

A Survey on Intelligent Recommendation Systems for Electric Vehicles Charging Stations

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ABSTRACT

Nowadays, the rapid adoption of electric vehicles (EVs) across modern countries has caused significant challenges in EV management in modern transportation systems. This creates a significant demand for efficient and intelligent recommendation systems to decrease EVs' travel time and cost and minimise charging wait time. Recently, many researchers have addressed this issue by designing AI-based EV charging station (EVCS) recommendation systems. In contrast to traditional routing problems, EVCS recommendations must consider dynamic demand that shifts across time and location and diverse infrastructure constraints. This survey article first introduces a categorisation of EVs and charging stations. Then, we provide a comprehensive review of different EVCS recommendation systems, including algorithmic and optimization frameworks, and recent deep learning (DL), multi-agent reinforcement learning (MARL), federated learning (FL), and blockchain approaches. Furthermore, this survey provides a unified problem formulation for EVCS recommendation systems and examines the performance of different recommendation categories in terms of reliability, cost-saving, and availability scores. Moreover, this paper reviews the characteristics of publicly available datasets in this realm and provides future research directions for designing EVCS intelligent recommendation systems. Experimental results on the UrbanEV dataset show the superior performance of MARL methods compared with other baselines in terms of the considered key performance metrics.

1 | Introduction

In the automotive domain, electric vehicles (EVs) are represented as practical alternatives to internal combustion engine vehicles (ICEVs) [1]. The reason why electric vehicles are increasingly gaining popularity across the globe is that they do not emit any greenhouse gases and are relatively affordable. Global EV sales reached 17.8 million units in 2024, comprising nearly 20% of all new vehicle sales [1]. This growing adoption is reshaping transportation infrastructure worldwide, as reflected in Figure 1. Moreover, EVs produce less noise pollution and are

more energy-efficient. They convert about 85% of electrical energy into mechanical energy, whereas ICEVs convert only about 40% of their chemical energy [2]. EVs are also a more cost-effective option in the long term since they require comparatively low maintenance costs [3]. As the number of EVs increases, it becomes an operational challenge to direct all of them to the right charging station (CS) at the right time. With more vehicles charging at the same time in one particular region, demand peaks and overloads the power system [4]. Each driver has their own preferences, whether it is cost, charging speed, or

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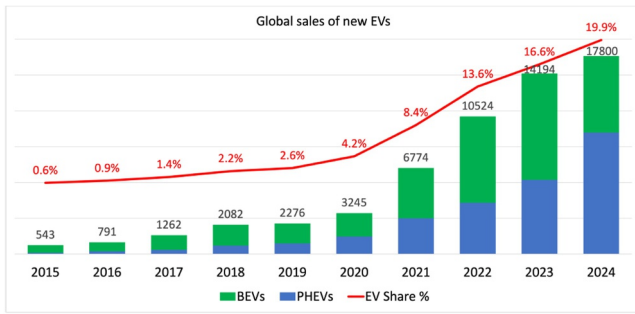


FIGURE 1 | Global sales of new electric vehicles (2015–2024). Global EV sales increased by 25% in 2024 to 17.8 million units, accounting for 19.9% market share, up from 4.2% in 2020 [1].

proximity to their route. Recommending the most suitable CS based on these preferences has become an important real-time decision problem.

To address this, researchers have directed attention to recommendation systems, which are generally developed to help users make better decisions based on their context and past behaviour. Recommendation systems can generally be classified into four categories including content-based filtering, collaborative filtering, knowledge-based recommendation systems, and hybrid recommendation systems [5]. In content-based filtering, recommendations are generated based on content that the user has shown an interest in, such as a streaming platform recommending movies with similar genres based on a user's historical activity. Collaborative filtering is a predictive approach that utilises data on user interactions, such as purchase history or ratings, to predict similar interests. For example, e-commerce platforms recommend products based on users' previous purchases [6]. Knowledge-based recommendation systems, on the other hand, provides multiple products and options based on what users need. For instance, while booking flight tickets, the system may also recommend potential hotel options according to a user's budget and location [7]. Hybrid approaches combine the advantages of different recommendation systems. This approach enhances the capability of the system by personalising it for each user and addressing data sparsity [5]. As the introduction of ML across different fields has improved overall performance, the implementation of ML in recommendation systems has played an important role. These ML models help capture complex non-linear relationships between users and items in large-scale applications such as video streaming and online advertising [8]. These principles across various recommendation systems enable developers to better understand the problem statement when developing domain-specific recommendation systems.

EVCS recommendations are built on these principles, but EV charging introduces real-world constraints that make direct application more complex. In traditional recommendation systems, items are always available. CS, however, have finite capacity and their availability changes by the minute. Charging an EV battery takes significantly longer than refuelling a conventional vehicle, which leads to long queues and poor station utilization. Even with more CSs available, demand tends to cluster in specific locations which overloads both station capacity and the power grid [4]. Figure 2 depicts an example of

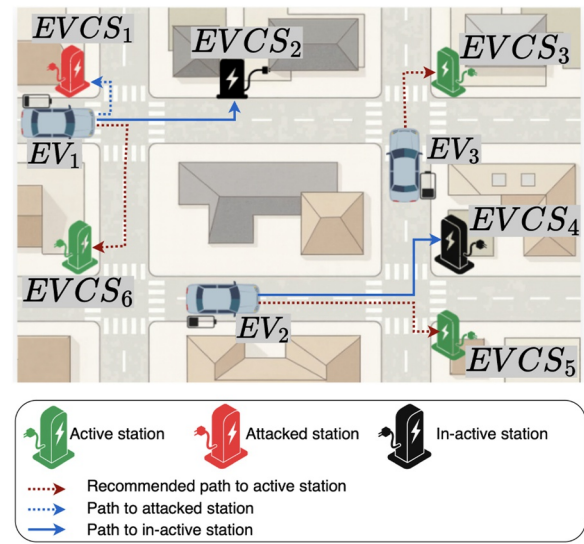


FIGURE 2 | Illustration of EV routing under heterogeneous EVCS states showing recommended paths within an urban road network.

EVCS routing in an urban environment with heterogeneous station states. For reducing wait times and even distribution of energy load on the grid, developing a recommendation system that efficiently routes drivers to the right CSs is essential. Developers must address real-time station availability, fluctuating energy prices, and varying driver preferences. These factors are interconnected, a driver's satisfaction depends on station availability and wait time. This motivates the need for intelligent data-driven approaches that go beyond traditional recommendation methods.

A variety of approaches have been explored to address the EVCS recommendation problem. These range from deterministic optimization methods that explicitly model multi-objective trade-offs, to Deep Learning (DL) models capable of capturing non-linear spatio-temporal demand patterns [9–11]. Reinforcement Learning (RL) and multi-agent systems enable decentralized agents to learn adaptive coordination strategies under uncertain conditions [12–14]. Distributed learning approaches such as Federated Learning (FL) have also been proposed to address privacy and data centralization concerns [15–17]. Blockchain-based mechanisms further provide secure and verified coordination across distributed participants [18, 19]. All these approaches differ in their assumptions about available data, scalability, and privacy requirements [20, 21]. A part of the problem is addressed by each method, with each involving its own trade-offs between accuracy, scalability, privacy, and computational cost [20, 22]. The suitability of each approach depends heavily on the deployment context, such as network size, available infrastructure, and the sensitivity of user data [20]. Their relative advantages and limitations must be understood for designing robust and intelligent EV charging ecosystems.

This paper presents the first structured survey focused specifically on EVCS recommendation systems. It systematically reviews existing approaches, categorizing them according to their modelling assumptions, learning frameworks, scalability characteristics, privacy considerations, and communication requirements. To the best of our knowledge, this is the first survey to

provide a unified evaluation framework comparing EVCS recommendation methods across standardized real-world datasets, assessing their relative strengths and limitations under practical deployment scenarios. Finally, key research gaps are identified and future directions are outlined toward building scalable, privacy-aware, and intelligent EV charging recommendation ecosystems.

The rest of the paper is structured as follows. In Section 2, the various types of EV and CS are introduced. In Section 3, the details of different intelligent approaches used to solve the EVCS recommendation problem are explained. In Section 4, a variety of real-world and simulated datasets are discussed. In Section 5, the performance of different groups of data-driven recommendation algorithms is evaluated. In Section 6, future research directions are provided. Finally, Section 7 concludes our paper.

2 | Types of Electric Vehicles and Charging Stations

The advancement in technology and growing utilization of available resources have led to evolution of EVs over time. Nowadays, there are variety of EVs available based on different types, energy resource utilization and its connectivity with the power grid [23]. CSs have also advanced alongside the vehicles. To develop a reliable and intelligent EVCS recommendation systems, it is crucial to highlight the objective of the recommendation system as well as different categorise EVs and CSs. An intelligent EVCS aims to maximise user's utilities such as cost, speed, and convenience, while keeping physical and environmental factors into consideration such as wait time, grid capacity, and battery health. This intelligent system must provide an optimal recommendation that considers all factors based on an objective function [20, 21]. To address this multi-objective recommendation problem, the distinction between EV types and EVCS variants is important as different categories could impose different constraints on the feasible and optimal solution. For example, different EV categories differ in battery capacity, acceptable charging power, connector standards; an optimal recommendation must consider these factors in finding the feasible solution. Additionally, different classifications of EVCS, based on multiple factors such as grid integration setup, affect a station's real-time pricing and availability and are fed into the recommendation algorithms [21]. Moreover, factors such as vehicle-to-grid (V2G) capability and mobile station deployment expand the decision space for further exploration of recommendation systems. These factors introduce bidirectional energy flow and enable stations that can be moved on demand [24]. To further clarify these distinctions, this section provides a classification of EVs and EVCS based on their characteristics.

2.1 | Classification of EVs

According to their primary energy source and engine type, EVs can be broadly categorised into three major types [25, 26].

2.1.1 | Hybrid Electric Vehicles (HEVs)

An HEV uses both an ICE and an electric motor to power the vehicle [27]. During acceleration and low-speed operation, the

electric motor assists the engine to improve fuel efficiency and reduce emissions. When the vehicle is in motion, the battery recharges through regenerative braking and the engine. Most HEVs depend on internal charging mechanisms rather than external grid connections, which means their interaction with public charging infrastructure is limited and they rarely need public charging stations [28]. Since HEVs do not rely on external charging, they are less relevant to EVCS recommendations compared with plug-in electric vehicles.

2.1.2 | Plug-In Electric Vehicles (PEVs)

PEVs are the main users of CSs as they get their power directly from the power grid [29]. There are two types of PEVs, Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs). BEVs rely entirely on electricity and have no combustion engine, so they need to charge regularly and their charging demand is higher than other EV types. PHEVs use an electric motor as the main power source but also have a petrol engine as a backup. The car switches to petrol when the battery runs out. PHEVs charge faster and less frequently because they have smaller batteries than BEVs.

2.1.3 | Fuel Cell Electric Vehicles (FCEVs)

FCEVs generate their own electricity onboard using hydrogen fuel cells [27]. When hydrogen and oxygen react inside the fuel cell, the electricity generated powers the motor. To handle short bursts of power and capture energy from braking, a small battery or supercapacitor is included. Although BEVs and PHEVs plug into the grid, FCEVs refuel at hydrogen stations instead. This means they require a completely different type of infrastructure. Some FCEVs that combine a fuel cell with a larger battery may still involve limited charging interactions.

2.2 | Classification of EVCS

EVCS, also known as Electric Vehicle Supply Equipment (EVSE), forms the backbone of EV charging infrastructure. EVCS classifications are based on factors such as electrical configuration, grid integration, charging speed, infrastructure architecture, mobility, and power flow direction.

2.2.1 | Based on Power Supply Type

Regarding the type of electrical supply delivered to the vehicle, CSs can be classified into two main types [30]. Alternating Current (AC) stations provide the AC to the vehicle and then it converts that AC power into Direct Current (DC) before storing it in the battery. As the conversion takes place inside the car and is limited by the onboard charger, and generally, AC charging stations are slower. This is the reason behind AC stations being commonly deployed at homes, workplaces, and parking lots where cars are parked for longer periods. Unlike AC stations, DC stations supply power directly to the battery without going through the car's converter, making DC charging much faster. As a result DC stations are usually placed where drivers need to charge quickly, such as on highways, in city charging hubs, and at busy commercial locations.

2.2.2 | Based on Grid Integration

EVCSs are categorised into on-grid, off-grid, and microgrid EVCS, according to the interaction between internal and external power supply [31]. On-grid EVCSs are directly connected to the utility grid and depend entirely on the distribution network. These are the standard EVCS type, as they convert AC from the grid to DC, and they are located in highly developed, stable, and easily accessible environments. Off-grid EVCSs generate their own power by utilising renewable energy sources (RES) such as solar panels or wind turbines. The generated energy is then stored in batteries known as energy storage systems (ESS). During the day, the ESS recharges using RES and, when needed supplies this stored energy to the vehicle such systems are typically deployed in remote highway, public, and restricted-access areas. Microgrid EVCS combines both approaches and it takes advantage of the local utility grid while simultaneously generating and storing its own power. Based on the available resources, its intelligent system decides whether to draw from the grid, RES, or ESS. This makes microgrid EVCS the most reliable option compared with on-grid and off-grid systems, since it remains functional both when the local grid is available and in its absence, as it can draw on stored power when needed.

2.2.3 | Based on Charging Power Level

EVCSs are categorised into three levels of charging based on multiple factors such as the type of current flowing through the CS cable, charging speed, and grid voltage [32]. Standard AC charging is Level 1, which has low throughput with single-phase AC flow and is located in residential areas. Since these utilise the electrical outlets at home, electricity flow is lower, leading to slower charging of the vehicle. Accelerated AC charging is Level 2, which provides optimal daily throughput and is deployed in residential and commercial areas with higher voltage and faster charging speed. These use larger outlets, having a steadier and stronger flow of energy. This is the most reliable level of charging, as it has the perfect balance of voltage flow and charging speed without accelerating battery degradation or triggering high electricity demand. DC Fast Charging (DCFC) is Level 3, with high throughput of DC delivered directly to the vehicle's battery, and is installed for long-distance travel, highways, and commercial use. This level is the fastest charging level, as it charges vehicles within minutes. These CSs have heavier and thicker cables for handling the high electrical supply passing through them.

2.2.4 | Based on Infrastructure Deployment

CSs can also be classified according to how they are deployed across transportation networks [33]. Distributed charging stations are spread across different locations such as homes, workplaces, parking facilities, and other decentralised locations, making charging more accessible to drivers. This allows EV users to charge close to where they spend most of their time. On the other hand, dedicated fast charging facilities consist of multiple high power CSs located strategically along highways, major transportation corridors, and high demand urban areas. These facilities are designed for long distance travel and rapid charging needs as they serve a large number of EVs within a short period of time. An alternative to conventional plug-in

charging is battery swapping infrastructure, where depleted batteries are replaced with fully charged ones. This approach reduces vehicle downtime since the battery exchange process is faster than conventional charging. However, it only works if battery designs are standardized, vehicles are compatible, and enough charged units are kept in stock.

2.2.5 | Based on Mobility

CSs are classified into two categories according to their mobility and deployment flexibility, Fixed CSs and Mobile CSs (MCSs) [34]. Fixed CSs are permanently installed at designated locations such as residential areas, workplaces, public parking facilities, commercial centres, and highway corridors. These stations form the primary infrastructure of most EV charging networks by providing reliable charging access at stable predictable locations. MCSs can be deployed and moved based on requirements and charging demand [34]. They are useful in areas with limited fixed CSs, during peak demand periods, at events, or in emergencies. This flexibility helps operators improve service coverage and reduce congestion at locations where fixed charging capacity is insufficient.

2.2.6 | Based on Power Flow Direction

CSs can be unidirectional or bidirectional depending on the direction of energy flow between the electrical grid and the EV battery [30]. In unidirectional charging, electricity flows from the grid to the battery, whereas in bidirectional charging, EV batteries can both receive and return electricity to the grid. Bidirectional charging is commonly referred to as vehicle-to-grid (V2G). Unidirectional charging represents the standard charging configuration used by most residential, workplace, and public CSs. EVs can support grid stability through V2G operation by supplying stored energy during periods of high demand. With a growing number of EVs, V2G has emerged as a promising approach for supporting grid services such as frequency regulation, peak load management, and energy trading.

3 | Intelligent Electric Vehicle Charging Station Recommendation Approaches

This section provides details on different approaches for designing intelligent EVCS recommendation systems. These include conventional optimization and heuristic methods, data-driven techniques such as DL and RL, FL frameworks, and blockchain-based mechanisms. Optimization methods typically use mathematical models and search strategies to identify suitable charging decisions, whereas learning-based methods use historical and real-time data to adapt to changing charging conditions.

3.1 | Algorithmic and Optimization Based Methods

Heuristic methods have long been used for solving the EVCS recommendation problem, especially in scenarios where decision-making must occur in real-time under dynamic and uncertain conditions [35]. Their main purpose is to identify an optimal or near-optimal CS for each EV while reducing travel time, waiting delay, and charging cost and maintaining balanced station utilization. Unlike RL-based methods, heuristic

approaches do not require large training datasets or repeated learning from environmental feedback. Instead, they use deterministic rules, mathematical heuristics, or metaheuristic search procedures to explore possible charging assignments. These methods are generally flexible and relatively easy to design, but they can become computationally demanding when many EVs and CSs must be coordinated at the same time. Even so, they remain useful because they can produce near-optimal solutions without the data requirements of learning-based approaches, making them suitable for many real-time charging decision problems.

Formally, the EVCS recommendation problem can be expressed as a constrained multi-objective optimization problem. Let $\mathcal{N} = \{1, 2, \dots, N\}$ represent the set of EVs and $\mathcal{M} = \{1, 2, \dots, M\}$ denote the set of available CSs. For each EV $i \in \mathcal{N}$, a binary decision variable x_{ij} is introduced to indicate whether EV i selects station j , defined as [36]

$$x_{ij} = \begin{cases} 1, & \text{if EV } i \text{ chooses station } j, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The weighted-sum scalarization of the multi-objective EVCS optimization problem can then be formulated as

$$\begin{aligned} \min_{x_{ij}} \quad & F = \sum_{i=1}^N \sum_{j=1}^M x_{ij} (\alpha_1 T_{ij} + \alpha_2 W_j + \alpha_3 P_j), \\ \text{s.t.} \quad & \sum_{j=1}^M x_{ij} = 1, \quad \forall i \in \mathcal{N}, \\ & \sum_{i=1}^N x_{ij} \leq C_j, \quad \forall j \in \mathcal{M}. \end{aligned} \quad (2)$$

Here, T_{ij} represents the estimated travel time from EV i 's location to station j , W_j denotes the expected waiting time at station j , and P_j is the charging price. The coefficients $\alpha_1, \alpha_2, \alpha_3 > 0$ incorporate the appropriate units/scales and evaluate the trade-off between travel efficiency, waiting time, and cost minimisation. The first constraint ensures that each EV selects exactly one station, whereas the second guarantees that the number of EVs assigned to a station does not exceed its service capacity C_j .

Since this problem is combinatorial and non-convex, obtaining the exact optimal solution becomes computationally expensive for large-scale systems [37]. To tackle this, heuristic and metaheuristic algorithms approximate the optimum by iteratively exploring the solution space utilising guided stochastic or deterministic rules. Two primary heuristic approaches for solving the EVCS recommendation problem are: (i) constructive and route-based metaheuristic algorithms and (ii) two-stage or metaheuristic algorithms that combine exact optimization with heuristic refinement.

In the first category, constructive and route-based metaheuristics build feasible solutions by repeatedly expanding and refining candidate paths according to a composite cost function. Common algorithms in this category include A*, Dijkstra-based search, Genetic Algorithms (GA) [38], Particle Swarm Optimization (PSO) [39], and Ant Colony Optimization (ACO) [40]. For the A* formulation, the route expansion is guided by an

evaluation function $f(n) = g(n) + h(n)$, where $g(n)$ is the travel cost from the source node to the current node n and $h(n)$ estimates the remaining cost to reach the target CS. This allows efficient exploration of feasible paths while reducing unnecessary search effort. Similarly, in population-based metaheuristics such as ACO or PSO, candidate routes are treated as solutions that evolve over successive iterations based on experience. For example, in the ACO framework, each artificial agent probabilistically selects the next station according to pheromone levels and heuristic desirability, which are updated as [40]

$$\tau_{ij}(t+1) = (1 - \rho)\tau_{ij}(t) + \Delta\tau_{ij}(t), \quad (3)$$

where $\tau_{ij}(t)$ represents the pheromone intensity between nodes i and j at iteration t , $\rho \in (0, 1)$ is the evaporation rate controlling exploration, and $\Delta\tau_{ij}(t)$ indicates the reinforcement based on route quality. Also, in PSO, each particle represents a potential route, and its position and velocity are updated using [39]:

$$v_i^{(t+1)} = \omega v_i^{(t)} + c_1 r_1 (p_i^{\text{best}} - x_i^{(t)}) + c_2 r_2 (g^{\text{best}} - x_i^{(t)}), \quad (4)$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}, \quad (5)$$

where $v_i^{(t)}$ and $x_i^{(t)}$ represent the velocity and position of particle i at iteration t , ω is the inertia weight, c_1 and c_2 are acceleration coefficients, and $r_1, r_2 \sim \mathcal{U}(0, 1)$ introduce stochastic variability. Here, p_i^{best} denotes the personal best position found by particle i so far, whereas g^{best} represents the best solution identified among all particles in the swarm. Through repeated iterations, the particles or agents leads to high-quality charging paths that minimise cost, waiting time, and travel distance.

The second category to solve the EVCS recommendation problem involves a two-stage or metaheuristic algorithm which combine global route optimization through mathematical programming with local improvement using heuristic refinements. In these methods, the first stage focuses on global decision making, such as route construction, clustering, or path feasibility using exact methods such as Mixed-Integer Linear Programming (MILP). The second stage then refines the charging sequence or recharging decisions through local search, insertion, or neighbourhood optimization techniques. The first stage optimization can be represented as

$$\min \sum_{(i,j) \in E} c_{ij} y_{ij}, \quad (6)$$

subject to flow conservation and energy feasibility constraints, where $y_{ij} \in \{0, 1\}$ denotes whether edge (i, j) is traversed and c_{ij} corresponds to the composite cost combining travel time, battery consumption, and charging expense. The local improvement phase seeks to reduce the total route cost through small modifications and can be expressed as

$$\Delta C = \min_{\text{swap}(i,j)} [F_{\text{new}} - F_{\text{current}}], \quad (7)$$

where the operator $\text{swap}(i, j)$ adjusts intermediate charging nodes to reduce the total objective function F . Here, F_{current} represents the total weighted cost of the existing route (as defined in Equation 2), and F_{new} is the total weighted cost of the

candidate solution after the $\text{swap}(i, j)$ operation is performed. Using global optimization with localised heuristic refinement, two-stage approaches can effectively manage the trade-off between computational complexity and solution precision. In EVCS recommendation, these search and refinement approaches are applied to candidate charging routes and station assignments, where the quality of each solution is evaluated using the objective function F in Equation (2). Specifically, the evaluation considers the travel time T_{ij} , expected waiting or charging delay W_j , charging price P_j , battery consumption and charging expense component c_{ij} , and station capacity constraint C_j . Therefore, candidate solutions are constantly improved to reduce the weighted EVCS cost while satisfying the assignment and capacity constraints.

Several studies have applied these methods to different aspects of the EV charging recommendation problem. For example, Chen [41] focused on improving the A* algorithm for optimal charging path planning. They used optimization goal-directed, linear, and exponential adaptation strategies to address low search efficiency and premature convergence, which resulted in a significantly improved path search efficiency. Similarly, Tan et al. [42] extended the ACO framework by proposing an Improved ACO (IACO) algorithm. They also used a discrete electricity dynamic programming (DE-DP) method to determine suitable charging times at chosen stations. Their combined approach delivered superior performance in EV routing and charging optimization. For routing problems with time windows, Schneider et al. [43] developed a hybrid heuristic that combines Variable Neighbourhood Search with a Tabu Search heuristic to solve the electric vehicle-routing problem with time windows and recharging stations (EVRPTW). Their method performed well on newly designed as well as benchmark instances of related problems. Furthermore, for multi-objective optimization, Chakraborty et al. [44] proposed a graph-based multi-objective heuristic algorithm (MoHA) for intelligent charge scheduling, where their energy-aware variant achieved 32.39% better results in minimising energy consumption compared with benchmarks. Their time-aware-MoHA performed better in optimising average time requirements by 24.32%. Addressing the need for real-time responsiveness, Dastpak et al. [45] developed a reoptimisation algorithm that uses real-time Occupancy Indicator (OI) information from CSs to dynamically adjust routes, which reduced waiting times by an average of 23.7%–95.4% and total trip duration by 1.4%–18.5%. Furthermore, preference based recommendation models have also been explored. For example, Ibrahim et al. [46] introduced a recommendation system based on a Restricted Boltzmann Machine optimised with the Waterwheel Plant Algorithm to provide personalised EVCS suggestions utilising real-time availability and user preference data. Similarly, a user preference-based CS recommendation scheme integrating analytical hierarchical process and technique for order of preference by similarity to ideal solution was proposed by Habbal and Alrifai [47] for ranking CSs according to charging time, waiting time, cost, and nearby facilities.

For large and highly constrained problems, exact optimization methods can become difficult to solve within a practical time. In these cases, metaheuristic approaches are often used to obtain good quality solutions more efficiently. Zhao and Lu [35] studied a real-world electric vehicle routing problem (VRP) that

included features of capacitated VRP (CVRP), time windows, heterogeneous fleets, and multi-trip requirements. They developed an Adaptive Large Neighbourhood Search (ALNS) heuristic with Integer Programming refinement, which achieved savings of 7.52% of operational cost on real-world instances. Similarly, Keskin and Çatay [48] combined ALNS with the CPLEX solver to address the EVRPTW with partial and fast recharges, demonstrating the effectiveness of the metaheuristic and the benefits of fast chargers on fleet size and cost. Two-stage solution methods have also been explored; for instance, Xia et al. [49] developed a two-stage heuristic (TSH) with a pseudo-node model that divides the EVRP into a CVRP and a Fixed Route Vehicle Charging Problem. Their algorithm outperformed state-of-the-art methods and even updated the best-known solution in one test case. Similarly, Luo et al. [10] also developed a two-stage heuristic. They used dynamic programming to solve the EVRPTW with heterogeneous recharging stations, which resulted in reduced travel and total recharging costs.

Heuristic approaches are useful because they are relatively simple to implement and can generate solutions quickly for small-to medium-scale problems. Their rule-based design makes them easy to deploy in scenarios without extensive training data. However, their primary limitation lies in two areas: (i) their reliance on fixed design rules and the absence of adaptive learning capability from historical experiences or unseen conditions and (ii) for large-scale applications, these optimization methods become computationally intensive and struggle with scalability as the number of EVs or CSs grows. The iterative search process results in high computational complexity that is unsuitable for continuous real-time coordination in large dynamic environments [37]. These limitations, particularly the inability to learn an optimal long-term policy from continuous environmental feedback, motivate the transition to learning-based solutions, where decision-making evolves through continuous interaction. Among the optimization based studies reviewed in this subsection, IACO [42] and ALNS [48] are later selected as representative heuristic and metaheuristic baselines for the comparative evaluation in Section 5.3.

3.2 | Deep Learning

DL is useful for modelling the complex and nonlinear behaviour of EV charging systems, particularly when spatial demand patterns, temporal charging behaviour, and network-level relationships must be considered together. Unlike heuristic methods, DL learns a parametric function $f_\theta : \mathcal{X} \rightarrow \mathcal{Y}$ that maps high-dimensional input features to an output decision. A DL based EVCS recommendation architecture is illustrated in Figure 3. Input features typically include the EV's current location, remaining battery range, estimated travel time to each station, expected waiting time, and station-specific charging price. The output is typically represented as the predicted utility of each CS or a direct station recommendation. The parameters θ are obtained by minimising an objective function of the form:

$$\theta^* = \arg \min_{\theta} \frac{1}{N} \sum_{i=1}^N \ell(f_\theta(x_i), y_i), \quad (8)$$

where $\ell(\cdot)$ represents a loss function such as mean squared error (MSE) or cross-entropy, depending on the decision task. In the

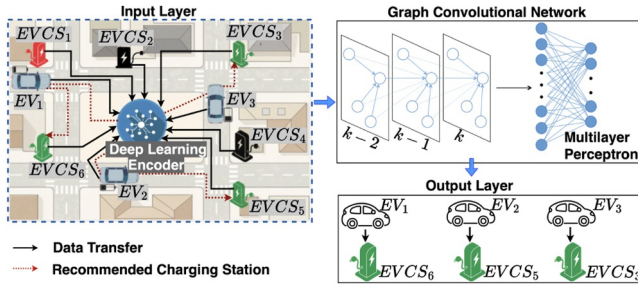


FIGURE 3 | Architecture of the deep learning based EVCS recommendation framework.

EVCS recommendation context, the input vector x_i for sample i may include the EV location L_i^{loc} , remaining battery range r_i , estimated travel time T_{ij} to candidate station j , expected waiting time W_j , charging price P_j , and station condition variables such as availability A_j and utilization level U_j . Depending on the learning task, the target variable y_i may represent future station occupancy $O_j(t + \Delta t)$, predicted queue delay $\widehat{W}_j(t + \Delta t)$, charging availability $A_j(t + \Delta t)$, or a utility score u_{ij} used to rank candidate CSs.

Since EV charging demand evolves over time, many studies such as [9, 50, 51] employ Recurrent Neural Network (RNN) [52] architectures, most notably Long Short-Term Memory (LSTM) [53] networks to capture sequential patterns in historical traffic flow and charging queues. LSTM networks are specifically designed to capture long-term dependencies and sequential patterns in time series data, overcoming the vanishing gradient problem faced by traditional RNNs. The LSTM achieves this by regulating the flow of information through specialized internal structures called gates that manage cell memory (c_t) across time steps. The LSTM is defined by the update rules:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \quad (9)$$

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f), \quad (10)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o), \quad (11)$$

$$\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c), \quad (12)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \quad (13)$$

$$h_t = o_t \odot \tanh(c_t), \quad (14)$$

where x_t denotes the state of the EV system at time t , i_t , f_t , and o_t are the input, forget, and output gates, c_t is the cell memory, and h_t is the latent state representation used for forecasting future station loads or waiting times for proactive CS recommendations.

However, time-series reasoning alone is insufficient for EV station selection because spatial topology plays a critical role. Recent studies use Graph Convolutional Networks (GCNs) [54, 55] to capture spatial relationships within EV charging networks. In the context of an EV charging ecosystem, GCNs treat CSs as nodes and the distance between CSs as weighted edges. These networks leverage the graph structure to capture spatial correlations between neighbouring stations, such as how congestion at one station affects nearby demand. This allows the model to learn localised features by aggregating information from adjacent nodes across the graph. Let the charging network be represented as a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with adjacency matrix A ,

where $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ is the set of edges. A GCN layer computes:

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2} H^{(l)} W^{(l)}), \quad (15)$$

where $\tilde{A} = A + I$, $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$ corresponds to the degree matrix, $H^{(l)}$ represents spatial feature matrix at layer l , and $W^{(l)}$ denotes the learnable weight matrix. This propagation mechanism diffuses spatial information across connected stations, enabling the model to learn correlations such as congestion propagation, demand clustering, and regional utilization patterns.

More recently, transformer [56] based architectures have gained prominence due to their ability to jointly capture long-range temporal dependencies and complex spatial interactions. Although LSTM processes input sequences (or ‘tokens’) sequentially, which limits its ability to model very long-term dependencies and parallel computation, the Transformer architecture overcomes these limitations by processing all tokens simultaneously. The Transformer achieves this capability through its core component, the self-attention mechanism, which allows every element in the input sequence to weigh the influence of every other element. In the context of EV charging, each token represents a spatio-temporal snapshot of the system, encoding variables such as the EV’s current position, remaining battery range, or estimated travel and waiting times. Using the self-attention mechanism:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \quad (16)$$

where Q , K , and V represent the query, key, and value matrices extracted from linear projections of the input embeddings, and d_k denotes the dimensionality of the key vectors. By calculating pairwise interactions between all tokens simultaneously, transformers capture long-range dependencies which are difficult for recurrent or convolutional models to learn, enabling more accurate forecasting of future congestion patterns and CS availability. These predicted spatio-temporal patterns can then be used to rank candidate CSs according to expected travel time, waiting delay, charging availability, and charging cost, thereby supporting EVCS recommendation decisions.

Unlike algorithmic and optimization-based methods, DL models learn nonlinear relationships directly from data, which can support more adaptive and accurate CS recommendations. Recent studies have applied these models to capture the combined temporal and spatial behaviour of EV charging networks. For instance, Al-Zuhairi et al. [9] combined Bi-LSTM and XGBoost models to predict energy consumption and identify optimal CSs by minimizing total travel time, considering queue wait times and charging speeds. Their approach outperformed conventional approaches that rely on mathematical calculations by reducing the Mean Absolute Error (MAE) of the total travel time from (5.1, 10) to (2.29, 4.5) minutes. Similarly, Kumari [50] used Random Forest, Linear Regression, and LSTM models to forecast CS availability with 87.4% accuracy. In another study, to enhance prediction stability and adaptivity, Joseph and Sebastian [51] combined auto-regressive models and LSTM with

Transfer Learning (TL) techniques. Their approach provides accurate 1-hour-ahead availability insights for EV charging activities.

Many earlier studies focus mainly on temporal prediction at individual CSs and do not fully capture the spatial relationships across the charging network. To address this, recent studies have increasingly adopted GCNs to model CSs as nodes and road connections as edges, enabling dynamic context-aware decision-making. For example, the Attribute-Augmented Spatio-temporal Graph Informer (AST-GIN) proposed by Luo et al. [10] combines the GCN layer and the Informer layer to extract both the external and internal spatio-temporal dependence of the relevant transportation data. The effectiveness of the model was tested using the Dundee City dataset, in which the model outperformed the best baseline model with an 8.97% higher accuracy. Similarly, an explainable, context-aware Graph Neural Network (GNN) approach (BiLSTM-Ensemble) was introduced by Kapoor [57] to optimize the EV routing by dynamically integrating contextual data in real-time, resulting in an 18.5% decrease in travel duration and a 22.3% decrease in charging waiting times compared with the shortest-path models. In addition, Douaidi et al. [58] proposed BipartiteSAGE, a two-stage GNN-based framework for EVCS recommendation. The first stage constructs a bipartite user-station graph to capture interaction dependencies and generate personalized charging recommendations using a GNN model. The second stage applies an optimization algorithm to assign users to stations while considering availability and proximity constraints. Experimental results demonstrated superior performance in recommendation accuracy and waiting-time reduction compared with baseline approaches. Furthermore, GCN has also been leveraged within a Deep Reinforcement Learning (DRL) framework to efficiently compress the complex system graph information into a compact state space vector. Specifically, work by Yuan et al. [59] demonstrated that this integration enables the DRL agent to solve the EV navigation problem efficiently and minimize the overall travel and charging costs.

Although graph and recurrent models address many spatio-temporal challenges, RNNs process sequences step by step, which can limit their ability to capture very long-range dependencies and reduce parallel processing efficiency. For this reason, recent studies have incorporated the Transformer's self-attention mechanism to model dynamic EV charging environments. For example, Zhang et al. [11] developed a heuristic algorithm with enhanced graph transformer networks (GTN-HA), leveraging the GTN's ability to incorporate time windows and constraints to generate robust initial solutions for the Dynamic EV Routing Problem. Similarly, studies solving the EV Routing Problem with Time Windows (EVRPTW) have shown that the Transformer's heterogeneous attention mechanism excels at capturing long-term dependencies [60]. Furthermore, a transformer-based DL model was employed by Yap et al. [61] to jointly solve the EV routing and scheduling problem. They worked on varying fleet sizes, demonstrating the transformer's crucial flexibility and generalizability essential for real-world scenarios. Among the DL based studies reviewed in this subsection, BipartiteSAGE [58] and BiLSTM-Ensemble [57] are later selected as representative DL baselines for the comparative evaluation in Section 5.3.

3.3 | Reinforcement Learning

RL provides a framework for modelling the EV charging recommendation problem, where each EV must decide which CS to visit under uncertainty in demand, availability, and cost of different CSs. This problem can be formulated as a Markov Decision Process (MDP) [62], $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{P}, R, \gamma \rangle$, where an EV acts as an autonomous agent interacting with an environment consisting of available CSs, their queue lengths, pricing policies, and the surrounding traffic conditions. At each time step t , the EV observes a state $s_t \in \mathcal{S}$, which includes its current location, battery state of charge, and the status of nearby stations. Based on this observation, the EV selects an action $a_t \in \mathcal{A}$, corresponding to the choice of a CS. The system then transitions to a new state s_{t+1} , for example reflecting the EV's arrival at the chosen station and the resulting change in queue length, according to the transition dynamics $\mathcal{P}(s_{t+1}|s_t, a_t)$. The EV receives a reward $R(s_t, a_t)$ that evaluates the quality of the decision in terms of reduced travel time, minimised waiting time, and lower charging costs. The objective is to learn an optimal policy $\pi(a|s)$ that maximises the expected discounted return:

$$J_\pi = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \right]. \quad (17)$$

where $\gamma \in [0, 1)$ is the discount factor balancing immediate utility against long-term efficiency.

Several studies have applied single-agent deep RL to EVCS recommendation within the MDP formulation. Fan et al. [63] developed an actor-critic framework that incorporates spatio-temporal preference modelling for personalised CS selection. By considering both user preferences and environmental costs, their approach achieved superior performance compared with existing baselines. Erüst and Taşçıkaraoğlu [64] proposed a spatio-temporal navigation method based on phasic policy gradients to reduce charging and travel costs under uncertain traffic and electricity price conditions. Their model achieved higher rewards and lower travel times than proximal policy optimization. Furthermore, a data-driven city-scale DRL system was developed by Nie et al. [65] to jointly optimise driver welfare and grid efficiency. Leveraging multi-source urban datasets, the framework reduced driver-to-charger distance and improved charging stability in large-scale deployments. Similarly, Wang et al. [66] formulated large-scale electric bus charging scheduling as an MDP and achieved significant reductions in charging cost and electricity usage using real-world operational data from Shenzhen. These approaches demonstrate the effectiveness of RL for adaptive charging decisions in dynamic environments.

In realistic transportation networks, however, the decision problem involves many EVs interacting simultaneously. Each EV seeks to minimise its own cost and delay, but its choice of CS influences the experiences of other vehicles by altering queue lengths, energy demand, and station availability. This interdependence transforms the problem into a Multi-Agent Reinforcement Learning (MARL) setting which is mathematically formalised using a Markov Game [67], $\mathcal{G} = \langle \mathcal{N}, \mathcal{S}, \{\mathcal{A}_i\}_{i=1}^N, \mathcal{P}, \{R_i\}_{i=1}^N, \gamma \rangle$, where the set of EVs $\mathcal{N} = \{1, 2, \dots, N\}$ constitutes the agents. At each timestep, the environment is in state $s_t \in \mathcal{S}$,

each EV i selects a CS $a_i^t \in \mathcal{A}_i$, and together the EVs form a joint action $\mathbf{a}_t = (a_1^t, \dots, a_N^t)$. The transition dynamics $\mathcal{P}(s_{t+1}|s_t, \mathbf{a}_t)$ capture how the system evolves as EVs arrive at different stations, generating new queue distributions and resource utilization levels. Each EV i receives an individual reward $R_i(s_t, \mathbf{a}_t)$, typically designed to capture its charging experience. The objective for EV i is to maximise its expected discounted return:

$$J_i^\pi = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t R_i(s_t, \mathbf{a}_t) \right], \quad (18)$$

where γ and $\pi = \{\pi_1, \pi_2, \dots, \pi_N\}$ denote the discount factor and the joint policy of all EVs. The overall MARL interaction process between EV agents and the charging environment is illustrated in Figure 4.

Training in MARL is commonly performed under the centralised training with decentralised execution (CTDE) [68] paradigm. During training, global system information, such as demand distribution and overall station occupancy, can be used to stabilise learning. During execution, however, each EV bases its decision only on its local observations, such as its own state of charge and nearby station information. This ensures scalability and practicality in real-world deployments, where full system knowledge is unavailable to individual drivers. The action-value function for EV i is defined as

$$Q_i^\pi(s, \mathbf{a}) = \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t R_i(s_t, \mathbf{a}_t) \mid s_0 = s, \mathbf{a}_0 = \mathbf{a} \right], \quad (19)$$

and policy optimization can be performed through gradient-based methods of the form:

$$\nabla_{\theta_i} J_i(\pi) = \mathbb{E}_{s \sim d^\pi, \mathbf{a} \sim \pi} [\nabla_{\theta_i} \log \pi_i(a_i | o_i) Q_i^\pi(s, \mathbf{a})], \quad (20)$$

where θ_i parameterises the policy of EV i and o_i denotes its local observation. Through repeated interactions, EVs collectively learn strategies that balance individual objectives with overall

network efficiency. By embedding the principles of RL into a multi-agent framework, the EVCS recommendation problem can be rigorously modelled as an MARL task. Each EV autonomously learns to select stations that minimise its travel time, waiting time, and cost, whereas the overall system benefits from reduced congestion and improved resource allocation.

The application of MARL to EV charging recommendation has been explored through several methodological directions. For instance, Park and Moon [12] proposed the COMA framework, a multi-agent deep RL approach with a centralised training and decentralised execution method that can derive charging schedules for each EV. Building on this foundation, more advanced approaches incorporated spatio-temporal modelling to capture the structural and temporal dependencies in EV mobility and station networks. For example, Zhang et al. [13] proposed the MASTER framework, where each CS is considered as an individual agent. They developed a multi-agent actor-critic framework with the centralised attentive critic to coordinate the recommendation between geo-distributed agents. To evaluate the effectiveness of the MASTER framework, they conducted extensive experiments on two real-world datasets collected from Beijing and Shanghai, achieving the best comprehensive performance compared with nine baseline approaches. Building on the need to model spatial dependencies in EV mobility, works by Xing et al. [69] and Li et al. [70] leveraged graph MARL to represent vehicle station interactions and network topology. Evaluations on large-scale datasets, such as charging transaction records from Xi'an and mobility traces from Shenzhen, demonstrated that these methods significantly improved system efficiency by distributing charging demand more evenly and alleviating congestion in high-traffic regions.

A limited number of studies have explored generative MARL methods. For example, Qi et al. [71], developed a novel generative model MARL algorithm that uses only the EV's local information to make decisions. Their framework combines a Conditional Variational Autoencoder Long Short-Term Memory (CVAE-LSTM) recommendation model with a novel competition encoder for training efficiency. Experiments using the Xi'an dataset showed that the method outperformed existing local information-based methods and achieved comparable results to state-of-the-art algorithms. Other studies have focused on uncertainty and charging scheduling. For example, Lee et al. [72] developed an adaptive charging scheduling strategy based on a multi-agent Rainbow Deep Q Network with Imparting Preference to select the CS and quantity based on dynamic prices and availability. Their method outperformed two benchmarks in terms of charging time, cost, and state-of-charge assurance in four scenarios using real-world data.

Beyond individual EV routing and decentralized decision-making, MARL has also been studied for system level optimization and charging demand balancing. Coulson et al. [73] developed a demand balancing system using various MARL algorithms to improve EV routing and reduce queuing time at CSs. Their best performing cooperative DQN model, evaluated on a real-world Berlin network, achieved a reduction of 88.09% in mean wait times compared with a greedy approach, demonstrating the system level benefits of cooperative strategies. Similarly, Suanpang and Jamjuntr [74] compared several

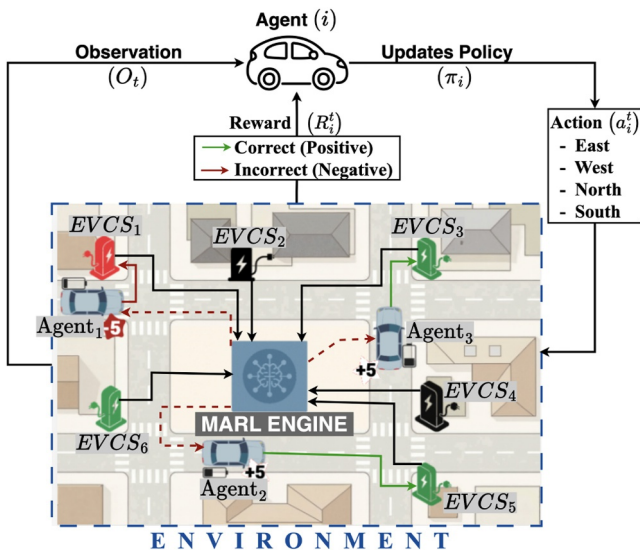


FIGURE 4 | Multi-agent reinforcement learning (MARL) framework for EVCS recommendation.

MARL algorithms for recommending EVCSs in smart cities. Their results showed that multi-agent deep deterministic policy gradient (MADDPG) performed better than the other evaluated methods for station placement and allocation. The approach achieved improved results for mean charging waiting time, Charging Fee Total (CFT), and Total Saving Fee.

MARL has also been extended to fleet-level charging problems, showing its potential to scale beyond individual vehicle decisions. Wang et al. [14] proposed a joint charging and relocation recommendation system for e-taxi drivers using a multi-agent Mean Field Hierarchical RL framework. Using data from Shenzhen e-taxi trajectory dataset, their study demonstrated scalability to thousands of agents and highlighted the potential of MARL in large-scale heterogeneous systems. Meanwhile, research has extended MARL beyond fixed stations and individual efficiency to address larger infrastructural and systemic challenges. Specifically, scheduling for Mobile Charging Stations (MCSs) to proactively track vehicles and enhance charging revenue was explored by Liu et al. [24]. The integration of real-time traffic conditions and routing decisions for adaptive charging recommendations was studied by Rabbani et al. [75], focusing on minimizing delays and improving travel efficiency. Across these diverse approaches, a consistent observation is that locally trained EV agents, even when optimizing selfish objectives, exhibit emergent cooperative behaviours that yield system-wide improvements in efficiency, fairness, and sustainability. Among the MARL based studies reviewed in this subsection, COMA [12] and MASTER [13] are later selected as representative MARL baselines for the comparative evaluation in Section 5.3.

Although MARL can achieve strong recommendation performance, it usually requires more computational resources and training effort than other approaches. Designing suitable reward functions and maintaining stable learning can also be difficult when many agents interact in large-scale environments. Therefore, FL and blockchain remain useful complementary options when privacy protection, secure decentralized coordination, or lower computational requirements are more important than highly adaptive real-time decision making.

3.4 | Federated Learning

As EV charging networks grow in size and become more geographically distributed data-driven decision-making faces increasing challenges related to scalability, privacy, and communication costs. Traditional centralised learning requires raw data from multiple participants to be sent to a central server for training, which may be difficult because of privacy regulations and bandwidth limitations [76–78]. FL addresses these concerns through a decentralised training process in which clients, such as EVs, CSs, or regional controllers, collaboratively train a shared model without exchanging their raw local data. Instead, each client performs training on its own dataset and sends only model updates or gradients to a central aggregator. The global FL objective can be written as the following optimization problem [76]:

$$\min_w F(w) = \sum_{k=1}^K \frac{n_k}{n} F_k(w), \quad (21)$$

where K denotes the total number of participating clients, n_k represents the number of data samples on client k , $n = \sum_{k=1}^K n_k$ is the total number of samples across all clients, and $F_k(w)$ is the local loss function for client k . The goal is to minimise the weighted sum of all local objectives to obtain a globally optimal model parameter w^* .

Each client performs local optimization by minimising its individual objective function:

$$F_k(w) = \frac{1}{n_k} \sum_{i=1}^{n_k} \ell(w; x_i^k, y_i^k), \quad (22)$$

where $\ell(\cdot)$ denotes the loss function evaluated over the local dataset $(x_i^k, y_i^k)_{i=1}^{n_k}$ of client k . The local parameters are then updated through Stochastic Gradient Descent (SGD) [79] as

$$w_k^{t+1} = w_k^t - \eta \nabla F_k(w_k^t), \quad (23)$$

where η is the learning rate, and $\nabla F_k(w_k^t)$ is the gradient computed over the local data.

After a predefined number of local iterations, all clients communicate their updated parameters to the central aggregator, which performs model aggregation using the Federated Averaging formulation denoted by:

$$w^{t+1} = \sum_{k=1}^K \frac{n_k}{n} w_k^{t+1}. \quad (24)$$

This aggregation step gives greater weight to clients with larger local datasets, which can improve the statistical quality of the shared model while preserving data privacy. The updated global model w^{t+1} is then sent back to all participating clients, and the process continues until convergence or a fixed number of communication rounds T is reached. For EVCS recommendation, each client $k \in \{1, \dots, K\}$ may correspond to an EV, a CS, a charging-network operator, or a regional controller. The local dataset (x_i^k, y_i^k) may include station occupancy $O_j(t)$, queue length $Q_j(t)$, charging duration $D_{ij}(t)$, electricity price $P_j(t)$, travel history features H_i^{trav} , mobility pattern features $M_i(t)$, and energy consumption data $E_i^{\text{cons}}(t)$. Depending on the application, the local objective $F_k(w)$ may be used to predict charging demand $\hat{D}_j(t + \Delta t)$, expected waiting time $\hat{W}_j(t + \Delta t)$, station availability $\hat{A}_j(t + \Delta t)$, or a utility score u_{ij} for ranking candidate CSs. By combining locally trained models, the global model can learn charging patterns across different regions without requiring participants to share raw mobility, transaction, or energy use data. These predictions may then support EVCS recommendation, charging scheduling, or MCS placement, as shown in Figure 5.

Several studies have explored the EVCS recommendation problem using an FL approach. For example, Wang et al. [17] developed a federated factorization machine that combines data and cross features from both EVs and CSs using encrypted entity alignment. Their results demonstrated a 6% improvement in Area Under Curve (AUC) compared with models using only CS side data, proving the value of joint analysis without raw data

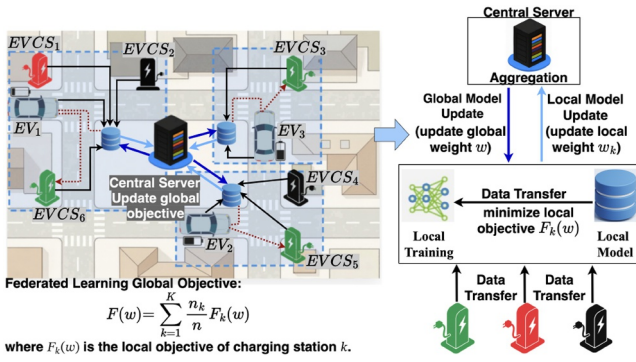


FIGURE 5 | Federated learning (FL) framework for EVCS recommendation.

exchange. A similar approach is presented by Teimoori et al. [80], which utilizes secure Vertical Federated Learning (VFL) to maintain data within the original platforms. They introduced VFL-Cloudlet, a cloudlet-based data aggregation and blockchain technology to replace centralized architectures. Their simulation results showed a 5.2 second reduction in processing time with 10 cloudlets compared with conventional centralized models.

Further enhancing security, Zhang et al. [16], proposed a hybrid security strategy for VFL that combines threshold Partially Homomorphic Encryption (PHE) and additive Secret Sharing Schemes (SSS). To reduce communication overhead, their method also uses asynchronous updates and gradient compression. They evaluated the framework on three datasets against four baseline models and reported strong recommendation accuracy, improved security, and lower communication costs. Similarly, Douaidi et al. [15] developed a federated DL framework using LSTM networks to predict station occupancy. They achieved an accuracy of 86.21% and an F1 score of 91.49%, while minimizing network transfer costs and maintaining privacy across CSs.

Expanding the scope to include MCS, Teimoori et al. [81] developed 6GFog-FL, a VFL system that recommends both stationary and MCS, utilizing fog-based aggregators and 6G communication to optimize EV distribution. Similarly, for MCS placements, Liu et al. [82] proposed a parallelized FL-based Placement Decision Method of Idle MCSs (FL-PDMIM) that takes advantage of historical routes to predict future charging positions for idle MCSs, significantly reducing waiting times and user expenses. Finally, Perry et al. [83], addressed data imbalance and changing temporal patterns through a trend-based clustering strategy within an FL framework. By grouping CSs with similar behaviour before training cluster-specific LSTM models, they reduced energy demand prediction error by 80%. Similarly, a real time distributed CS recommendation framework based on federated meta-RL was proposed by Zhang et al. [84]. Their approach allows CSs to learn adaptive recommendation policies collaboratively without sharing local data, reducing communication requirements while preserving privacy. Experiments on real-world datasets showed performance close to centralized approaches and improved charging duration reduction compared with existing distributed methods. Among the FL based studies reviewed in this subsection, VFL-Cloudlet

[80] and 6GFog-FL [81] are later selected as representative FL baselines for the comparative evaluation in Section 5.3.

3.5 | Blockchain

The expansion of distributed EV charging networks has increased the need for secure, transparent, and decentralised coordination among EVs, CSs, and grid operators. Centralised scheduling and optimization systems may be vulnerable to single points of failure, privacy risks, and limited transparency. Blockchain technology offers a distributed and tamper resistant ledger that can support secure energy trading, CS recommendation, and payment settlement without requiring a central trusted authority.

A blockchain can be represented as an ordered sequence of blocks [85]:

$$\mathcal{B} = (B_1, B_2, \dots, B_T), \quad (25)$$

where each block B_t contains a finite set of verified transactions $T_t = \{T_1, T_2, \dots, T_m\}$, a timestamp τ_t , and the cryptographic hash of the preceding block $H(B_{t-1})$. The hash value ensures immutability as any change in previous records would invalidate all subsequent hashes. Each transaction T_i is signed using the private key of the sender u_i , formulated by:

$$\text{Sig}_{u_i} = \text{Enc}_{K_{u_i}^{\text{priv}}}(H(T_i)), \quad (26)$$

Here, $K_{u_i}^{\text{priv}}$ is the private encryption key. Validation across the peer-to-peer network is achieved through a *consensus mechanism* such as Proof-of-Stake (PoS) or Practical Byzantine Fault Tolerance (PBFT) [86]. For a generic threshold-based abstraction, block validation can be represented as:

$$C(B_t) = \begin{cases} 1, & \text{if } \sum_{n \in \mathcal{N}_v} \text{vote}_n(B_t) \geq \theta, \\ 0, & \text{otherwise,} \end{cases} \quad (27)$$

where $\mathcal{N}_v$ denotes the set of validating nodes and θ is the minimum approval threshold.

Smart contracts (SC) are deployed on the blockchain to automate interactions among participating entities [87]. These self-executing protocols can manage tasks such as matching, reservation, and payment settlement once predefined conditions are met. Their execution logic can be expressed as

$$\text{SC}(T_i, \text{State}) \rightarrow \text{State}', \quad (28)$$

where the contract transitions the system from the current state (e.g., 'Available') to a new state (e.g., 'Reserved') upon the fulfilment of predefined conditions. In blockchain-enabled EV charging, each charging request can be formulated as a transaction tuple:

$$T_i = (EV_i, CS_j, E_{ij}, p_{ij}, t_{ij}), \quad (29)$$

where EV_i denotes the requesting vehicle indexed by i , CS_j is the selected CS indexed by j , E_{ij} represents the requested charging energy, p_{ij} is the agreed price, and t_{ij} is the timestamp of the transaction. Figure 6 illustrates the overall blockchain-

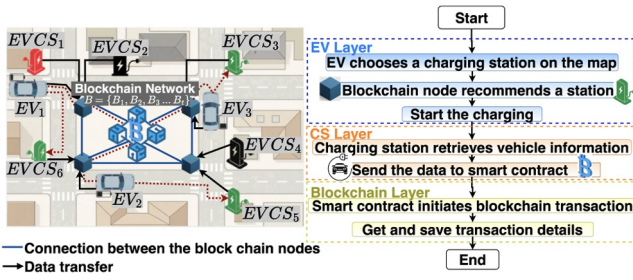


FIGURE 6 | Blockchain enabled EVCS recommendation and transaction workflow.

enabled charging and transaction process. In EVCS recommendation, this transaction structure enables the recommended charging decision to be securely executed after a station has been selected. Smart contracts can reserve the selected CS, confirm the requested charging energy and agreed price, record the charging session, and support payment settlement after service completion. Therefore, blockchain does not directly calculate the optimal CS recommendation; instead, it provides a secure, transparent, and auditable coordination layer for reservation, transaction execution, and service verification. Although blockchain improves transparency, additional privacy-preserving mechanisms, such as Zero-Knowledge Proofs (ZKPs), are often used to protect sensitive user data. For example, a vehicle can provide a proof π showing that it meets the financial and technical requirements for charging without revealing its identity [88]:

$$\text{Proof}(\pi) : \{\exists w, \text{St}(w) = \text{True} | \text{Public } \mathcal{V}\}, \quad (30)$$

where w represents the private witness data and $\mathcal{V}$ represents the public verification parameters. When blockchain is integrated with an EVCS recommendation engine, the underlying CS selection objective may minimise the joint charging cost and delay for all EVs, whereas blockchain provides the secure and auditable coordination layer, expressed as

$$\min_{x_{ij}} F = \sum_{i=1}^N \sum_{j=1}^M x_{ij} (\alpha_1 T_{ij} + \alpha_2 W_j + \alpha_3 p_{ij}), \quad (31)$$

subject to capacity and feasibility constraints identical to the multi-objective optimization problem in Section 3.1. Here, the blockchain acts as a trust layer, ensuring that each bid (p_{ij}, W_j) and station response are publicly auditable and immutable.

Blockchain technology has been applied across various dimensions of the EV ecosystem, ranging from secure energy trading to privacy-aware station recommendation. Several works focused on the use of smart contracts to facilitate machine-to-machine (M2M) negotiation without human intervention. For instance, Pustišek et al. [18] proposed an autonomous selection framework in which EVs execute smart contracts based on Ethereum to request bids from CSs along a planned route, selecting the optimal provider based on real-time price and waiting time parameters. This shift towards decentralised energy markets was further validated by Dorokhova et al. [19], who provided a real-world implementation of an Ethereum-supported framework in Switzerland. Their work demonstrated that Solidity-based smart contracts can significantly reduce costs and

accelerate billing processes in private and semi-private charging infrastructures.

Auction based models have also been used to address resource allocation challenges in EV charging systems. Guo et al. [89] proposed a double auction mechanism implemented on a Directed Acyclic Graph (DAG) blockchain. Their framework uses the Truthful Mechanism for Charging (TMC) and Efficient Mechanism for Charging (EMC) to support truthful bidding and efficient allocation even when charging pile capacity is limited. Similarly, Barnawi et al. [90] combined game theory with blockchain to manage demand response activities in vehicle-to-grid (V2G) environments. Their approach uses designated miner nodes and block verifiers based on processing capability to support secure energy trading and peak load management.

A primary motivation for blockchain adoption is the mitigation of privacy risks such as location leakage. To mitigate this challenge, Danish et al. [91] introduced a privacy preserving framework where EVs perform intelligent station selection locally, utilising the blockchain only for trusted reservations and secure services. This prevented the ‘centralised trust’ issue common in legacy systems. Addressing the risk of targeted advertisements and data selling, Li and Yang [92] combined the decentralised structure of blockchain with a K-anonymity based algorithm. Their approach ensured that a user’s precise location remained hidden while participating in the recommendation process, and was supported by an incentive mechanism to encourage vehicle participation. Similarly, Danish et al. [93] proposed BlockEV, a blockchain-based CS selection protocol that enables secure reservation and local station selection without exposing sensitive user information. The framework leverages smart contracts to guarantee trusted scheduling and Quality of Service while maintaining low transaction and storage overhead.

Recent research has also explored the intersection of blockchain with advanced heuristic optimization. For instance, Hamed et al. [94] proposed a novel Secure Optimization for EV Charging (SO-EVC) model, which utilises a novel ‘Fox Optimization Algorithm’ on the Ethereum blockchain (FOA-B). This model simultaneously optimises station locations and EV routing, achieving a high throughput of 1200 TPS and demonstrating resilience against common blockchain vulnerabilities such as selfish mining. Finally, to resolve scheduling conflicts at high-density stations, Kakkar et al. [95] proposed a novel ‘COME’ consensus mechanism. By integrating the InterPlanetary File System (IPFS) protocol for cost-efficient data storage and utilising algorithms such as coalition game theory, the COME mechanism outperforms traditional PBFT protocols in terms of scalability and bandwidth efficiency, ensuring conflict-free scheduling for both EVs and station operators. Among the blockchain-based studies reviewed in this subsection, K-Anon [92] and FOA-B [94] are later selected as representative blockchain baselines for the comparative evaluation in Section 5.3.

Although the methods reviewed in this section address the same EVCS recommendation problem, they are designed for different types of decisions and operating conditions. Algorithmic and optimization based methods are useful when the system objectives and constraints are known in advance and can be

expressed mathematically [20]. DL methods are commonly used to learn charging demand and station utilization patterns from historical spatial and temporal data [96]. MARL is better suited to dynamic settings in which multiple EVs or CSs must coordinate decisions in real time [22]. FL is valuable when participants need to build shared models while keeping their raw data local [21], whereas blockchain based approaches are primarily intended to support secure, transparent, and decentralised coordination [97]. Table 1 summarises the major differences, advantages, and recommended application scenarios of these approaches.

4 | Datasets

For assessing the performance of the different methods discussed in Section 3, researchers utilise a variety of real-world and simulated datasets. This section discusses those datasets that are typically used to evaluate EVCS recommendation methods.

- **Dundee City EV Charging Dataset [98]:** Provided by Dundee City Council, this dataset contains public EV charging session records from charging locations throughout Dundee. Although data collection began in 2021, the release in 2024 comprises over 113,000 unique charging sessions. Each record has a unique identifier and includes information such as the charging site name, charging-point ID, connector type, energy consumed in kWh, and session duration. These data are instructive as operational information to evaluate charging behaviours, usage, and demand patterns. Figure 7 shows the aggregated hourly charging-load profile obtained from this dataset.

- **Beijing Taxi Trajectory Dataset [99]:** This dataset which is released by Microsoft Research Asia, provides large-scale GPS trajectory data of over 10,000 taxis in Beijing area. It contains over 15 million GPS records collected over 1 week and captures detailed spatiotemporal travel patterns across the city. All records contain a taxi identifier, timestamp, and latitude–longitude coordinates to reconstruct vehicle paths. The data can help analyse traffic prediction, intelligent transportation, and EVCS recommendation methods.
- **Adaptive Charging Network (ACN) Dataset [100]:** The ACN-Data dataset contains real-world EV charging session data collected from adaptive charging networks operated by PowerFlex Systems in collaboration with Caltech and NASA's Jet Propulsion Laboratory. The dataset includes over 30,000 workplace charging sessions. Every record includes a specific session identifier, connection, charging-completion, and disconnection timestamps and delivered energy, as well as site and CS identifiers. Furthermore, the

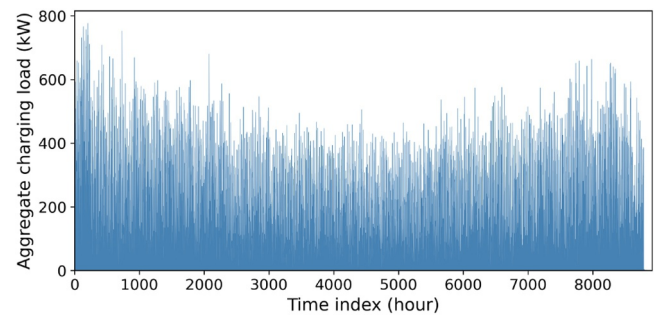


FIGURE 7 | Aggregate hourly charging load in the Dundee City EV Charging dataset.

TABLE 1 | Comparison of intelligent EVCS recommendation approaches and their applications.

Approach	Key characteristic	Advantages	Applications
Algorithmic and optimization based methods	Uses mathematical models, heuristics, or metaheuristics to optimise predefined objectives	Provides transparent decision rules and effective solutions when objectives and constraints are clearly specified	EV routing, charger assignment, and cost-aware charging schedules when system constraints are known in advance [20]
Deep learning (DL)	Learns complex spatiotemporal patterns from historical data	Captures nonlinear demand and utilization patterns with high predictive capability	Forecasting charging demand and station occupancy, estimating wait times, and ranking stations based on user needs [96]
Multi-agent reinforcement learning (MARL)	Learns coordinated sequential decisions among multiple EVs and/or CSs	Supports adaptive coordination among interacting agents and balances competing operational objectives	Real-time CS selection in busy urban networks where traffic, queues, prices, and competing EV requests change continuously [22]
Federated learning (FL)	Trains shared models across distributed participants without exchanging raw data	Enables collaborative learning while reducing privacy and data-sharing concerns	Charging networks operated across different regions or organisations where participants need to learn collaboratively without sharing raw local data [21]
Blockchain	Uses distributed ledgers and smart contracts for decentralised coordination	Provides trusted, auditable, and tamper-resistant coordination among participants	Secure station reservations, user authentication, payment settlement, peer-to-peer energy exchange, and coordination among charging network participants [97]

dataset provides high-resolution time-series measurements of charging current and pilot signals. Certain sessions also provide user-provided information, including requested energy and estimated departure time. These properties render the dataset suitable for research on adaptive charging control, demand flexibility, charging behaviour, and EV infrastructure optimization. The aggregated hourly charging load profile extracted from the dataset is depicted in Figure 8.

- **UrbanEV Dataset [101]:** Developed by the Intelligent Systems Lab, it is an open benchmark for studying and predicting EV charging demand in Shenzhen, China. It covers the period from September 2022 to February 2023 and includes data from 1682 public CSs with 24,798 charging piles. The original records were collected at 5-minute intervals and processed into hourly data for benchmarking. The dataset includes charging occupancy, session duration, charging volume, dynamic electricity prices, temperature, and rainfall. These features make UrbanEV useful for evaluating spatiotemporal prediction models and graph-based recommendation methods in densely populated urban areas. Figures 9 and 10 show the aggregated urban charging demand profile and the spatial distribution of the charging infrastructure, respectively. In this survey, UrbanEV is used as the primary case study dataset for the comparative evaluation in Section 5 because it provides large-scale real-world charging records and detailed spatiotemporal information under practical urban operating conditions.
- **Didi Corporation Xi'an and Chengdu city Dataset [102]:** Published by Didi Chuxing's Gaia Initiative, this dataset

contains high-resolution trajectory and traffic flow data for Xi'an and Chengdu, China. Unlike other datasets that divide cities into regular grids, this dataset organizes urban areas into irregular semantic regions based on Point of Interest (POI) information. This is a better match for real urban land use and functional areas. The datasets capture shifting mobility characteristics and traffic flows, which are useful in estimating the spatiotemporal energy demand in EV systems. By associating traffic patterns, travel behaviour, and urban geography, they aid research into the connection between congestion and EV charging needs in smart city environments.

- **Norway Residential EV Charging Dataset [103]:** This dataset provides detailed information on residential EV charging behaviour in a mature EV market. It includes 35,377 charging sessions from 267 users across 12 residential locations in Norway. The dataset contains variables such as EV battery capacity, charging power, and state of charge (SoC) at the start of each charging session. It also provides hourly data on energy consumption and connected energy capacity. These features make the dataset useful for research on residential charging behaviour, energy flexibility, load modelling, and the integration of large-scale EV charging into power-grid systems. The aggregated residential charging load profile derived from this dataset is illustrated in Figure 11.

5 | Discussion

To evaluate the performance of different categories of data-driven recommendation algorithms, we compare their performance

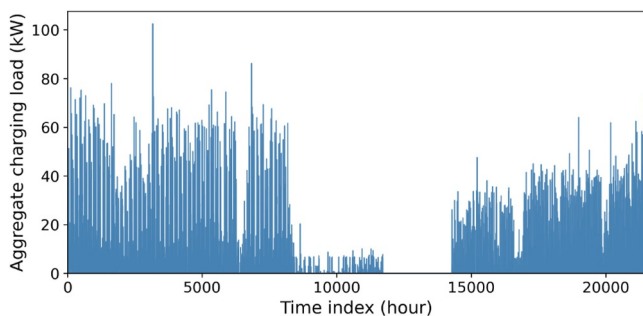


FIGURE 8 | Aggregate hourly charging load in the ACN dataset.

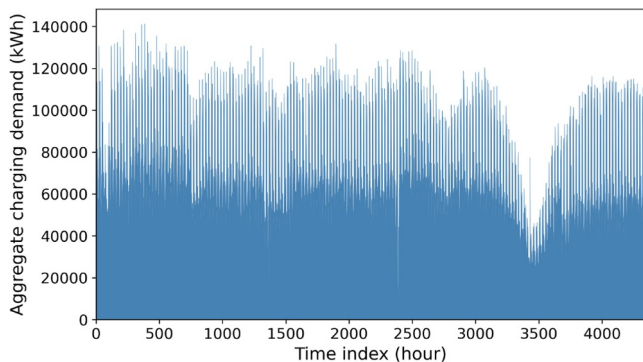


FIGURE 9 | Aggregate hourly charging demand in the UrbanEV dataset (Shenzhen).

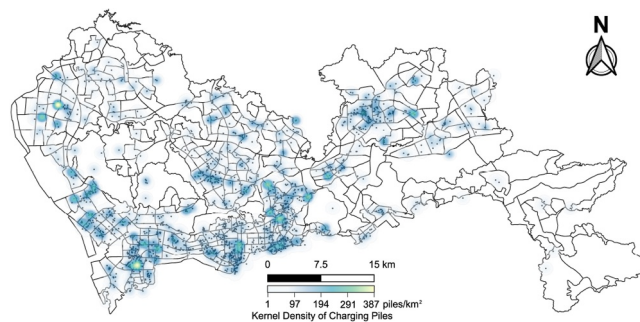


FIGURE 10 | Spatial distribution of public EV charging infrastructure in the UrbanEV dataset (1682 CSs and 24,798 charging piles) [101].

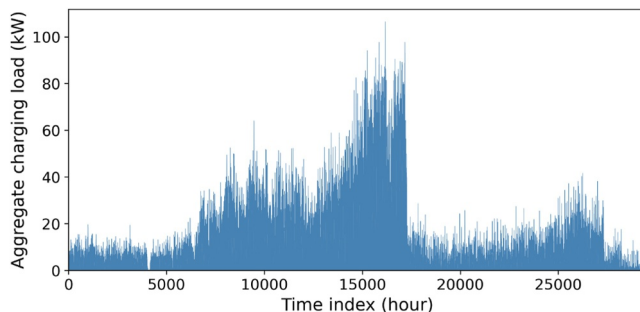


FIGURE 11 | Aggregate hourly charging load in the Norway Residential EV Charging dataset.

using a designed experiment on the UrbanEV dataset. Here, we consider the zone-level hourly data from 12 November 2022 to 1 January 2023 which includes 336,600 samples. Assuming $\mathcal{Q}^a$ as the set of charging requests that accept the recommendation provided by the system. We further define $\mathcal{Q}^s \subseteq \mathcal{Q}^a$ as the subset of charging requests that accept the recommendation and successfully complete the charging process. The cardinalities of these sets are denoted as $|\mathcal{Q}^a|$ and $|\mathcal{Q}^s|$, respectively.

5.1 | Evaluation Metrics

Following [13], we adopt Mean Charging Price (MCP), Total Saving Fee (TSF), and Charging Failure Rate (CFR), also we define Expected Availability Score (EAS) to quantify charging-station availability at the estimated EV arrival time. These metrics are discussed below:

5.1.1 | Expected Availability Score

To assess the probability of successful charging of an EV after arriving at a recommended station, we define the Expected Availability Score (EAS). It represents the change in CS utilization over time by predicting what percentage of the charging piles is estimated to be available as soon as an EV reaches a given location. At time t , for a charging request q_t proposed to station c^i , the availability at the estimated arrival time (ETA) $T_t + \text{ETA}(l_t, c^i)$ is calculated as a function of the ratio of idle charging piles to total charging capacity. Mathematically, the EAS over all charging requests $q_t \in \mathcal{Q}^a$ is formulated as

$$\text{EAS} = \frac{1}{|\mathcal{Q}^a|} \sum_{q_t \in \mathcal{Q}^a} \frac{n_{\text{idle}}^{i(q_t)}(\tau_t + \text{ETA}_t)}{n_{\text{idle}}^{i(q_t)}(\tau_t + \text{ETA}_t) + n_{\text{busy}}^{i(q_t)}(\tau_t + \text{ETA}_t)}, \quad (32)$$

Here, $n_{\text{idle}}^i(\cdot)$ and $n_{\text{busy}}^i(\cdot)$ represent the number of idle and occupied charging piles at station c^i at a specific time, respectively. The term $\text{ETA}_t = \text{ETA}(l_t, c^i)$ denotes the estimated travel time from the location l_t of charging request q_t to the recommended CS c^i at time step t . A higher EAS suggests that the recommendation method is more likely to direct EVs to stations with available charging piles, which can reduce waiting time and lower the risk of unsuccessful charging.

5.1.2 | Mean Charging Price

To assess the economic performance of the EVCS recommendation algorithms, we define the Mean Charging Price (MCP) across all charging requests $q_t \in \mathcal{Q}^s$ that successfully completed in a charging session. This metric is defined as

$$\text{MCP} = \frac{\sum_{q_t \in \mathcal{Q}^s} \text{CP}(q_t)}{|\mathcal{Q}^s|}, \quad (33)$$

where $\text{CP}(q_t)$ denotes the charging unit price, measured in (CNY/kWh), for charging request q_t . It is calculated as the sum of the electricity price $p_e(q_t)$ and service fee $p_s(q_t)$ charged at the recommended station during the charging period, such that $\text{CP}(q_t) = p_e(q_t) + p_s(q_t)$. A lower MCP indicates that the recommendation algorithm directs users to more cost effective charging options.

5.1.3 | Total Saving Fee

To measure the overall economic benefit of the recommendation system relative to users' original charging choices, we define the Total Saving Fee (TSF) as the average daily cost savings achieved by recommended charging decisions. This metric is formulated as

$$\text{TSF} = \frac{\sum_{q_t \in \mathcal{Q}^s} (\text{CP}_{\text{ref}}(q_t) - \text{CP}(q_t)) \times \text{CV}(q_t)}{N_d}, \quad (34)$$

where $\text{CP}_{\text{ref}}(q_t)$ denotes the charging price, measured in CNY/kWh, associated with the reference charging action, such as the observed user choice or a baseline strategy. In contrast, $\text{CP}(q_t)$ represents the charging price at the station recommended for request q_t , whereas $\text{CV}(q_t)$ denotes the charging volume in kWh. The term N_d is the total number of evaluation days. The charging volume can be calculated from the charging duration and the rated power of the selected charging pile. A negative TSF indicates that the recommended charging decisions produced higher overall costs than the reference charging behaviour.

5.1.4 | Charging Failure Rate

The Charging Failure Rate (CFR) is considered as a metric to assess the reliability of the recommendation system. This metric is defined as the proportion of accepted recommendations that result in unsuccessful charging attempts:

$$\text{CFR} = \frac{|\mathcal{Q}^a| - |\mathcal{Q}^s|}{|\mathcal{Q}^a|}. \quad (35)$$

A charging failure occurs when the recommended CS has no available charging piles at the EV's arrival time and the resulting waiting time exceeds the predefined threshold $\tau_{\text{max}} = 20$ minutes, causing the user to abandon the charging attempt. The CFR measures how well the recommendation system accounts for spatiotemporal charging demand patterns and avoids directing users to fully occupied stations. A lower CFR indicates that the system provides more reliable recommendations and distributes charging demand more effectively across the available infrastructure.

5.2 | Baselines

To evaluate the effectiveness of different categories, we compare the performance of different baselines. To ensure consistency with the taxonomy introduced in Section 3, the evaluated methods are grouped into six categories: a non-intelligent Random baseline, algorithmic and heuristic optimization methods, DL methods, blockchain based methods, FL methods, and MARL based methods. The Random method is included as a non-intelligent reference baseline, in which CSs are selected without using system state information. IACO and ALNS are evaluated as representative algorithmic and heuristic optimization methods, corresponding to the approaches discussed in Section 3.1. BipartiteSAGE and BiLSTM-Ensemble are included as representative DL methods from Section 3.2. K-Anon and FOA-B represent the blockchain enabled recommendation approaches reviewed in Section 3.5, whereas VFL-Cloudlet and 6GFog-FL represent the FL approaches described in Section 3.4. Finally, MASTER and COMA are evaluated as representative

MARL based methods corresponding to Section 3.3. Together, these baselines enable a structured comparison across the principal EVCS recommendation paradigms reviewed in this survey. The evaluated baselines are described as follows:

- *Random* recommendation system randomly recommends CSs for each EV charging request without considering any contextual information.
- *ALNS* [48] is a metaheuristic approach that couples ALNS with CPLEX for solving the EVCS recommendation. The algorithm employs multiple destroy-repair operators with roulette wheel selection to minimise total recharging cost while operating a minimum fleet size.
- *IACO* [42] integrates topology optimization, heuristic path and station selection functions, and a discrete electricity dynamic programming (DE-DP) component. Together, these elements reduce computational complexity while helping determine suitable CSs and the optimal charging quantity at each selected station.
- *BipartiteSAGE* [58] is a two-stage EVCS recommendation framework that combines GNNs with an optimization module. In the initial phase, a user-station bipartite graph is built, and GraphSAGE is used to learn personalised charging preferences from historical user behaviour. In the second phase, an optimization algorithm assigns users to CSs by considering predicted station availability and proximity constraints.
- *BiLSTM-Ensemble* [57] presents an intelligent charging framework which combines a stacking and voting meta-ensemble regressor for EV charging load prediction with a bidirectional LSTM model for forecasting national net energy exchange. The outputs of these models are then integrated through a weighting mechanism to generate probabilistic recommendations for suitable charging periods.
- *FOA-B* [94] introduces a blockchain-enabled Fox Optimization Algorithm (FOA) for EV charging applications. The framework combines the Fox Optimiser with the Ethereum blockchain, using smart contracts to support secure transactions while optimising CS locations and EV routing decisions.
- *K-Anon*. [92] proposes a privacy preserving CS recommendation system built on blockchain technology. It uses k-anonymity methods to protect users' location information while relying on the decentralised blockchain structure to improve service trust. The framework also includes an incentive mechanism to encourage EV participation.
- *VFL-Cloudlet* [80] presents a secure cloudlet-based recommendation framework built on VFL. The system uses cloudlet aggregators instead of a fully centralised architecture and incorporates blockchain to create a trusted network for exchanging locally computed model parameters. This design allows EV related data to remain on the original local platforms while supporting collaborative recommendation training.
- *6GFog-FL* [81] extends FL to 6G-enabled vehicular communication environments and considers both fixed CSs and mobile CSs (MCSs). The framework uses fog-based data aggregators and secure VFL to support EV distribution decisions while preserving user privacy through decentralised model training.

- *MASTER* [13] proposes a multi-agent spatio-temporal RL (MASTER) model to optimise the multi-objective EVCS charging recommendation problem. MASTER treats each CS as an individual agent. The framework features a centralised attentive critic with delayed access strategy to exploit future charging competition information, and a dynamic gradient re-weighting strategy for multi-objective optimization of charging wait time, charging price, and failure rate.
- *COMA* [12] proposes a counter-factual multi-agent policy gradient approach with centralised training and decentralised execution for EV charging scheduling. Each EV is modelled as an agent deriving individual charging schedules while considering time-of-use, electricity pricing, and energy storage systems to minimise operating costs.

Following subsection discusses comparative results of considered baselines.

5.3 | Results

Table 2 depicts the comparative analysis of all evaluated EVCS recommendation approaches on the UrbanEV dataset. The need for intelligent EVCS recommendation systems is solidified by the results depicted in table, as all learning-based methods outperform the Random baseline. The Random baseline's negative TSF of -523 CNY indicates that uninformed recommendations result in net economic loss for users, whereas MASTER generates daily savings of 14,567 CNY. The heuristic optimization methods including IACO and ALNS achieve moderate performance with EAS values of 0.412 and 0.398, respectively, representing 27.2% and 22.8% improvements over Random. However, these methods exhibit a relatively high CFR with 32.4% and 35.8%, which is attributable to their deterministic assumption of station availability. IACO achieves the second lowest MCP of 1.487 CNY/kWh, which is consistent with its explicit focus on cost minimisation. This result indicates that heuristic methods can remain effective for narrowly defined single objective charging optimization tasks.

As shown in Table 2, DL based approaches, BipartiteSAGE and BiLSTM-Ensemble, show clear improvements over heuristic approaches, with EAS values of 0.623 and 0.587, respectively. The GNN based architecture of BipartiteSAGE results in 6.1% and 15.4% better values of EAS and TSF, respectively, when compared with BiLSTM-Ensemble. Both DL methods also achieve lower CFR values, at 10.8% for BipartiteSAGE and 12.3% for BiLSTM-Ensemble, compared with 32.4%–35.8% for heuristic methods. These results suggest that learning-based availability prediction can improve charging reliability. Since these methods do not explicitly optimise multiple objectives at the same time, their MCP values remain higher at 1.578 CNY/kWh and 1.612 CNY/kWh, respectively.

Blockchain based methods, including K-Anon and FOA-B, achieve moderate EAS values of 0.512 and 0.548, respectively. FOA-B performs 7.0% better than K-Anon in EAS, likely because its Fox Optimizer supports routing optimization. However, both methods have the highest MCP values among the learning-based baselines, at 1.689 CNY for K-Anon and 1.634 CNY for FOA-B. This may be related to the additional

TABLE 2 | Performance of recommendation architectures on the UrbanEV dataset.

Category	Model	Performance metric			
		EAS↑	MCP↓	TSF↑	CFR↓ (%)
Random	—	0.324	1.856	−523	48.7
Heuristic optimization	IACO	0.412	<u>1.487</u>	8234	32.4
	ALNS	0.398	1.523	7156	35.8
Deep learning	BiLSTM-Ensemble	0.587	1.612	6842	12.3
	BipartiteSAGE	0.623	1.578	7893	10.8
Blockchain	K-Anon.	0.512	1.689	4523	18.6
	FOA-B	0.548	1.634	5678	14.2
Federated learning	VFL-Cloudlet	0.712	1.534	9234	6.4
	6GFog-FL	0.734	1.512	10,123	5.8
MARL	MASTER	0.823	1.478	14,567	1.2
	COMA	<u>0.756</u>	1.498	<u>11,234</u>	<u>3.4</u>

Note: The best and second best results are shown in bold and underlined fonts, respectively.

computational and communication demands associated with cryptographic operations and consensus mechanisms, which can increase system complexity and limit responsiveness in recommendation tasks.

Table 2 depicts that FL is the second best performer after MARL in terms of EAS as VFL-Cloudlet and 6GFog-FL achieve EAS values of 0.712 and 0.734, respectively. 6GFog-FL achieves superior performance of 3.1% and 9.6% in terms of EAS and TSF, respectively, over VFL-Cloudlet, using 6G-enabled communication and supporting MCSs. This indicates that distributed learning helps in better load and availability prediction, with VFL-Cloudlet and 6GFog-FL achieving low CFR values of 6.4% and 5.8%, respectively. Moreover, FL achieves better trade-off between privacy preservation and recommendation performance as compared with blockchain approaches. For instance, VFL-Cloudlet improves EAS by 29.9% over FOA-B, while maintaining privacy using VFL.

Compared with other frameworks, MARL-based approaches, including MASTER and COMA, achieve the best overall performance. As shown in the table, MASTER achieves improvements of (100.0%, 0.6%, 76.9%, 96.3%) for (EAS, MCP, TSF, CFR) over IACO, (32.1%, 6.3%, 84.6%, 88.9%) over BipartiteSAGE, (50.2%, 9.5%, 156.6%, 91.5%) over FOA-B, and (12.1%, 2.2%, 43.9%, 79.3%) over 6GFog-FL. MARL based models perform well because they can represent the sequential and interactive nature of EV charging decisions under changing operating conditions. In practical charging networks, multiple EVs may compete for a limited number of CSs while traffic conditions, queue lengths, electricity prices, and station availability change over time. MARL allows agents to adjust their charging decisions according to these dynamic conditions while also accounting for the actions of other agents. This can support better resource utilization, lower charging failure rates, and improved overall system efficiency. Unlike heuristic or single-objective optimization methods, MARL can optimize a long term cumulative reward that combines several objectives within the reward function. During training, the reward may include charging cost, charging success, waiting time, and efficient use of station capacity. This allows agents to learn balanced policies instead of optimizing

each objective separately. In addition, the centralized training with a decentralized execution framework allows agents to use broader system information during training while making decisions from local observations during deployment. This coordinated learning process helps MARL balance conflicting objectives and may explain its stronger performance across the four evaluation metrics.

In contrast, DL approaches mainly learn spatiotemporal patterns from historical data and can provide accurate predictions of charging demand, station occupancy, or availability. However, these models typically focus on prediction and may not directly optimize sequential charging decisions or account for competition among multiple EVs for shared charging resources. Similarly, FL supports privacy preserving collaborative model training, but it often relies on additional prediction or optimization modules to make final charging decisions. This may reduce its ability to respond quickly when charging conditions change rapidly. Blockchain based approaches mainly support secure and decentralized reservation, transaction, and payment processes. However, consensus and cryptographic mechanisms can introduce additional communication and computational overhead, which may increase decision latency. Therefore, blockchain may be more suitable for secure coordination than for time-sensitive EVCS recommendations. Overall, MARL is generally more suitable for real-time EVCS recommendation in dynamic operating environments, which may explain its stronger EAS, TSF, and CFR results in Table 2. Table 2 also shows that MASTER outperforms COMA by 8.9% in EAS, 29.7% in TSF, and 64.7% in CFR. This difference may be related to MASTER's centralized attentive critic, which supports coordination among changing sets of agents, and its dual critic design with dynamic gradient re-weighting for multi objective learning.

6 | Future Works

6.1 | Quantum Machine Learning

As EV networks continue to expand towards millions of interconnected agents, the computational burden of real-time coordination is expected to surpass the limits of classical high

performance computing. Quantum computing (QC) [104, 105] has been proposed as a possible future direction for addressing highly complex EV charging problems, particularly multi-objective optimization tasks [106]. QC can help exponentially boost the processing speed for combinatorial problems such as pathfinding and station allocation. Quantum systems may also handle conflicting objectives such as travel time, cost, and grid load more effectively than classical metaheuristics, which tend to converge on suboptimal solutions. QC and classical frameworks have potential in the security domain, as FL data decentralisation could be further protected through Quantum Key Distribution (QKD). This would add a physical layer security guarantee for model updates and keep EVCS systems secure against future cryptographic vulnerabilities [107, 108].

To apply QC to EVCS recommendation systems, researchers need to convert conventional charging data into their quantum compatible representations. Methods such as amplitude encoding or angle encoding are used to encode spatiotemporal datasets, such as ACN-Data and T-Drive into the quantum Hilbert space [109]. This technique allows larger datasets to be encoded utilising fewer parameters compared to traditional DL approaches.

6.2 | Fuzzy Logic and Fuzzy Inference Systems

Fuzzy logic's [110, 111] ability to handle uncertainty and support decisions where multiple objectives contradict each other has gained attention in EVCS recommendation systems. Existing approaches [112, 113] use fuzzy inference mechanisms for evaluating and ranking CSs based on factors such as cost, waiting time, and charging infrastructure characteristics. These approaches are suitable for capturing what users demand and presenting data into recommendations that are easy to interpret [111, 114]. Manually designed rules and fixed membership functions are the downside of most of the systems, making them less flexible in dynamic environments. Traditional fuzzy systems are designed around structured numerical data, which limits them to unstructured inputs such as natural language, user feedback, or contextual information. For large-scale real-time systems these approaches are not suitable, especially when the system needs to handle a wide range of EV types and charging needs.

Future fuzzy logic should move towards more adaptive and data-driven approaches to overcome its limitations. MARL agents representing vehicles, stations, or grid components can learn good behaviours when combined with fuzzy modules that handle uncertainty and user preferences. In a distributed and large-scale setting, this kind of setup could refine charging decisions in real time as conditions change. Another approach includes combining Large Language Models (LLMs) with fuzzy systems, which allow natural language inputs to be turned into fuzzy rules. This would let recommendation systems take in conversational or qualitative input from users while still producing interpretable outputs through the fuzzy framework. Furthermore, neuro-fuzzy networks, federated training of fuzzy models across several stations, and adaptive tuning of membership functions using real-world feedback offer opportunities.

6.3 | Large Language Models

As EV charging management approaches evolve, Large Language Models (LLMs) [115, 116] may be used for more than simply providing conversational interfaces. LLMs could be used to support decision making in the future. A dynamic model generator can translate user goals and environmental context directly into formal optimization problems, which can be adjusted based on real-time conditions by deploying LLMs as dynamic model generators. The development of recommendation systems that verify LLM-generated suggestions before presenting them to users is another promising direction. To determine whether a recommendation system is feasible for particular conditions these systems could rely on simulation models, digital twins, or constraint-checking layers. Users can benefit from clear and auditable explanations to understand why a particular CS was recommended.

Personalised charging decisions may be further supported by LLMs learning from prior user behaviour, travel routines, and changing preferences. The combination of these models with predictive models for traffic congestion would allow EVCS recommendations to move from reactive decisions towards more proactive ones. The use of contextual language reasoning to support personalised CS selection and adaptive decision making has been demonstrated in recent research on LLM-enabled EVCS recommendations [117]. Privacy and security should remain central considerations. Federated approaches for training language models across multiple charging networks may allow organisations to benefit from shared knowledge while reducing the need to exchange sensitive user or transaction data. In addition, LLM supported negotiation among EVs, CSs, and energy providers may enable more cooperative and market oriented charging decisions. Overall, LLMs may eventually function as part of an integrated EV charging decision support system that combines forecasting, optimization, personalisation, and reliability.

7 | Conclusion

The rapid proliferation of electric vehicles (EVs) into modern transportation systems has created an increasing demand for designing intelligent recommendation systems for routing EVs to charging stations (CSs). These recommendation systems aim to solve a challenging constrained multi-objective optimization problem that minimises routing travel time, cost, and charging waiting time while meeting the constraints of the power grid market, CS availability, and user preferences. This survey provides a comprehensive review of traditional and recent electric vehicle charging station (EVCS) recommendation systems by categorising them into conventional optimization and algorithmic methods, deep learning (DL), multi-agent reinforcement learning (MARL), federated learning (FL), and blockchain. By reviewing recent literature in each category, their pros and cons for the underlying problem are studied. Additionally, we review different publicly available datasets in this realm and compare their characteristics. Furthermore, by introducing a unified problem formulation, this survey article provides a quantitative comparison between EVCS recommendation systems of different categories on UrbanEV, one of the most widely used

datasets, for evaluating the performance of recommendation results in terms of cost, availability, and reliability scores.

The obtained results show superior performance of learning-based recommendation approaches compared with random recommendation which highlights the reason to integrate these intelligent recommendation systems into modern transportation systems. Within all categories, MARL-based methods show higher performance scores due to the interactive sequential approach of EV charging decisions in a constrained environment. However, MARL-based approaches face scalability challenges and sample inefficiency, as the complexity of training the proposed algorithms increases rapidly with the number of EV agents and charging stations that operate at large scale in urban systems. Designing robust, scalable, and reliable EVCS recommendations in the future will need increasingly advanced machine learning methodologies. In this regard, we also provide a discussion on future algorithmic research lines for potential improvement of EVCS recommendation systems performance by investigating innovative machine learning approaches such as quantum machine learning, large language models (LLMs), and fuzzy logic. By consolidating existing literature, benchmark datasets, and future research direction in designing EVCS recommendation systems, this review paper aims to accelerate the development of these intelligent recommendation systems by providing a foundational research for active researcher in the field.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data sharing not applicable—no new data generated, or the article describes entirely theoretical research.

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