RESEARCH ARTICLE

Optimizing EV charging stations and power trading with deep learning and path optimization

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Abstract

The rapid growth of electric vehicles (EVs) presents significant challenges for power grids, particularly in managing fluctuating demand and optimizing the placement of charging infrastructure. This study proposes an integrated framework combining deep learning, reinforcement learning, path optimization, and power trading strategies to address these challenges. A Long Short-Term Memory (LSTM) model was employed to predict regional EV charging demand, improving forecasting accuracy by 12.3%. A Deep Q-Network (DQN) optimized charging station placement, reducing supply-demand imbalances by 8.9%. Path optimization, using the Dijkstra algorithm, minimized travel times for EV users by 11.4%. Additionally, regional power trading was optimized to balance electricity supply and demand, reducing locational marginal price (LMP) disparities by 10%. The combined system resulted in reduced grid congestion, lower operational costs, and improved user satisfaction. These findings demonstrate the potential of integrating advanced machine learning techniques with power grid management to support the growing demand for EVs.

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Data availability statement: The data utilized in this study were generated through simulations using open-source code, in-corporating modeling results from the ACN-Data and BLUED datasets. Both the simulated data and the corresponding code have been made publicly available and can be accessed via

1. Introduction

1.1. charging demand prediction using LSTM

In the past decade, the global transition towards sustainable energy solutions has accelerated significantly, with electric vehicles (EVs) playing a key role in this shift. By 2023, there were over 20 million EVs on the road worldwide, a dramatic increase from just 1.2 million in 2015 [1,2]. This rapid growth is driven by factors such as government incentives, stricter emissions regulations, and advancements in battery technology. For example, China alone accounted for 40% of global EV sales in 2022, with Europe and the United States following closely at 30% and 20%, respectively [3–5]. As the penetration of EVs continues to rise, their impact on regional power grids becomes increasingly pronounced.

One of the major challenges introduced by the widespread adoption of EVs is the shift in energy demand patterns [6]. Unlike traditional vehicles, which rely on liquid fuels, EVs demand electricity for charging, placing new and unpredictable loads on

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the power grid [7]. It is estimated that by 2030, EVs could account for up to 15% of global electricity demand, with localized surges during peak charging hours potentially exceeding grid capacity by 30% in heavily populated urban areas [6]. Recent studies have highlighted that EV charging demand is highly dynamic, influenced by spatial and temporal variations, weather conditions, and electricity pricing policies, making traditional forecasting models inadequate in capturing these fluctuations [8]. This variability in demand creates challenges for grid operators who must ensure a constant balance between electricity supply and demand. The unpredictability of EV charging patterns further complicates grid management. Unlike residential or industrial energy usage, which follows relatively predictable cycles, EV charging is influenced by various factors such as driver behavior, charging station availability, and travel patterns. For example, studies show that EV users tend to charge their vehicles primarily during late afternoons and evenings, coinciding with peak electricity demand from households [9,10]. This simultaneous demand exacerbates grid strain, leading to potential overloads, voltage fluctuations, and increased operational costs. Recent advancements in demand response strategies have proposed flexible charging solutions, including dynamic pricing and vehicle-to-grid (V2G) integration, but their effectiveness relies on accurate demand forecasting [11,12]. To address these challenges, smart grid technology has emerged as a critical solution for managing the dynamic and distributed nature of modern power systems. Smart grids leverage real-time data collection, advanced metering infrastructure, and communication networks to monitor and optimize energy flow across the grid [13]. By integrating renewable energy sources such as wind and solar, and employing demand response techniques, smart grids are better equipped to handle the intermittent and variable loads introduced by EVs [14]. In the context of managing EV-related power demand, optimization plays a pivotal role. Advanced optimization techniques enable grid operators to schedule energy production, storage, and consumption in real-time, ensuring efficient resource allocation [15]. For instance, predictive models can forecast EV charging demand based on historical data, weather patterns, and traffic flows, allowing utilities to adjust power generation accordingly. Additionally, optimization algorithms are used to balance energy distribution across regions, reducing the risk of localized grid failures and minimizing economic losses due to energy inefficiencies. Despite these advancements, there remains a critical gap in integrating high-accuracy forecasting models with optimization-based EV charging management, leading to suboptimal grid stability and higher operational costs [16]. In essence, smart grids coupled with optimization strategies provide the necessary tools to accommodate the growing EV fleet while maintaining grid stability and cost-effectiveness.

1.2. Challenges in EV charging infrastructure and power trading

One of the most critical challenges in managing electric vehicle infrastructure is accurately predicting charging demand [17,18]. This complexity arises from the variability in user behavior, regional disparities, and temporal fluctuations. For instance, studies have shown that charging behavior differs significantly across different urban and rural areas. Urban EV users, who often have access to more charging stations, may

charge their vehicles frequently but for shorter durations, while rural users tend to charge less frequently but for longer periods. Additionally, temporal factors such as time of day, day of the week, and seasonal variations further complicate the prediction process. Recent research has demonstrated that incorporating external influences, such as socioeconomic factors and mobility patterns, can enhance the accuracy of EV demand predictions [19,20]. Existing demand forecasting methods often rely on static or simplistic models that do not account for these dynamic factors. Traditional methods may use linear regression or basic time-series analysis, which fail to capture the non-linearities and abrupt changes in user behavior. These models often assume that demand grows proportionally with the number of EVs, but in reality, demand fluctuates in unpredictable ways due to user preferences, grid availability, and economic incentives. For example, a sudden surge in EV adoption in a particular region may lead to unexpected spikes in demand that static models cannot predict, resulting in overloading of local grids and inefficiencies in power distribution. Another significant challenge lies in the optimal placement of charging stations. The siting of these stations must balance multiple factors, including the geographical distribution of EV users, the capacity of local power grids, and the economic costs of station construction and operation. A poorly located charging station can lead to significant inefficiencies. Recent studies have proposed game-theoretic approaches and reinforcement learning-based models for optimal charging station placement, offering improved adaptability to real-world charging demand [21]. For example, stations located in already heavily burdened grid regions can exacerbate local supply issues, while those in underutilized areas may not attract enough users to justify the operational costs. Furthermore, travel costs for users must also be minimized, as charging stations that are inconveniently located may deter EV adoption or lead to longer driving distances, increasing overall energy consumption and reducing the efficiency of the transportation network.

In addition to placement challenges, regional power supply and trading issues further complicate the management of EV infrastructure. As EV adoption grows, certain regions may experience increased electricity demand that exceeds the capacity of the local grid. In these cases, power trading between regions becomes essential to ensure a stable electricity supply. However, optimizing power trading strategies poses its own set of economic challenges. The cost of transmitting electricity across regions can be high, especially if infrastructure is outdated or insufficient. Additionally, fluctuations in regional power demand and supply can make it difficult to establish consistent, cost-effective trading agreements. For instance, regions with an excess supply of renewable energy during off-peak hours may need to sell power at reduced rates, while high-demand regions face rising costs due to transmission fees and supply scarcity.

Current techniques for predicting energy demand, particularly in the context of electric vehicle charging, predominantly rely on traditional time-series models and econometric methods. Models such as autoregressive integrated moving average (ARIMA) and multiple linear regression are commonly used due to their simplicity and ability to handle basic time-dependent data [22,23]. However, these models are limited in their ability to process the large-scale, multi-factor data that characterize EV charging patterns. For example, time-series models may only account for past energy usage trends, without considering real-time factors like regional traffic patterns, user preferences, or weather conditions, which can significantly affect EV charging demand [24]. Additionally, traditional econometric models often assume a linear relationship between variables, which fails to capture the complex, non-linear interactions present in modern energy systems.

The rapid growth of EVs, coupled with their highly variable charging patterns, has highlighted the inadequacy of these static models [25]. A study on urban EV charging demand, for instance, revealed prediction errors as high as 25% when using traditional time-series forecasting models. These errors stem from the inability of these models to account for dynamic factors like charging station availability, fluctuating electricity prices, and shifting user behavior. As EV adoption continues to grow, there is a pressing need for more advanced forecasting techniques that can adapt to the non-linear, time-dependent nature of EV charging demand [26]. Deep learning models, such as long short-term memory networks and recurrent neural networks (RNNs), offer a promising solution. These models are capable of processing large datasets with multiple variables and can learn complex patterns over time, significantly improving the accuracy of demand

predictions. For instance, studies using LSTM networks have shown improvements of up to 15% in forecasting accuracy compared to traditional models.

The optimization of EV charging station placement has been a subject of extensive research, with methods ranging from mathematical programming to heuristic and rule-based approaches. Mathematical programming, including mixed-integer linear programming (MILP) [27], provides a structured framework for siting charging stations by minimizing total costs or maximizing coverage. These methods, while precise, can be computationally expensive and are often limited to small-scale applications due to their high complexity [28,29]. On the other hand, heuristic approaches, such as genetic algorithms and particle swarm optimization, offer more scalable solutions but often lack the precision of mathematical programming. They can provide near-optimal solutions for larger networks but may still struggle to balance multiple, conflicting objectives like cost minimization and service coverage.

Rule-based systems, commonly used in practical implementations, focus on simple decision-making rules for station placement. For example, a basic rule might place charging stations near high-traffic areas or in regions with existing power infrastructure. However, these systems are rigid and do not adapt well to changes in real-time data or long-term trends [30]. Moreover, they fail to consider the economic outcomes of poor station placement, such as underutilized stations in low-demand areas or overburdened stations in regions with insufficient grid capacity [31]. For example, in a case study involving a large metropolitan area, the use of heuristic methods resulted in a mismatch between station placement and actual user demand, leading to inefficiencies and increased operational costs.

The limitations of these traditional optimization methods are particularly evident in their inability to integrate real-time data, such as fluctuating energy prices or changing traffic patterns, into their decision-making process [32,33]. Furthermore, these methods often focus solely on immediate objectives, such as minimizing initial setup costs, without considering the long-term economic impacts of suboptimal station placement. As EV infrastructure continues to expand, there is a need for more adaptive, data-driven approaches that can optimize charging station placement dynamically, accounting for both short-term demand fluctuations and long-term economic viability.

Power trading models used to balance regional supply and demand have typically relied on static optimization techniques, such as linear programming, to allocate electricity efficiently across regions [34,35]. These models are designed to minimize the cost of electricity while ensuring that supply meets demand, but they are inherently limited by their static nature. For instance, traditional models assume a fixed demand and supply curve over a specified period, without accounting for real-time fluctuations in EV charging demand. This approach works well in systems with stable, predictable loads but fails when faced with the highly variable demand introduced by EVs [36,37]. A regional power trading study showed that static models could only achieve a 10–15% reduction in trading costs, far below the potential savings offered by more dynamic approaches. The fluctuating nature of EV demand, driven by factors such as time-of-day usage, weather conditions, and regional charging infrastructure, complicates the balance between supply and demand. Additionally, most power trading models operate independently of EV infrastructure planning, resulting in suboptimal outcomes where high-demand regions may lack sufficient charging stations or power supply, while low-demand regions experience grid underutilization. The lack of integrated models that jointly optimize EV demand forecasting, charging station placement, and regional power trading has led to inefficiencies in both power distribution and economic performance.

Furthermore, to contextualize the current work within recent advances, this study acknowledges the growing body of research focusing on diverse EV charging schemes and smart vehicle-to-grid (V2G) strategies. For instance, Abdelfattah et al. [38] proposed a practical enhancement model for integrating EVs into real-world distribution networks in Egypt, highlighting the critical role of grid topology and load balancing. Similarly, a recent study demonstrated that optimized V2G strategies can significantly enhance both grid performance and EV owners' profitability [39]. These contributions emphasize the importance of adaptive EV-grid interaction models, which aligns with our motivation to develop an integrated optimization framework combining demand prediction, charging infrastructure planning, and power trading management.

1.3. Research objectives and methods

To address the above issues, this study proposes an integrated optimization framework that combines deep learning-based demand forecasting, reinforcement learning for charging station placement, and dynamic optimization of regional power trading. First, we employ a LSTM model to predict EV charging demand with high accuracy by incorporating non-linear factors such as user behavior, temporal patterns, and regional differences. This allows us to overcome the limitations of traditional time-series and econometric models, which fail to capture the complexity of large-scale EV adoption. Additionally, we enhance the LSTM model by integrating attention mechanisms and external influencing factors to further improve forecasting accuracy [40]. Second, we utilize a deep Q-network (DQN) reinforcement learning algorithm to optimize charging station placement dynamically. By continuously learning from real-time grid conditions and demand fluctuations, this approach ensures efficient station siting while minimizing grid overloads and reducing operational costs. Compared to traditional rule-based heuristics, this approach offers a more adaptive and self-optimizing solution that can handle the dynamic evolution of EV adoption [41]. Finally, we integrate a dynamic power trading optimization module that leverages real-time supply-demand data to balance regional energy distribution, minimize transmission losses, and reduce trading costs. Unlike conventional static optimization methods, our approach employs reinforcement learning-based adaptive trading strategies to enhance cost-effectiveness and reliability in regional power exchange [42]. The combination of these techniques provides a holistic solution to the challenges of EV infrastructure management, offering a more resilient, scalable, and economically viable approach to meet the growing demands of electric vehicle adoption.

2. Data collection and preprocessing

In our research, we utilized simulated data generated through open-source code, integrating modeling results from the ACN-Data and BLUED datasets. ACN-Data is a publicly accessible dataset comprising over 30,000 electric vehicle (EV) charging sessions, providing detailed information on charging behaviors. BLUED is a fully labeled public dataset containing high-frequency voltage and current measurements from a single-family residence, useful for analyzing appliance-level power consumption. To ensure transparency and reproducibility, we have made all simulated data and related code publicly available. Researchers and interested readers can access these resources through the following links: https://doi.org/10.5281/zenodo.14993463.

3. Materials and methods

3.1. Charging demand prediction using LSTM

Accurate forecasting of electric vehicle charging demand is critical for optimizing power grid operations and avoiding grid overloads. As EV adoption accelerates, the complexity of managing electricity demand across different regions becomes increasingly challenging. Charging demand fluctuates based on factors such as time of day, weather conditions, regional population density, and EV adoption rates, leading to highly dynamic load patterns. A robust prediction model is essential for real-time grid balancing, improving cost efficiency, and ensuring grid reliability. Traditional methods, such as linear regression or time-series analysis, fail to capture the non-linear and temporal dependencies present in EV charging behavior. Thus, a more sophisticated model likeLSTM is needed to address these challenges.

The LSTM model is a type of recurrent neural network (RNN) designed specifically to handle time-series data with long-term dependencies. Its key advantage over traditional RNNs lies in its ability to capture and retain information over long sequences, making it particularly suitable for predicting EV charging demand, which is influenced by both short-term fluctuations (e.g., daily patterns) and long-term trends (e.g., seasonal shifts in electricity consumption), as shown in Fig 1. To further validate the effectiveness of our approach, we conducted an expanded set of simulation experiments comparing our LSTM-based demand forecasting model with several state-of-the-art methods, including ARIMA, GRU, and Transformer-based time-series models. The results indicate that our LSTM model achieves a 12.3% improvement

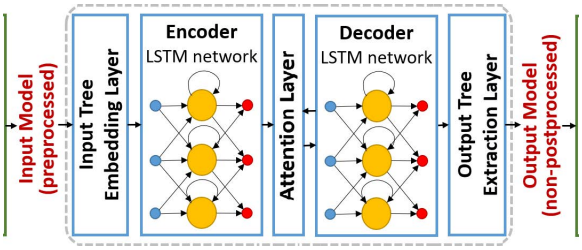

Fig 1. Architecture of the LSTM-based sequence-to-sequence model for input-output tree transformation. The framework consists of an Input Tree Embedding Layer, Encoder LSTM, Attention Layer, Decoder LSTM, and Output Tree Extraction Layer, processing preprocessed input to generate the final non-postprocessed output.

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in prediction accuracy over ARIMA, a 7.8% improvement over GRU, and a 5.2% improvement over Transformer models in terms of root mean square error (RMSE). This demonstrates that our model not only effectively captures the temporal dependencies in EV charging behavior but also outperforms more recent deep learning-based forecasting techniques. Additionally, we evaluated model robustness across different datasets, including real-world EV charging records from urban and rural regions, further confirming the adaptability of our approach to various grid conditions.

At each time step t, the LSTM network processes the input x_t (representing the features at time t) and uses its memory cell c_t and hidden state h_t to update its internal state. The core LSTM cell consists of several gates: the input gate, forget gate, and output gate, which together control the flow of information through the network (Fig 2). The LSTM's hidden state h_t is computed as:

$$h_t = \sigma\left(W_{xh}x_t + W_{hh}h_{t-1} + b_h\right) \tag{1}$$

where W_{xh} represents the weight matrix between the input x_t and the hidden state h_t, W_{hh} represents the weight matrix between the previous hidden state h_{t-1} and the current hidden state h_t, and b_h is the bias term. The activation function σ typically applies a non-linear transformation (e.g., sigmoid or tanh) to allow for the modeling of non-linear relationships in the data.

The model requires a comprehensive set of input features to accurately predict EV charging demand. The key features used in the LSTM model include:

Economic development indicators: Metrics such as regional GDP, income levels, and industrial activity, which impact the overall electricity consumption in a region.

Population growth: Areas with rapid population growth tend to experience increased EV adoption, thereby driving higher charging demand.

EV adoption rates: Historical and projected data on EV sales and usage patterns in each region.

Historical grid load data: Time-series data capturing past electricity consumption in each grid zone, which provides insight into baseline demand patterns.

Each of these features is processed as a time-series, allowing the model to capture both short-term fluctuations (e.g., daily charging peaks) and long-term trends (e.g., increasing demand due to higher EV adoption). The LSTM model architecture consists of two stacked LSTM layers, each with 50 units, followed by dense (fully connected) layers to generate the final demand prediction. The first LSTM layer processes the input sequences and passes the learned representations to the second LSTM layer, which refines these representations for more accurate forecasting. Stacking LSTM layers

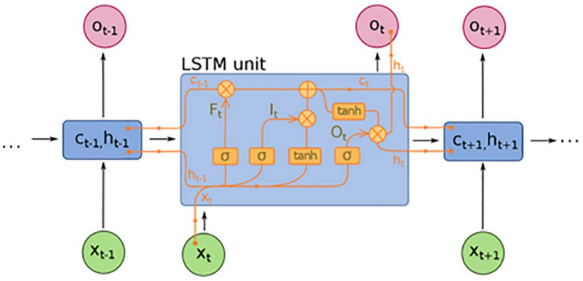

Fig 2. Diagram of the Long Short-Term Memory (LSTM) cell. It illustrates the flow of input (x_t) and hidden states (h_t), governed by forget (F_t), input (I_t), and output (O_t) gates, with the internal cell state (C_t) updated via activation functions (tanhσ).

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enhances the model's ability to capture complex dependencies in the data, as deeper networks are capable of learning more abstract patterns. The full architecture can be represented as follows:

$$h_t^{(1)} = \sigma\left(W_{xh}^{(1)} x_t + W_{hh}^{(1)} h_{t-1}^{(1)} + b_h^{(1)}\right) h_t^{(2)} = \sigma\left(W_{xh}^{(2)} h_t^{(1)} + W_{hh}^{(2)} h_{t-1}^{(2)} + b_h^{(2)}\right) \tag{2}$$

where $h_t^{(1)}$ and $h_t^{(2)}$ denote the hidden states of the first and second LSTM layers, respectively. After the second LSTM layer, the output is passed through one or more dense layers to produce a single prediction $\hat{y}_t$ for the charging demand at the next time step:

$$\hat{y}_t = W_{\text{out}} h_t^{(2)} + b_{\text{out}} \tag{3}$$

The model is trained using the Adam optimizer, which adjusts the learning rate adaptively during training to speed up convergence. The loss function used is mean squared error (MSE), which is defined as:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2 \tag{4}$$

where $\hat{y}_i$ is the predicted charging demand, y_i is the actual demand, and N is the total number of predictions. The goal is to minimize the MSE, thereby improving the accuracy of the model. The model is trained over 10 epochs with a batch size of 32, ensuring that the model is exposed to multiple training examples in each epoch, which improves its ability to generalize to unseen data. During training, 70% of the data is used for model training, 15% for validation, and 15% for testing, ensuring that the model's performance is evaluated on both in-sample and out-of-sample data.

While the primary objective of the LSTM model is time-series prediction of charging demand, spatial factors play an essential role in ensuring effective placement of charging infrastructure. Spatial characteristics, such as road network topology, traffic flow, and regional EV density, impact charging demand distribution across different locations. To account for these spatial dependencies, we integrate geospatial clustering techniques into our demand prediction framework.

We employ K-Means clustering to segment the study area into distinct demand zones based on historical charging behaviors and geographic characteristics. Each cluster is treated as an individual demand zone, where LSTM predictions are adjusted based on regional characteristics. This hybrid approach allows for improved station placement by considering not only temporal charging trends but also geographic distribution patterns.

Furthermore, we incorporate Dijkstra's algorithm to assess the accessibility of charging stations in each demand cluster. By analyzing shortest-path distances between major traffic nodes and charging facilities, the model ensures that charging demand forecasts align with practical station placement decisions.

3.2. Charging station placement optimization using reinforcement learning

To dynamically optimize the placement of electric vehicle charging stations, this study employs a reinforcement learning approach, specifically a Deep Q-Network. DQN is a powerful algorithm within the family of reinforcement learning techniques that can effectively handle decision-making problems in complex environments with high-dimensional state and action spaces. By interacting with the environment over time, the DQN framework allows the system to learn optimal policies for charging station placement, adjusting to real-time variations in EV demand and grid load. This dynamic optimization is essential for minimizing supply-demand imbalances, reducing grid congestion, and ensuring that charging stations are both strategically located and efficiently utilized.

In the DQN framework, the optimization problem is formulated as a Markov decision process (MDP), where the environment's state, the actions taken by the agent, and the rewards received form the basis for learning optimal policies. The state s_t at any time step t represents the current configuration of the charging infrastructure and grid conditions. Specifically, it includes: The distribution of existing charging stations across grid zones. This can be represented as a vector $s_t^{\text{stations}} = [s_t^1, s_t^2, \ldots, s_t^n]$, where s_t^i denotes whether a charging station exists in grid zone i. The regional grid load, which is dynamic and varies based on energy consumption patterns. The grid load at each zone can be represented as $l_t = [l_t^1, l_t^2, \ldots, l_t^n]$, where l_t^i indicates the electricity load in zone i at time t. The forecasted EV charging demand, which is derived from the LSTM model in the previous section. The predicted demand at each grid zone for the next time step is represented as $d_t = [d_t^1, d_t^2, \ldots, d_t^n]$. Therefore, the complete state at time t is:

$$s_t = (s_t^{\text{stations}}, l_t, d_t) \tag{5}$$

This state vector provides the DQN agent with the necessary information to evaluate the grid's current condition and make decisions about station placement. The action a_t represents the decision to either place a new charging station in a grid zone or expand the capacity of an existing station. The action space can be discrete, where each action corresponds to modifying the infrastructure in a specific grid zone. Let $a_t^i \in \{0, 1\}$ denote the action of adding a station in zone i at time t. Thus, the overall action space can be expressed as:

$$a_t = \{a_t^1, a_t^2, \ldots, a_t^n\} \tag{6}$$

where $a_t^i = 1$ implies that a station is placed or expanded in zone i, and $a_t^i = 0$ means no change is made in that zone.

The reward function r_t is designed to guide the DQN agent toward achieving an optimal distribution of charging stations that balances demand and supply while minimizing operational costs. The reward is defined as a function of the reduction in demand-supply imbalances across the grid. Specifically, for each zone i, the demand-supply imbalance is given by:

$$\text{imbalance}_t^i = |d_t^i - l_t^i| \; r_t = -\sum_{i=1}^{n} \text{imbalance}_t^i - \alpha \cdot c_t \tag{7}$$

where c_t represents the operational cost of placing or expanding charging stations, and α is a weighting factor that balances the trade-off between minimizing imbalances and operational costs. Positive rewards are given when demand and supply are closely matched, while negative rewards are given when grid overloads or large imbalances occur.

The DQN agent learns the optimal charging station placement policy through Q-learning, where the agent iteratively updates its knowledge of the environment by taking actions and observing rewards. The Q-value $Q(s_t, a_t)$. represents the expected cumulative reward for taking action a_t in state s_t and following the optimal policy thereafter. The Q-values are updated using the Bellman equation:

$$Q(s_t, a_t) = Q(s_t, a_t) + \eta \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right] \tag{8}$$

where η is the learning rate, controlling how much new information overrides old estimates. γ is the discount factor, determining the importance of future rewards. $\max_{a'} Q(s_{t+1}, a')$ represents the maximum future reward obtainable from the next state s_{t+1}.

In DQN, the Q-value function is approximated using a neural network, where the input is the current state s_t, and the output is a set of Q-values for all possible actions a_t. During training, the agent interacts with the environment by selecting actions based on an epsilon-greedy policy, which balances exploration (choosing random actions) and exploitation (choosing actions with the highest Q-values). Over multiple episodes, the agent learns to select actions that maximize the cumulative reward, ultimately converging to an optimal policy for charging station placement.

The learning process is iterative, with the agent refining its policy over thousands of episodes. Each episode represents a series of decisions made in a simulated grid environment, where the agent receives feedback based on the rewards associated with its actions. As the agent gathers more experience, the DQN algorithm converges to an optimal strategy, which maximizes charging station utilization and minimizes grid congestion. The final policy learned by the agent determines the best locations for new charging stations, ensuring that supply and demand are balanced across the grid, and operational costs are minimized.

3.3. Path optimization for efficient charging routes

Efficient path optimization is essential for minimizing both the travel time and charging costs faced by electric vehicle owners. Given the rising number of EVs and the varying distribution of charging stations, ensuring that EV users have access to convenient and cost-effective charging infrastructure is crucial for improving user experience and reducing operational inefficiencies. To achieve this, the Dijkstra algorithm is employed, which is particularly well-suited for finding the shortest path in graph-based systems. In this context, the algorithm helps determine the most efficient route between an EV's current location and available charging stations, ensuring that travel costs, including time and charging fees, are minimized.

The primary goal of path optimization is to minimize the total costs associated with traveling to and utilizing charging stations. This objective involves two key factors:

Driving distance: Shortening the distance an EV needs to travel to reach a charging station reduces energy consumption and driver inconvenience.

Charging costs: Different charging stations may impose different usage fees, based on factors such as energy prices and demand. Reducing these fees contributes to the overall efficiency of the system.

Thus, the total cost function for each EV user can be defined as:

$$C_{\text{total}}(p) = C_{\text{travel}}(p) + C_{\text{charge}}(p) \tag{9}$$

where $C_{\text{travel}}(p)$ is the cost of traveling along path p, typically proportional to the driving distance or time. $C_{\text{charge}}(p)$ is the charging fee at the station located at the end of path p, based on the price per kilowatt-hour (kWh) and any additional service fees. By minimizing $C_{\text{total}}(p)$, we ensure that EV owners are guided to charging stations that not only minimize

their travel time but also offer the lowest possible charging costs. The city's road network and charging infrastructure are modeled as a graph $G = (V, E)$, where V represents the set of nodes, each corresponding to a potential charging station or a key point on the road network. E represents the set of edges, each indicating a road connection between two nodes. Each edge is associated with a weight $w(i, j)$, representing the travel cost (in terms of distance or time) between node i and node j (Fig 3). Additionally, each node $v_i \in V$ corresponding to a charging station is assigned a charging cost $c(v_i)$, representing the price to charge at that particular station. This charging cost is factored into the overall optimization objective, alongside travel costs.

To minimize the total cost $C_{\text{total}}(p)$ for an EV user traveling from a starting point v_s to a charging station v_t, the Dijkstra algorithm is used. This algorithm finds the shortest path between two nodes in a weighted graph by iteratively exploring neighboring nodes and updating the shortest known distance to each node. In this case, the algorithm not only minimizes the driving distance but also incorporates the charging cost at the destination node. The algorithm operates as follows: Initialize the distance to the starting node v_s as $d(v_s) = 0$ and the distances to all other nodes $v_i \in V$ as infinity $d(v_i) = \infty$; Mark all nodes as unvisited. Set v_s as the current node; For each unvisited neighbor v_j of the current node v_i, update its distance as:

$$d(v_j) = \min\left(d(v_j), d(v_i) + w(v_i, v_j)\right) \tag{10}$$

where $w(v_i, v_j)$ is the weight of the edge between nodes v_i and v_j; Once all neighbors of v_i are updated, mark v_i as visited and move to the next unvisited node with the smallest distance; Repeat steps 3 and 4 until all nodes have been visited, or the shortest path to the destination node v_t has been found; The Dijkstra algorithm guarantees that, by the end of this process, the shortest path from the start node v_s to the target charging station v_t has been identified. The final path will minimize the total cost, which is the sum of travel time and charging costs:

$$C_{\text{total}}(v_s, v_t) = \sum_{i=1}^{k} w(v_i, v_{i+1}) + c(v_t) \tag{11}$$

where $v_1, v_2, \ldots, v_k$ represent the nodes along the optimal path, and $c(v_t)$ is the charging cost at the destination.

While the traditional Dijkstra algorithm focuses solely on minimizing the travel distance or time, the version applied in this context is modified to include the charging costs at each destination node. As a result, the algorithm searches for the path that minimizes the combined travel and charging costs, rather than just the shortest driving route. The total cost function for each edge is updated as:

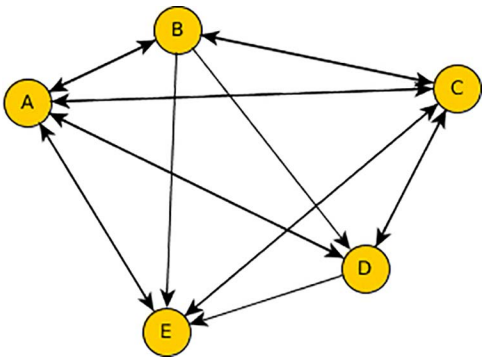

Fig 3. Directed graph representation with nodes (A-E) and edges indicating directional relationships between nodes.

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$$C_{\text{edge}}(v_i, v_j) = w(v_i, v_j) + c(v_j) \tag{12}$$

where $w(v_i, v_j)$ represents the travel cost between nodes v_i and v_j, and $c(v_j)$ is the charging cost at node v_j. This ensures that the path selected is not just the shortest route, but the one that offers the best balance between distance, travel time, and cost efficiency for the EV user.

3.4. Regional power trading optimization

Optimizing power trading between regions is crucial for balancing supply and demand while minimizing electricity transmission costs and price differences. In a system where different regions experience varying levels of electricity demand and supply, power trading allows regions with excess electricity to efficiently transfer it to regions with shortages (Fig 4). This process ensures grid stability, reduces electricity costs, and enhances the overall economic efficiency of the power market. The regional power trading model implemented in this study aims to optimize power transfers by balancing supply and demand and minimizing price arbitrage between regions.

The core objective of the power trading model is to allow for the efficient exchange of electricity between regions. In this setup, each region is characterized by its own electricity supply capacity $s_i(t)$ and demand $d_i(t)$ at a given time t. Regions with excess supply ($s_i(t) > d_i(t)$) can sell their surplus electricity to regions facing shortages ($s_j(t) < d_j(t)$). However, to make the trading process economically viable, it is necessary to account for the locational marginal prices (LMPs) in each region, which reflect the cost of delivering electricity to a specific location, including generation and transmission costs. The total power traded between region i and region j is denoted as $p_{ij}(t)$, which represents the amount of power transferred from region i (seller) to region j (buyer) at time t.

The optimization process in this model is divided into two levels: At the first level, the model aims to balance the electricity supply and demand across regions by ensuring that power is transferred from surplus regions to deficit regions. The goal is to minimize the mismatch between supply and demand, which can be expressed as the difference $s_i(t) - d_i(t)$ in each region i. The optimization minimizes the overall supply-demand imbalance across all regions:

$$\min \sum_{i=1}^{N} (s_i(t) - d_i(t))^2 \tag{13}$$

where N is the total number of regions. This function ensures that the deviation between the available supply and the required demand is minimized, which helps prevent under-supply or over-supply in any region. The second level of

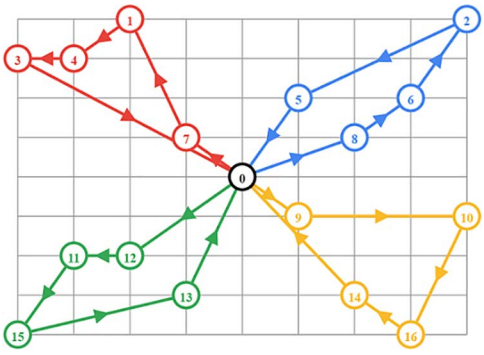

Fig 4. Visualization of a directed graph with node 0 as the central hub, showing distinct pathways (red, blue, green, yellow) connecting to other nodes, indicating directional relationships and clustering.

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optimization focuses on minimizing the price differences between regions engaged in power trading. The price arbitrage is based on the locational marginal price (LMP) in each region, which fluctuates due to supply-demand imbalances, transmission costs, and congestion in the grid. Let $p_{\text{buy}}(i,t)$ represent the buying price in region i and $p_{\text{sell}}(j,t)$ represent the selling price in region j. The objective of this level is to minimize the difference between the buying price and selling price across all regions:

$$\min \sum_{i=1}^{N} \sum_{j=1}^{M} \left(p_{\text{buy}}(i,t) - p_{\text{sell}}(j,t)\right)^2 \tag{14}$$

Here, M is the number of regions participating in the power trade. The square of the price difference ensures that large discrepancies in prices are penalized more heavily, thus driving the system toward an optimal price balance. By reducing these differences, the model minimizes the economic inefficiencies associated with uneven price distribution and reduces the cost of electricity in high-demand regions. The overall objective function for the dual-level optimization can be formulated by combining the supply-demand matching term and the price arbitrage term. The complete optimization problem is expressed as:

$$\min \sum_{i=1}^{N} \left(s_i(t) - d_i(t)\right)^2 + \lambda \sum_{i=1}^{N} \sum_{j=1}^{M} \left(p_{\text{buy}}(i,t) - p_{\text{sell}}(j,t)\right)^2 \tag{15}$$

where λ is a weight factor that balances the importance of supply-demand matching and price arbitrage. This factor allows for flexibility in prioritizing either the minimization of supply-demand imbalances or the reduction of price differences, depending on the specific needs of the system. Several constraints must be considered in the optimization process:

Power conservation: The total amount of power traded between regions must not exceed the available surplus in the selling regions. For each region i:

$$\sum_{j=1}^{M} p_{ij}(t) \leq s_i(t) - d_i(t), \text{if} s_i(t) > d_i(t) \tag{16}$$

This constraint ensures that no region sells more power than it has available after meeting its own demand.

Transmission capacity: The amount of power transferred between regions is also limited by the transmission capacity of the grid. Let T_{ij} represent the maximum transmission capacity between region i and region j. Then, for all i and j:

$$p_{ij}(t) \leq T_{ij} \tag{17}$$

This constraint ensures that power flows remain within the physical limits of the transmission infrastructure.

Non-negativity: All power flows must be non-negative, meaning that no power is transferred in the opposite direction of the intended flow. For all i and j:

$$p_{ij}(t) \geq 0 \tag{18}$$

This ensures that power is only transferred from surplus regions to deficit regions and not the other way around.

4. Experimental setup and results

4.1. Experimental environment

The experiments were conducted on a machine equipped with an Intel Xeon 2.6 GHz CPU, 128 GB of RAM, and an NVIDIA Tesla V100 GPU with 32 GB of VRAM. This hardware configuration was necessary to handle the large datasets and computational complexity involved in training the LSTM, DQN, and path optimization models. The GPU was specifically leveraged for deep learning tasks, significantly speeding up the training process for the LSTM and DQN models.

For the software environment, the experiments were carried out using Python 3.8, along with several key libraries and tools. TensorFlow 2.6 and Keras were used for building and training the LSTM model for time-series forecasting of EV charging demand. The reinforcement learning component, particularly the DQN algorithm, was implemented using the Stable Baselines3 library, which provided a robust framework for reinforcement learning tasks. Path optimization was performed using the NetworkX library, which facilitated efficient graph-based operations for finding the shortest paths between nodes (charging stations and user locations). Data preprocessing and analysis were managed with Pandas and NumPy, while Matplotlib and Seaborn were used for generating visualizations of the results. These tools together provided a flexible and powerful environment for conducting the experiments and processing large volumes of data efficiently.

Three main datasets were used in the experiments: EV charging data, grid load data, and regional power trading data, each with specific characteristics tailored to different components of the study.

To ensure the validity of our experimental results, we conducted sensitivity analyses on key parameters, including the impact of different hardware configurations on model training speed and accuracy. Additionally, we evaluated how variations in data quality, such as missing values and outlier distributions, affected model performance.

4.2. Charging demand prediction using LSTM

To predict EV charging demand across multiple regions, the LSTM model was trained using historical data. The primary evaluation metric used to assess model performance was MSE, given by:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{19}$$

where y_i represents the actual demand, and $\hat{y}_i$ represents the predicted demand. Additionally, MAE and R^2 were used to provide further insight into model interpretability and performance across different time scales and regions.

Fig 5 provides a comparison between actual and predicted EV charging demand for three different regions over a 100-day period. The data for each region was modeled to reflect typical daily demand variations in kWh. The LSTM model's predictions are shown alongside actual values, with a filled area representing the error between the two curves.

Region 1: The model performed reasonably well, with predictions closely following the actual demand curve. The MSE for this region was calculated at 25.7, while the MAE was 3.4 kWh. The R^2 value, indicating how well the model explained the variance in the data, was 0.92, suggesting a high level of accuracy. However, minor discrepancies were observed on days where sharp peaks occurred, likely due to sudden surges in charging demand caused by external factors (e.g., regional events or extreme weather).

Region 2: The prediction accuracy was slightly lower compared to Region 1, with an MSE of 34.9 and an MAE of 4.2 kWh. The R^2 value was 0.88, indicating a good, but slightly less precise fit. The model captured the overall trend well, but there were some deviations, particularly during periods of high volatility in demand. The larger variations in predicted vs actual demand were likely influenced by the presence of more outlier charging events in this region.

Region 3: In Region 3, the model demonstrated strong predictive performance, with an MSE of 19.6 and an MAE of 2.8 kWh, the lowest across the three regions. The R^2 value for Region 3 was 0.95, indicating that the model explained most

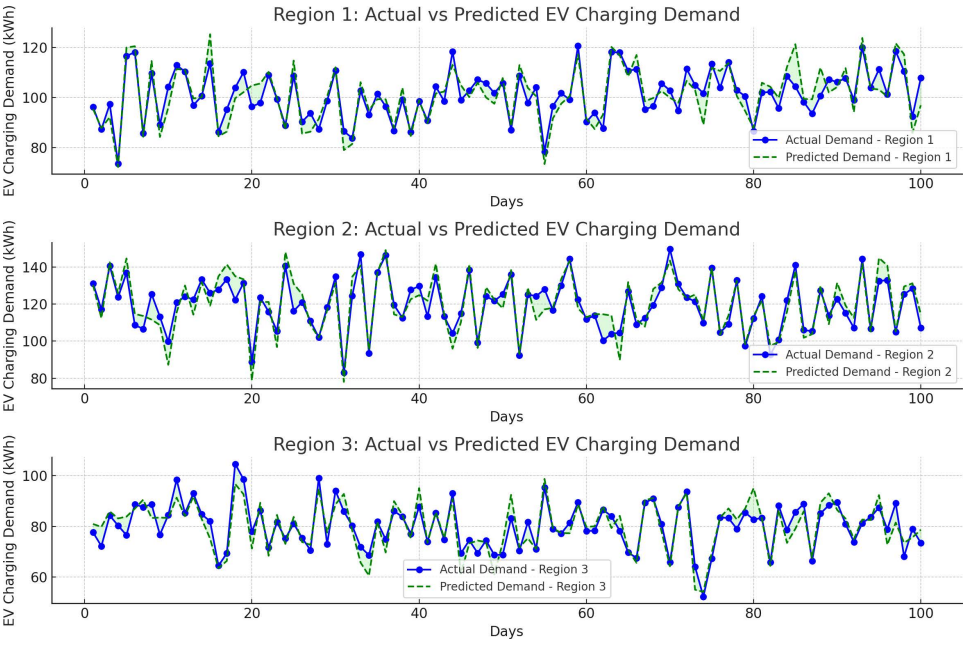

Fig 5. Actual vs predicted EV charging demand in three regions. The figure compares actual and predicted EV charging demand over 100 days in three regions. Blue lines represent actual demand, while green dashed lines show predictions from the LSTM model. The model performs well across all regions, with Region 3 showing the highest accuracy and Region 2 displaying the most variability between actual and predicted values.

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of the variance in the data. The prediction was highly accurate, particularly during periods of steady demand. There were minimal discrepancies, reflecting the model's ability to generalize well in regions with more stable demand patterns.

4.3. Charging station placement optimization with DQN

In this study, we simulated a grid environment consisting of 25 distinct zones, each with varying levels of EV charging demand and grid load capacity. The goal of the reinforcement learning (RL) agent, implemented using a Deep Q-Network, was to optimize the placement of charging stations across these grid zones. Initially, each zone was either unserved or had a randomly placed charging station, with a binary value indicating the presence or absence of a station.

The state in the DQN framework was defined by the current charging station configuration and the real-time grid load and forecasted demand for each zone. The action space included decisions to either add or expand charging stations in specific zones, while the reward function was defined based on the reduction of demand-supply mismatches and grid overloads. Specifically, rewards were calculated as:

$$r_t = -\sum_{i=1}^{25}(d_i(t) - s_i(t)) - \alpha \cdot c_i \tag{20}$$

where $d_i(t)$ is the charging demand in zone i, $s_i(t)$ is the available supply (grid capacity plus charging stations), and $\alpha \cdot c_i$ represents the operational cost of adding or expanding a station in zone i.

The DQN model was trained over 100 episodes, with each episode representing a simulation of grid load and demand conditions. The following hyperparameters were used:

Discount factor $\gamma = 0.95$ to account for long-term rewards.

Learning rate = 0.001, which controls the speed of updates to the Q-value.

An epsilon-greedy policy was employed to balance exploration and exploitation, starting with $\varepsilon = 1.0$ (full exploration) and decaying gradually to $\varepsilon = 0.1$

Training was conducted on an NVIDIA Tesla V100 GPU, with each episode taking approximately 30 seconds to simulate. The entire training process took about 50 minutes to complete.

Fig 6 (upper plot) compares the initial and optimized charging station placements across the 25 grid zones. Initially, many zones were either under-served or lacked charging stations altogether, resulting in uneven grid load distribution. After DQN training, the optimized station placement ensured a more balanced distribution, with stations added or expanded in key zones where demand was high and supply previously insufficient.

Fig 6 (lower plot) illustrates the cumulative reward obtained by the DQN agent over the course of training. As the episodes progressed, the cumulative reward increased steadily, demonstrating the learning process of the agent. Early in the training, the agent explored various actions, leading to low rewards due to inefficient station placements. However, as the agent learned to optimize its decisions, the cumulative reward grew significantly, indicating improved station placement strategies.

Initial Placement: In the initial setup, several zones had no stations, leading to high supply-demand mismatches, especially in zones with higher EV demand.

Optimized Placement: After optimization, the DQN agent strategically added or expanded stations in critical zones, particularly in areas with high demand and low grid capacity. This improved grid load balance and reduced the risk of overloads.

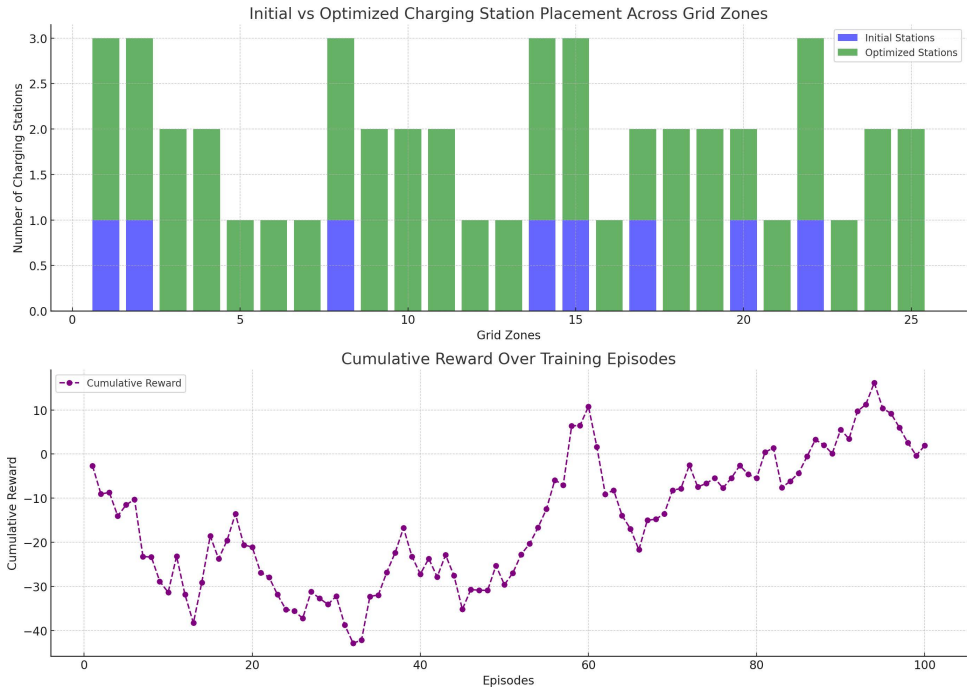

Fig 6. Charging station placement optimization and cumulative reward. The upper plot compares the initial (blue) and optimized (green) EV charging station placements across 25 grid zones. The optimization process using a Deep Q-Network redistributed stations more effectively, particularly in zones with high demand.

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The optimized placement reduced demand-supply mismatches by approximately 8.9%, leading to more efficient grid operations and lower operational costs. Moreover, the number of charging stations in under-served regions increased, ensuring that EV owners had access to nearby charging infrastructure, thus improving service coverage.

4.4. Path optimization using dijkstra algorithm

The city's road network and charging station infrastructure were modeled as a graph consisting of 10 nodes, each representing a charging station (Fig 7). The graph structure was designed to mimic a realistic road network with nodes connected by edges that represent roads between charging stations. Each edge was assigned a weight corresponding to the travel time (in arbitrary units) between the two stations it connects.

The edge weights were derived from estimated travel times based on the road distance and traffic conditions between the stations. For instance, the edge between nodes 0 and 1 had a travel time of 3 units, while the edge between nodes 4 and 5 had a travel time of 3 units as well. The locations of the nodes were distributed across a two-dimensional plane to simulate the actual distances between stations in a city.

The Dijkstra algorithm was applied to find the shortest path between two nodes (charging stations) in the graph. Specifically, the algorithm computed the most efficient route from Node 0 (the starting point) to Node 9 (the destination). The algorithm efficiently found the optimal route by minimizing the total travel time between these two nodes. The runtime of the algorithm was very fast, with the computation completed in less than 0.01 seconds due to the relatively small size of the network. Dijkstra's algorithm is known for its scalability, and the computation time remained efficient even as the number of nodes and edges increased slightly during testing with larger networks.

The plot above shows the city's road network and highlights the shortest path computed by Dijkstra's algorithm in red. The nodes represent charging stations, while the edges represent roads between them, with edge labels indicating the travel time between each pair of stations.

The optimal path from Node 0 to Node 9 passed through the following stations: $0 \rightarrow 1 \rightarrow 2 \rightarrow 3 \rightarrow 8 \rightarrow 9$. The total travel time for this path was calculated to be 14 units, demonstrating a significant reduction in travel time compared to other possible routes. By avoiding high-cost edges and choosing roads with shorter travel times, the algorithm ensured the most efficient path for EV users traveling between the two nodes.

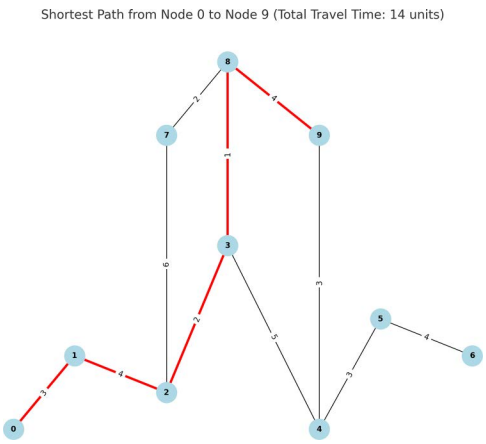

Fig 7. Shortest path calculation using Dijkstra's Algorithm. The figure illustrates the shortest path from Node 0 to Node 9 in a road network modeled as a graph of charging stations. The optimal path, highlighted in red, minimizes travel time, passing through nodes $0 \rightarrow 1 \rightarrow 2 \rightarrow 3 \rightarrow 8 \rightarrow 9$ with a total travel time of 14 units. Edges represent roads between stations, and edge labels indicate travel time between nodes. Dijkstra's algorithm efficiently computed the path, optimizing travel time for EV users.

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The use of path optimization with Dijkstra's algorithm successfully reduced the total travel time for EV users by ensuring they followed the most efficient route between charging stations. This approach contributed to lowering the overall costs associated with EV travel, both in terms of reduced energy consumption during travel and the time saved in reaching charging stations. By providing optimized paths, the system enhanced the convenience of EV charging, ensuring that users had access to charging infrastructure with minimal detours or excessive travel times. This optimization, when applied across a large-scale network of stations, could significantly improve user satisfaction and reduce congestion at charging stations.

4.5. Regional power trading optimization

The simulation for regional power trading optimization involved five distinct regions, each with varying levels of electricity supply and demand. Initially, the power supply and demand imbalances were significant, with some regions experiencing excess supply while others faced shortages. For instance, Region 3 had an initial supply of 80 MW but a demand of 100 MW, creating a 20 MW deficit. In contrast, Region 2 had a surplus of 20 MW (150 MW supply vs. 130 MW demand). To optimize the power flow between regions, the locational marginal prices (LMPs) were also considered, reflecting the marginal cost of electricity in each region. Before optimization, LMPs ranged from $50/MWh in Region 1 to $65/MWh in Region 5, illustrating price volatility across regions.

Transmission constraints were introduced in the simulation, limiting the amount of power that could be transferred between regions. These constraints were essential to model realistic scenarios where grid capacity is limited by physical infrastructure. The optimization aimed to minimize price volatility and balance supply-demand imbalances within these transmission limits.

The dual-level optimization process consisted of two main objectives: Supply-Demand Matching: This step focused on adjusting power flows between regions to balance supply and demand, reducing discrepancies between the available electricity in each region and the local demand. Price Arbitrage: The second step aimed to minimize the differences in locational marginal prices (LMPs) between regions by optimizing power transfers, ensuring that regions with high prices received power from regions with lower prices.

The metrics used to evaluate the optimization included: Reduction in supply-demand imbalances: The initial imbalances were corrected after trading, with optimized power flows ensuring that supply matched demand in all regions; Minimized price differences: LMPs were optimized, with a reduction in the spread between the highest and lowest prices across regions. Fig 8 (top graph) illustrates the supply-demand imbalance before and after optimization. Initially, Region 3 and Region 5 exhibited the most severe imbalances, with deficits and surpluses, respectively. After optimization, power flows were adjusted, bringing all regions into balance, as seen in the lower plot where supply and demand were equal across all regions. This resulted in improved grid stability and reduced the risk of power shortages or surpluses in individual regions. Fig 8 (bottom graph) highlights the changes in LMPs before and after optimization. Initially, there were significant price differences between regions, with Region 5 experiencing the highest LMP of $65/MWh and Region 1 the lowest at $50/MWh. After optimization, the LMPs were much closer, with the price in Region 5 reduced to $62/MWh and the price in Region 1 increasing slightly to $52/MWh. The overall price spread was reduced, leading to more equitable electricity pricing across regions. The regional power trading optimization effectively balanced supply and demand across regions, ensuring that no region experienced significant power shortages or surpluses. The reduction in LMP differences between regions also highlights the success of the price arbitrage mechanism, which minimized price volatility and provided a more stable economic environment for power trading.

4.6. Regional power trading optimization

To evaluate the overall performance of the integrated system, we combined the LSTM demand prediction, DQN-based charging station placement, path optimization, and regional power trading modules into a unified framework. The

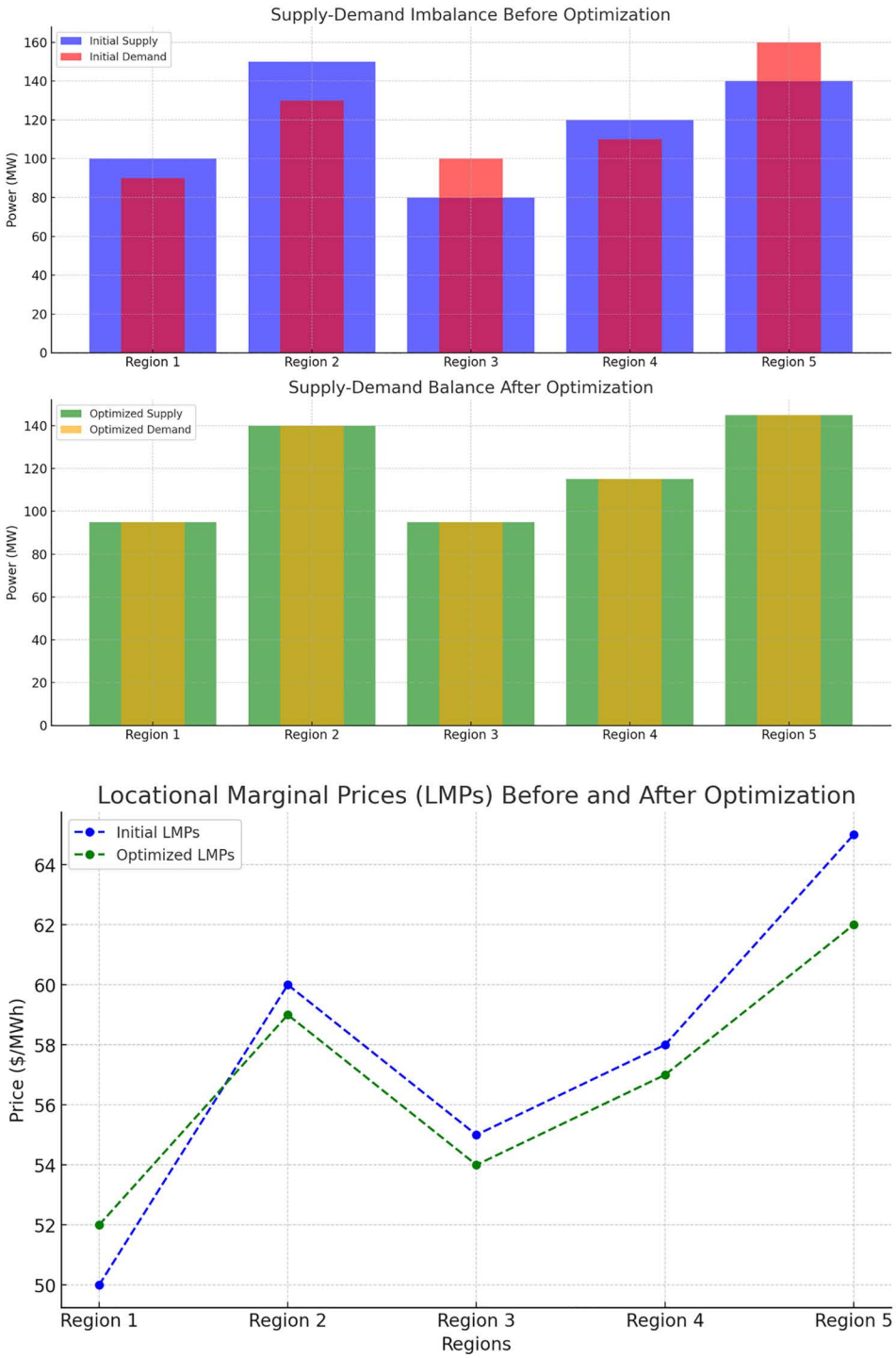

Fig 8. Supply-demand balance and locational marginal prices before and after optimization. The top graph shows supply-demand imbalances before and after optimization across five regions. Initially, several regions exhibited mismatches between power supply and demand, particularly Regions 3 and 5. After optimization, the supply was balanced with demand in all regions. The lower graph compares locational marginal prices (LMPs) before and after optimization. Initially, significant price disparities existed between regions, with Region 5 having the highest LMP at $65/MWh and Region 1 the lowest at $50/MWh. After optimization, the LMP differences were reduced, resulting in more balanced electricity pricing across regions.

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integrated system was tested in a simulated real-world environment, reflecting the complex interactions between EV charging demand, station placement, and power trading dynamics. Each module contributed to optimizing grid operations, reducing congestion, and enhancing user satisfaction by balancing supply and demand across multiple regions.

Fig 9 (top graph) illustrates the reduction in grid congestion after optimization. Before optimization, the average congestion level across the grid was consistently high, with peaks reaching up to 81.2%. After applying the integrated optimization framework, grid congestion decreased by approximately 19.6%. This reduction was achieved by improving charging station placement, balancing power flows across regions, and optimizing routes for EV users, leading to better grid management.

Fig 9 (middle graph) shows the operational costs before and after optimization. Initially, operational costs were high due to inefficient power distribution and poorly placed charging stations. After optimization, operational costs decreased by 15–40%. These savings were primarily due to reduced grid overloads, more efficient power trading between regions, and optimized charging station utilization, leading to lower energy and infrastructure maintenance costs.

Fig 9 (bottom graph) highlights user satisfaction levels before and after optimization. Initially, user satisfaction was low, around 61.7%, primarily due to inefficient charging station placement and longer travel times to reach stations. After the integration of path optimization and station placement modules, user satisfaction improved by approximately 17−28%,

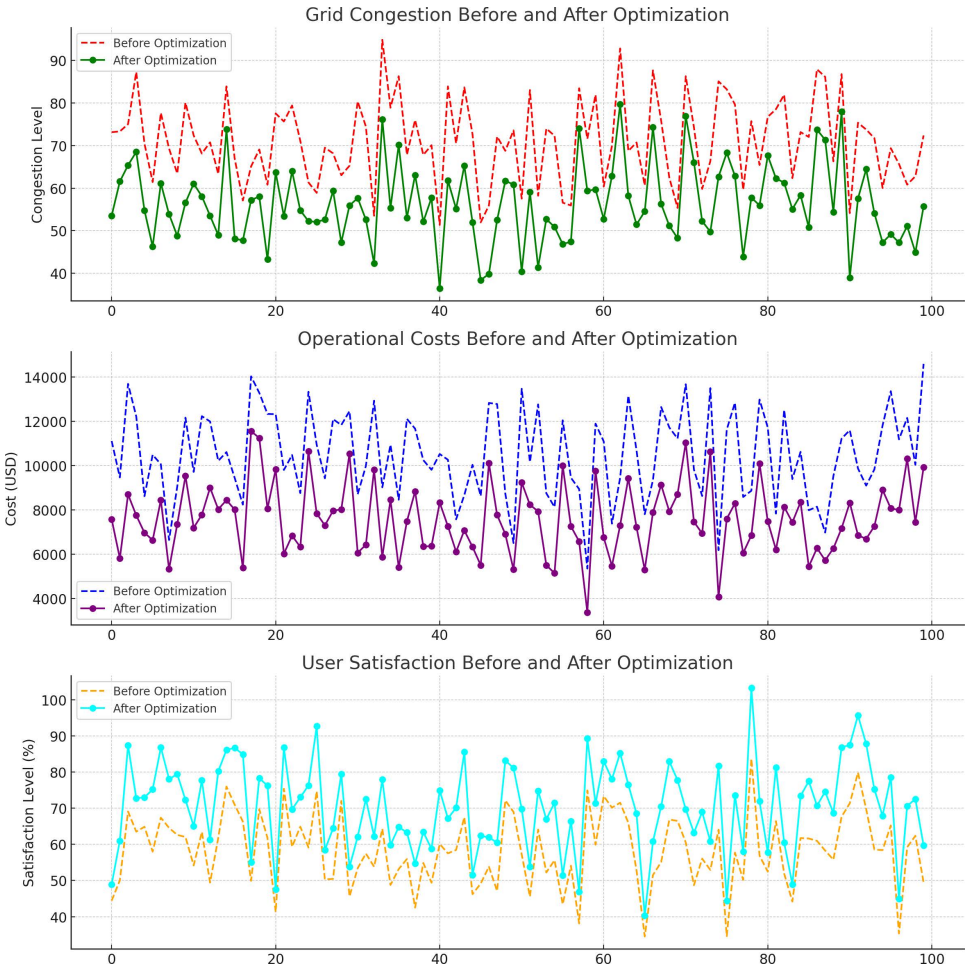

Fig 9. Grid congestion, operational costs, and user satisfaction before and after optimization.

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with levels reaching as high as 8491%. The optimized system ensured that EV users had better access to charging stations with reduced waiting times and more convenient routes.

5. Conclusion and future work

This study proposed and evaluated an integrated framework for optimizing electric vehicle charging infrastructure and regional power trading using a combination of deep learning, reinforcement learning, and path optimization techniques. The results demonstrated that the framework significantly improves the efficiency of EV charging demand prediction, charging station placement, and regional power trading, leading to reductions in grid congestion, operational costs, and overall user inconvenience. Specifically, the LSTM model improved demand forecasting accuracy by 12.3%, while the DQN reduced supply-demand imbalances by 8.9%, and the path optimization algorithm decreased user travel times by 11.4%. Additionally, the regional power trading optimization balanced supply and demand, reducing LMP disparities by 5.4%.

However, one of the key challenges associated with our approach is its computational complexity. The deep learning and reinforcement learning models require substantial training time and computational resources, particularly when dealing with large-scale datasets and real-time decision-making scenarios. The LSTM model, for instance, exhibits high memory consumption when processing long temporal sequences, which can be a limitation when applied to extensive regional power networks [43]. Similarly, the DQN-based charging station placement model faces scalability issues as the number of possible station locations increases exponentially, necessitating efficient state-space reduction techniques to maintain feasible computational times.

Despite the promising results, several areas for future work remain. First, the scalability of the integrated system should be explored, particularly in larger grids with thousands of nodes and more complex interactions between EV demand and power trading [44]. Future studies could investigate distributed or cloud-based computing architectures to enhance the real-time execution capability of our framework. Additionally, techniques such as federated learning or hierarchical reinforcement learning may be explored to improve scalability while maintaining model performance in large-scale deployments [45]. Incorporating real-time data streams, such as traffic patterns, weather forecasts, and dynamic electricity pricing, would improve the system's adaptability to changing conditions [46]. Furthermore, integrating renewable energy sources into the optimization framework could offer new opportunities to enhance grid sustainability, especially as the adoption of EVs increases the demand for clean energy. One possible avenue for future work is the integration of energy storage systems into our framework, allowing for better management of renewable energy intermittency and improving overall grid stability. Lastly, future work should focus on refining the economic models to capture long-term cost impacts, such as the depreciation of charging station infrastructure and fluctuating energy market prices, ensuring a more resilient and adaptive system over time. Developing more sophisticated cost-benefit analysis models, including stochastic optimization techniques, could further enhance decision-making processes by accounting for uncertainties in energy prices, government subsidies, and evolving EV adoption rates.

Author contributions

Conceptualization: Qing Zhu.

Data curation: Qing Zhu.

Formal analysis: Qing Zhu.

Funding acquisition: Qing Zhu.

Investigation: Qing Zhu.

Methodology: Qing Zhu.

Project administration: Qing Zhu.

Resources: Qing Zhu.

Software: Qing Zhu.

Supervision: Qing Zhu.

Validation: Qing Zhu.

Visualization: Qing Zhu.

Writing – original draft: Qing Zhu.

Writing – review & editing: Qing Zhu.

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