
LR-DP	0.95	41.45	1.63	0.91	41.32	1.71	0.94	24.93	1.03	0.95	27.38	1.13
LRE	0.98	33.48	1.37	0.96	32.97	1.37	0.99	22.48	0.93	0.97	23.62	0.98
RF	0.93	42.78	1.77	0.90	45.84	1.90	0.94	24.02	0.99	0.94	24.03	0.99
XGBoost	0.94	39.12	1.66	0.90	42.90	1.78	0.94	22.41	0.93	0.94	22.28	0.92
RNN	–	46.29	19.23	–	55.12	2.29	–	27.37	1.13	–	31.56	1.31
Ours	**0.98**	**27.29**	**1.13**	**0.97**	**26.67**	**1.10**	**0.98**	**21.03**	**0.87**	**0.97**	**20.62**	**0.85**

threshold. This parameter can be interpreted as the minimum allowed time a driver needs to spend to find a charging station and sufficiently charge their battery in the network. Any number above this threshold will mean the driver spent too much time, and the quality of service depletes, resulting in more time being spent. Therefore, the QoS with Threshold is computed as:

$$\text{QoS}\ |\text{Threshold} = \text{Threshold} - \text{QoS} \tag{38}$$

Eq. (38) indicates that a higher time spent from demand to battery charging results in a lower quality of service, and values above the threshold become negative, making the QoS measure more interpretable.

To test the robustness and stability of the algorithm, we conducted 100 simulations and calculated the mean and standard deviation. We compared the performance of our method with a naïve baseline and several state-of-the-art heuristic and intelligent optimization methods. The algorithms were modified to align with our objective, using the parameters proposed by the respective authors. The approaches we used for comparison include:

1. **No Change (NC):** The NC scenario involves no new infrastructure being built in the network in the following year, serving as a baseline to assess the performance of the model without additional infrastructure.
2. **Random Addition (RA):** This involves random allocation of new infrastructure based on unbuilt charging stations in the network. For every free charging slot without a charging station, we randomly select which type of station to build or decide not to install any charger. Each type of station is equally weighted in the selection process.
3. **Build All (BA):** In the "Build All" scenario, the objective is to maximize the utilization of the charging infrastructure by filling any remaining capacity with the fastest chargers. This approach involves allocating chargers to charging stations to reach full capacity.
4. **PSO:** The PSO algorithm proposed in Bai et al. (2022) is used with the parameter settings as described in the paper.
5. **GA:** The genetic algorithm proposed by Altundogan, Yildiz, and Karakose (2021) for finding optimal locations of EV charging stations is adopted, with the location of the charging station used as a proxy to determine where a charging station is allocated.
6. **HA:** The heuristic algorithm proposed by Gagarin and Corcoran (2018) for optimizing the placement of EV charging stations based on demand, charging services, and infrastructure cost is also used.
7. **ES:** The Evolutionary strategy approach proposed by Niccolai, Bettini, and Zich (2021), which optimized EV infrastructure considering demand, cost, and accessibility, is used with the objective changed to the designed metric in this study.

5.3. Experiment results and discussion

Our technique was implemented in Python, making use of Google OR-Tools (Google, 2023a) to solve the knapsack problem and the PULP solver (Frisch & Biscani, 2019) for demand allocation. The parameters for demand ensemble $D_i^{EnsembleModel}$ at any given demand point are optimized using CMA-ES (Hamano, Saito, Nomura, & Shirakawa, 2022). We evaluate the performance of our methodology and compare the performance with state-of-the-art algorithms outlined in the results tables.

5.3.1. Demand prediction

Demand prediction is an important first step in having quality information for infrastructure allocation. In our case, the demand error (D_{error}) is a good metric to show the demand mismatch. Our results show that our approach is significantly more accurate and robust in reducing the demand mismatch than other methods, while still being interpretable, as indicated by its R-squared value in both datasets.

The good performance of the proposed ensemble technique, which weights and utilizes information from neighboring demand points for prediction, addressing a limitation of the LRE model. This information can also be captured by the RF and XGBoost models, but the non-linearity and small data size pose challenges for these models. The RNN model performs poorly, likely due to the small nature of the data and long term dependency (Chandar, Sankar, Vorontsov, Kahou, & Bengio, 2019) as neural networks depend on a large amount of training data for good performance. In our experiments, we found that RNNs tended to fit well to the patterns seen in the earlier years, but their predictive power diminished as the data moved further into the future due to the lack of representation of the recent exponential growth.

As shown in Table 2, the linear regression models exhibit high interpretability but have higher cost errors, which our model addresses. On the other hand, the tree-based methods are less interpretable but have lower cost errors. We recognize that for a problem of this nature, a simple linear regression model, tuned with an understanding of the dataset, significantly improves performance.

The empirical findings and performance evaluations indicate that models constructed on a per-individual demand point basis, denoted (LRE and Ours) exhibit superior predictive efficacy compared to models employing geolocation-derived features, namely Random Forest (RF), XGBoost, and Recurrent Neural Network (RNN). This delineates that despite the evident significance of geolocation features in prediction tasks, their utility falls short in comparison to the outcomes attained by tailoring models for individual demand points.

In terms of model performance, cost, and complexity, models designed specifically for each demand point show better predictive accuracy. On the other hand, building separate models for each demand point consumes a lot of resources. It brings difficulties in creating, maintaining, and using many different models. This trade-off should be considered when deciding how to use or deploy the model.

Table 3
Infrastructure evaluation for 2017 without RCS.

	DnI + RCS				ADnI + RCS			
	$Cost_{IF}$	$Cost_{DS}$	Cost	$Cost_{DS}^{error}$	$Cost_{IF}$	$Cost_{DS}$	Cost	$Cost_{DS}^{error}$
NC	**1499**	2422144	58132974	890790	**1499**	2784554	66599635	1021497
BA	3465	**1047848**	**25151829**	483506	3482	**1054957**	**25036472**	481741
PSO	2144	1693467	40645372	162113	2369	1877195	44998246	176756
GA	1935	1876379	45035052	345025	2032	1973513	47154118	364544
HA	1872	1939527	46550527	408172	1923	1989970	48705273	416544
ES	2128	1706200	40950944	174846	2156	1707689	41402413	176175
Ours	2293	1583425	38004509	**52071**	2291	1583045	38079006	**52093**

Table 4
Infrastructure evaluation for 2017 with RCS.

	DnI + RCS				ADnI + RCS			
	$Cost_{IF}$	$Cost_{DS}$	Cost	$Cost_{DS}^{error}$	$Cost_{IF}$	$Cost_{DS}$	Cost	$Cost_{DS}^{error}$
NC	**1499**	2422144	58132955	890790	**1499**	2690274	64568075	1181266
BA	4447	**964982**	**23164015**	476902	**4479**	**1067487**	25624167	569534
PSO	2680	1600269	38409136	143496	3064	1827562	43864552	206380
GA	2370	1884401	45227994	308843	2669	2164852	51959117	425243
HA	2293	1904248	45704245	392393	2487	2119819	50878143	484686
ES	2819	1748134	41958035	155382	2776	1626803	39046048	206648
Ours	3038	1479341	35507222	**46870**	2970	1652478	39662442	**50728**

Table 5
Infrastructure evaluation for 2018 without RCS.

	DnI − RCS				ADnI − RCS			
	$Cost_{IF}$	Cos_{DS}	Cost	$Cost_{DS}^{error}$	$Cost_{IF}$	$Cost_{DS}$	Cost	$Cost_{DS}^{erro}$
NC	**1499**	3524597	84591834	1350211	**1499**	4032105	96365578	1514158
BA	4120	**1282216**	**30777306**	892169	4113	**1277745**	**30695568**	887065
PSO	2282	2314375	55547287	139989	2490	2523736	61050234	153890
GA	2060	2564357	61546640	389971	2148	2723751	65355918	411009
HA	1993	2650658	63617789	476272	2084	2710849	66207753	470847
ES	2265	2331780	55964995	157394	2277	2346175	56456120	157669
Ours	2441	2163985	51938101	**10399**	2439	2162759	51918412	**10385**

Table 6
Infrastructure Evaluation for 2018 with RCS.

	DnI + RCS				ADnI + RCS			
	$Cost_{IF}$	$Cost_{DS}$	Cost	$Cost_{DS}^{error}$	$Cost_{IF}$	$Cost_{DS}$	Cost	$Cost_{DS}^{error}$
NC	**1499**	3524597	84591827	1350211	**1499**	4032105	96772019	1620303
BA	5697	**1714106**	**41144241**	892169	5588	**915180**	**21969908**	886744
PSO	3153	2174503	52191225	139989	3316	1923029	46156012	145745
GA	2867	2151040	51627827	389971	2995	2205302	52930243	379099
HA	2691	2322999	55754667	476272	2721	1903332	45682689	440496
ES	2989	2064417	49548997	157394	3133	2070283	49689925	164674
Ours	3413	1557114	37374149	**10399**	3347	1528166	36679331	**10183**

Table 7
Quality of service for 2017 without RCS.

	DnI − RCS					ADnI − RCS				
	NCT^{avg}	NTT^{avg}	NWT^{avg}	QoS	QoS | 50	NCT^{avg}	NTT^{avg}	NWT^{avg}	QoS	QoS | 50
NC	30	15	29	74	−24	30	17	32	79	−29
BA	**13**	**6**	**1**	**20**	**30**	**13**	**6**	**1**	**20**	**30**
PSO	18	10	18	46	4	18	11	19	48	2
GA	23	12	21	56	−6	23	15	22	60	−10
HA	24	12	22	68	−18	24	12	22	58	−8
ES	14	11	18	43	7	14	11	20	45	5
Ours	15	10	3	28	22	15	11	3	29	21

5.3.2. Infrastructure cost

Costs, which include infrastructure cost, demand supply balancing cost, and cost error, demonstrate that our proposed methodology achieves the best balance among all methods, as reflected in Tables 3–7. Additionally, our method exhibits robustness with stable results in both the original and augmented datasets, unlike the other methodologies. Specifically, we observe that the BA method has a high cost of infrastructure, which helps reduce the cost of demand supply balancing. However, due to blindly building all infrastructure, it fails to address the demand supply cost error, whereas our proposed methodology excels in this aspect. While our method incurs a relatively high infrastructure cost, it is well distributed to handle demand, resulting in significantly lower demand supply balancing cost and demand supply error that offsets the infrastructure cost.

In general, the NC method consistently demonstrates the lowest infrastructure costs across a range of scenarios which is expected as no new infrastructure is added in this case. On the contrary, methods like BA and PSO tend to exhibit higher costs, suggesting potential

Table 8
Quality of service for 2017 with RCS.

	DnI + RCS					ADnI + RCS				
	NCT^{avg}	NTT^{avg}	NWT^{avg}	QoS	QoS | 50	NCT^{avg}	NTT^{avg}	NWT^{avg}	QoS	QoS | 50
NC	30	15	29	74	−24	30	18	32	80	−30
BA	**10**	**6**	**1**	**17**	**33**	**11**	**6**	**1**	**18**	**32**
PSO	14	10	15	39	11	15	13	16	44	6
GA	16	12	14	42	8	16	13	15	44	6
HA	15	12	21	48	2	17	14	20	51	−1
ES	12	11	15	38	12	12	12	16	40	10
Our	11	10	**1**	22	28	12	11	**1**	24	26

Table 9
Quality of service for 2018 without RCS.

	DnI − RCS					ADnI − RCS				
	NCT^{avg}	NTT^{avg}	NWT^{avg}	QoS	QoS | 50	NCT^{avg}	NTT^{avg}	NWT^{avg}	QoS	QoS 50
NC	30	22	34	86	−36	30	27	34	91	−41
BA	**13**	**8**	4	**25**	**25**	**13**	**9**	5	**27**	**23**
PSO	19	15	16	50	0	19	19	19	57	−7
GA	21	16	19	56	−6	21	17	17	55	−5
HA	29	17	20	66	−16	29	17	21	67	−17
ES	17	15	16	48	2	17	16	16	49	1
Ours	12	13	**3**	28	22	12	12	**4**	28	22

Table 10
Quality of Service for 2018 with RCS.

	DnI + RCS					ADnI + RCS				
	NCT^{avg}	NTT^{avg}	NWT^{avg}	QoS	QoS | 50	NCT^{avg}	NTT^{avg}	NWT^{avg}	QoS	QoS | 50
NC	30	22	34	86	−36	30	27	34	91	−41
BA	**6**	**8**	**0**	**14**	**36**	**7**	**9**	**0**	**16**	**34**
PSO	9	15	8	32	18	11	19	10	40	10
GA	12	16	7	35	15	13	17	11	41	9
HA	15	17	9	41	9	18	17	9	44	6
ES	7	15	8	30	20	8	16	8	32	28
Ours	**6**	13	1	20	30	6	12	1	19	31

inefficiencies in these approaches. It is worth noting that our approach shows promise by achieving competitive cost reductions, especially when RCS is implemented.

5.3.3. RCS impact

When RCS are introduced, we observe an increase in infrastructure cost. However, the cost for balancing demand and demand error decreases significantly. This highlights the importance of implementing more efficient chargers, which may be costly to maintain, but with a well-designed allocation algorithm and management, they can provide a better service.

The introduction of RCS consistently results in cost reduction and improved accuracy in cost estimation. Notably, while ADnI+RCS sometimes leads to slightly higher costs compared to DnI+RCS, the overall positive impact of RCS on costs is apparent.

5.3.4. Quality of service

Quality of Service (QoS) is an important indicator of how well the built infrastructure serves its purpose, and the results in Tables 7–10 demonstrate that our method performs well on this metric. The BA method achieves the best QoS|50 score since it builds infrastructure in all available supply points without optimizing for cost. However, our method matches its score with a significantly lower infrastructure cost, as shown in Figs. 3 and 4. In Figs. 3 and 4, we illustrate the relationship between QoS and infrastructure cost. It is evident that in all cases, the infrastructure cost of our proposed methodology provides significantly better QoS. Our method effectively balances infrastructure cost, demand supply cost, and QoS better than any of the other approaches.

Looking at Network Cost Time (NCT), Network Task Time (NTT), and Network Wait Time (NWT), it becomes evident that the BA approach consistently excels which is expected as it naively builds all chargers at available charging slots at supply points without any cost nor demand consideration. It demonstrates shorter NCT, NTT, and NWT values, indicating more efficient QoS. On the other hand, Our proposed approach also showcases commendable efficiency by achieving lower values in these metrics with the advantage that it ensures balancing the QoS infrastructure cost as shown in Figs. 3 and 4.

5.3.5. Consistency in performance

The QoS|50 provides insight into the tolerable QoS and the consistency of performance across different scenarios. BA and our method exhibit higher QoS|50 values, suggesting that they maintain a more uniform level of service quality. Meanwhile, other methods exhibit higher QoS|50 values, potentially implying greater variability in their performance as seen in Tables 3 and 4.

5.3.6. Dealing with insufficient charging slots

Satisfying demand is a challenge and some supply points do not have enough charging slots to meet the demand posed to them, as observed in Figs. 5–7, particularly with supply point 37 and a few others. The maximum charging capacity of each charging station is

Fig. 3. Comparing Quality of Service with threshold of 50 vs Infrastructure cost for the different algorithms of different datasets (a) top left 2017 DnI-RCS data (b) top right 2017 ADnI–RCS (c) bottom left 2018 DnI-RCS data (b) bottom right 2018 ADnI-RCS.

Fig. 4. Comparing Quality of Service with a threshold of 50 vs Infrastructure cost for the different algorithms of different datasets: (a) top left 2017 DnI+RCS data, (b) top right 2017 ADnI+RCS, (c) bottom left 2018 DnI+RCS data, (d) bottom right 2018 ADnI+RCS.

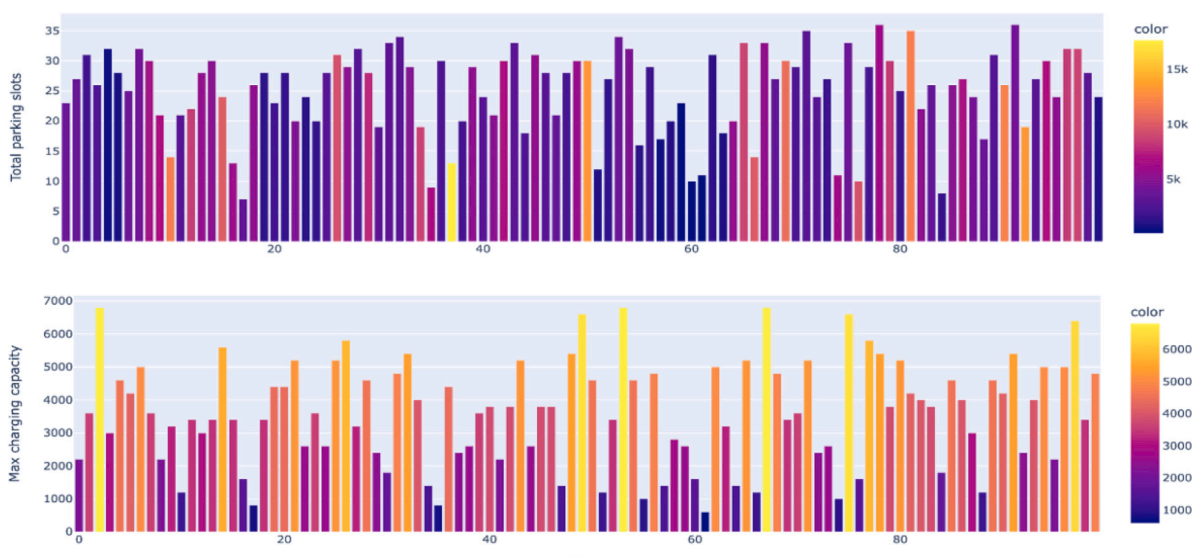

Fig. 5. EV Network charging Infrastructure (a) Top shows the number of parking slots at each supply point (b) Maximum charging capacity of a supply point (assuming all charging stations used FCS).

Fig. 6. EV Network demand capacity and Infrastructure optimization for 2017. (a) Charging capacity demand for each supply point in the network (b) demand satisfied by keeping 2016 infrastructure in 2017 (c) demand satisfied by supplying max capacity available in 2017 (d) demand satisfied by using our proposed allocation algorithm.

determined by the number of parking slots available in the supply point, as shown in Fig. 5. Consequently, it becomes challenging to precisely meet the charging capacity demand at each supply point, as depicted in Figs. 6a and 7a. In Figs. 6b and 7b, we visualize the level of demand satisfaction at each supply point without building any new infrastructure. Conversely, in Figs. 6c and 7c, we show the demand satisfaction if all free slots had built infrastructure.

It is evident that not building new infrastructure results in undersupply, while naively building infrastructure in all slots leads to oversupply. Our approach, as illustrated in Figs. 6d and 7d, strikes a good balance between these extremes, albeit falling short in supply points where demand exceeds the maximum capacity. This demonstrates the effectiveness of our approach in satisfying demand in the EV infrastructure network (see Figs. 6 and 7).

6. Conclusion

This study focused on designing a prediction and optimization framework for efficient EV charging network infrastructure that balances demand and supply while minimizing cost and maximizing QoS. Based on the analysis presented in this study, it is clear that the demand for EVs is on the rise and will continue to grow in the coming years. The continuous innovation in the ecosystem and availability of EV models, the growing awareness and concern for the environment, and the increasing push by governments by providing supportive government policies are some of the factors driving this demand. To accommodate this growing demand, it is essential to optimize the charging infrastructure for both cost and quality of service in order to increase adoption. We provide a robust solution to optimize for infrastructure and QoS in a given region and our approach through the use of an augmented dataset shows that this solution is easily transferable to other regions.

In the future, we aim to construct a digital twin Gao et al. (2021) that can simulate a more intricate real-world scenario. This enhanced simulation will enable us to monitor the QoS on a daily and monthly basis, facilitating the timely scheduling of infrastructure repairs when necessary. In an era shaped by the prominence of EVs, the optimization of network infrastructure becomes paramount. By refining and fine-tuning the charging infrastructure to harmonize both cost-effectiveness and uncompromising QoS, we are poised to usher in an era where the surge in EV adoption is not only environmentally conscientious but also a boon to economic sustainability.

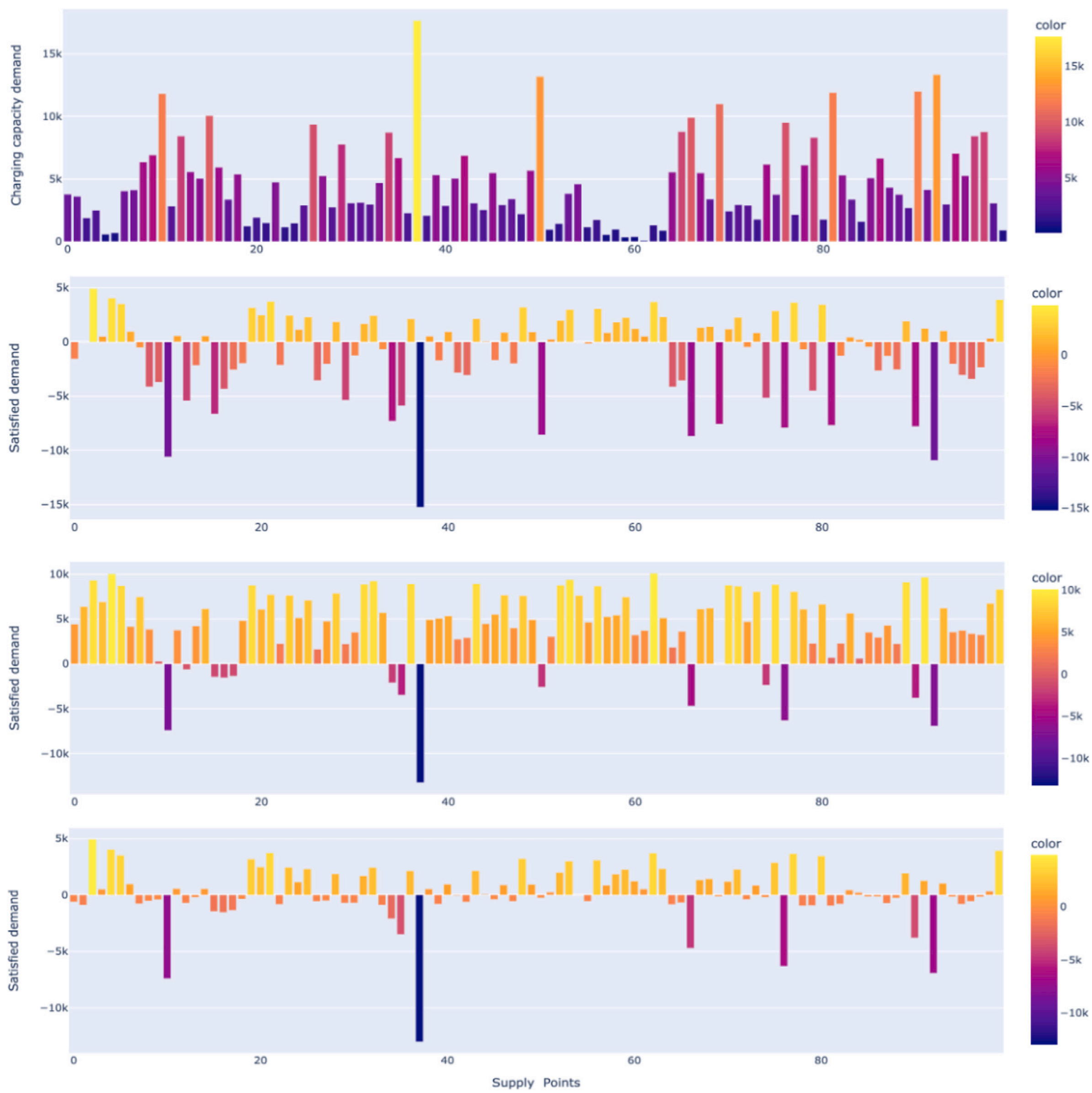

Fig. 7. EV Network demand capacity and Infrastructure optimization for 2018 (a) Charging capacity demand for each supply point in the network (b) demand satisfied by keeping 2017 infrastructure in 2018 (c) demand satisfied by supplying max capacity available in 2018 (d) demand satisfied by using our proposed allocation algorithm.

CRediT authorship contribution statement

Chia E. Tungom: Conceptualization, Methodology, Software, Validation, Data curation, Investigation, Writing – original draft. **Ben Niu:** Data curation, Software, Validation, Writing – original draft. **Hong Wang:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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