Optimizing EV Charging Recommendations Using Graph Neural Networks

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Abstract—**Electric vehicles (EVs) offer low carbon emissions; however, drivers frequently encounter difficulties scheduling charging sessions and locating available Charging Stations (CSs). These stations not only need to be conveniently located but also tailored to meet individual charging preferences. Addressing these challenges is crucial for overcoming barriers to the widespread adoption and efficiency of electric mobility, consequently enhancing the overall user experience. This paper introduces an innovative two-stage framework that improves the accessibility of EVCSs by integrating Graph Neural Networks (GNNs) with optimization algorithms. A bipartite graph representing user-station interactions is constructed in the first stage, and a GNN is utilized to leverage this structure. The GNNs efficiently capture complex relational patterns within the graph, enabling the generation of personalized station recommendations. In the subsequent stage, an optimization algorithm is employed to strategically assign users to these recommended stations. This algorithm considers station availability and proximity factors, ensuring optimal user assignments. The proposed recommender framework's effectiveness is verified using data collected from the Yonne department in France. Experimental evaluations highlight the framework's efficiency, achieving a high-performance measure of 98%, significantly reducing waiting times and maximizing user satisfaction for drivers compared to baseline approaches.**

Index Terms—**Charging Stations, Bipartite Graphs, Graph Neural Networks, Deep Learning, Optimization Algorithms**

I. Introduction

The growing adoption of Electric Vehicles (VEs) within the automotive industry and the urgent need for decarbonization strategies pave the way for EVs to replace fossil fuel-driven counterparts. In Europe, EV sales continued to rise by over 15% in 2022 compared to the previous year, culminating in a total of 2.7 million units sold [1]. This upward trajectory underscores the mounting demand for EV charging infrastructure. Nevertheless, users frequently face challenges in finding Charging Stations (CSs) that meet their charging habits, proximity, and availability. Consequently, manufacturers are intensifying their efforts to optimize the charging experience for drivers and enhance charging efficiency. Implementing a personalized CS recommender system is indispensable for EV adoption and transitioning from traditional gasoline-based vehicles to electric mobility. Such a system is pivotal in enhancing the overall charging experience by making it convenient and tailored to individual needs and preferences, reinforcing consumer confidence in the transition to EVs.

In the existing literature, several studies have addressed the challenge of locating CSs or providing intelligent charging recommendations [2–4]. These methods suggest the most appropriate CS for an EV driver based on various real-time factors (e.g., State of Charge (SoC) and traffic data). However, a limitation of these systems is their failure to account for the charging behavior of users or their individual preferences. Charging an EV differs from refueling a traditional gasoline vehicle, as it involves longer durations and varying power needs. Thus, personalized recommendations considering user charging habits and preferences are essential for enhancing the charging experience, as they recognize the varying convenience and feasibility of charging options among users. This research utilizes recent advancements in Graph Neural Networks (GNNs) to effectively analyze graph-based data, addressing the complex optimization challenge of recommending the most appropriate CSs. It introduces a two-stage solution where the first stage involves utilizing GNNs to model and learn users' historical charging behaviors, and the second stage implements an optimization algorithm similar to those used in warehouse logistics. This algorithm uses real-time data to allocate users to CSs efficiently. This two-stage framework meets personalized user demands and improves the overall efficiency of CS utilization.

The main contributions of this paper are:

- The EV charging recommendation problem is formulated as a two-stage framework. The first stage involves processing a user-CS bipartite graph with a GNN due to its superiority in graph representation learning. This enables the generation of initial personalized recommendations, enhancing the user experience by customizing suggestions to reflect past charging patterns and preferences.
- The second stage of the framework first predicts the availability of CSs. Then, it uses an optimization algorithm to efficiently assign users to these stations based on CS availability, vehicle SoC, and travel distance, ensuring optimal charging infrastructure utilization.
- The effectiveness of the proposed two-stage framework is thoroughly tested and validated using a real-world dataset from Yonne, France. Its efficacy is rigorously evaluated against baseline methods across various metrics, highlighting the framework's robustness and superior

performance in recommending CSs.

The remainder of the paper is structured as follows. Section II provides an overview of the literature concerning CS recommendation and assignment. Section III introduces the two-stage modeling approach, which uses a bipartite GNN followed by an optimization algorithm. Section IV outlines the details of conducted experiments and presents the obtained results. Finally, Section V offers concluding remarks and proposes directions for future research.

II. Related Work

With the rise of EV adoption, significant scholarly attention has focused on efficiently recommending CSs for drivers, categorized into traditional optimization methods and Artificial Intelligence (AI)-based approaches.

Ferro et al., in their work [5], developed a comprehensive optimization model for electric bus fleet CSs that addresses site selection, station sizing, line assignment, and fleet sizing while ensuring service quality with a hybrid nonlinear planning approach. Adachi et al. in [4] utilized a decentralized approach where EVs select a CS and paths via a linear integer programming problem and a Lagrangian relaxation heuristic, resulting in fair allocations and emphasizing the importance of waiting and charging times over travel time. In [6], researchers proposed an EV assignment algorithm based on the Lyapunov optimization method, comparing it to strategies such as assignment to the nearest station and join-the-shortest-queue policy.

Recent advancements in Deep Reinforcement Learning (DRL) for sustainable EV charging have significantly increased. Authors in [7] proposed a DRL-based algorithm for optimal route and CS selection to minimize the total travel time of EVs by considering uncertain traffic conditions and dynamic charging requests, comparing its performance against conventional strategies across various scenarios. A framework developed in [8] intelligently recommends public CSs using long-term spatiotemporal factors and outperforms nine baseline approaches, as demonstrated by experiments on real-world datasets. Peidong et al. in [9] presented a fast CS recommendation platform using DRL and Graph Attention Networks (GATs) to integrate information from CSs, traffic nodes, and power grid buses into a graph. This system dynamically allocates EVs to suitable CSs, addressing the evolving demands and complexities of coupled power-transportation networks in urban settings. Simulation results using SUMO demonstrate efficient handling of real-time requests. Another investigation has introduced a Spatio-Temporal Multi-Agent Reinforcement Learning (STMARL) framework to optimize public-accessible CSs, aiming to reduce charging wait time, average price, and failure rate. Its effectiveness is evaluated by comparing it to random selection systems [3].

Although these studies offer valuable insights into recommending CSs, many must pay more attention to users' preferences and charging behaviors. Charging preferences are essential; many EV drivers may be more likely to conform to their charging habits when making charging choices [10].

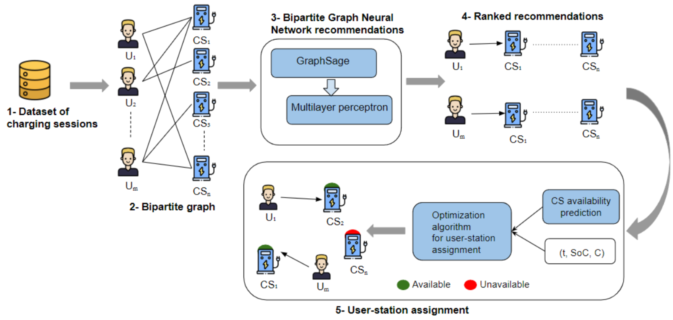

Fig. 1: Architecture of the proposed recommendation system.

Therefore, understanding user preferences, such as preferred charging times and location preferences, is crucial for providing personalized and effective charging recommendations. This study aims to develop a recommender system by addressing the EV charging demand from two perspectives: user charging preferences and optimizing charging assignment.

III. System Model

This section presents the proposed framework, modeling the system as a bipartite graph of driver and CS nodes. A GNN projects these nodes into distinct feature spaces to capture intricate relationships, generating embeddings for both users and CSs. The GNN architecture implementation is detailed, explaining how it learns features and relationships for each node type. Additionally, an optimization algorithm named CS Linear Programming (CSLP) is developed to efficiently assign users to optimal CSs by minimizing travel distance and considering predicted CS availability. Figure 1 illustrates the integrated architecture of the system.

A. Preliminaries

The User-CS bipartite graph is a quadruple $G = (U, CS, E, S)$ constructed from charging sessions dataset (see Section IV-A), where users $U = u_1, u_2, ..., u_M$ and CSs $CS = cs_1, cs_2, ..., cs_N$ are two sets of vertices. Each vertex in the sets U and CS is associated with weights denoting certain characteristics and denoted as w_u and w_{cs}, respectively. The graph compromises a set of edges E, each denoted by $e = (u_m, cs_n)|u_m \in U, cs_n \in CS$, symbolizing instances where a user u_m utilizes a specific CS cs_n for charging his vehicle. These edges are associated with weights $S(e)$ to denote the connection strength. An edge (u_m, cs_n) exists if a user u_m uses station cs_n at least once in the charging history, with its weight encoding multifaceted aspects like charging duration, energy consumption, session initiation time, and price of energy. Hence, it reflects the dynamic user-station interaction within the network. The prediction aims to learn a function between a user u_m and a CS cs_n, enabling the prediction of the probability that cs_n will be utilized by u_m.

B. Bipartite Graph Recommendations

The proposed model, named BipartiteSAGE, is a data-efficient GNN training framework inspired by existing GraphSAGE (SAmple and aggreGatE) known for its effectiveness

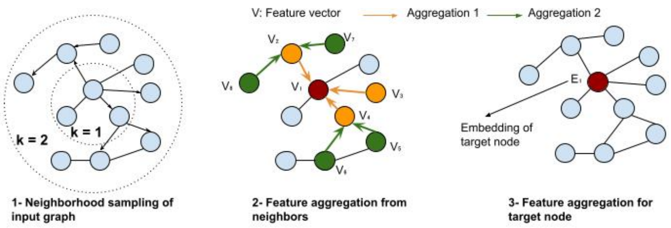

Fig. 2: Illustration of GraphSAGE message passing: 1) Neighborhood sampling selects immediate and extended neighbors of a target node. 2) Features from these neighbors are aggregated in successive layers. 3) The target node's final embedding is obtained by combining its features with the aggregated neighborhood features (inspired by [11]).

in learning representations for time-evolving graphs [11]. The intuition behind the BipartiteSAGE is to iteratively aggregate information between the user and CS neighbors, allowing vertices to accumulate insights from distant parts of the graph gradually. It samples fixed-size neighborhoods for each node and uses learnable aggregation functions such as mean, sum, or max-pooling, ensuring adaptability without relying on the complete graph Laplacian. Figure 2 illustrates GraphSAGE message passing, which uses neighborhood sampling to efficiently manage computational graphs, enhancing GPU efficiency. This method scales to billions of nodes and generalizes unseen nodes without requiring the entire graph structure during training. Let $N(v)$ be the neighborhood of node v in G, the mean aggregation function used is defined as:

$$h_v^k = \sigma\left(W^k \cdot \text{MEAN}\left(\{h_v^{k-1}\} \cup \{h_u^{k-1}, \forall u \in N(v)\}\right)\right) \quad (1)$$

where h_v^k is the feature vector of node v at the k-th iteration, σ denotes the activation function, and W^k is the weight matrix at the k-th layer.

The proposed BipartiteSAGE employs the aggregator function outlined in Equation 1 to learn node embeddings by leveraging features from neighboring nodes in a bipartite user-station graph. This neighborhood-based training enables the GNN to generate embeddings for unseen nodes during inference. Subsequently, it inputs the learned embeddings of users and CSs, concatenated with their respective linear transformations and embeddings, to predict links between nodes. This process facilitates the generation of top-N station recommendations for users based on their historical use.

C. Optimization Algorithm for User-Station Assignment

After training the GNN model to capture user charging behaviors, it predicts a set of CSs for each user. In a real-world scenario, users submit requests for charging demand at time t, prompting the need for efficient assignment to the recommended CSs. Figure 1 illustrates this second stage of the problem, where a finite set N of CSs constitutes the charging infrastructure, represented as $CS = cs_1, cs_2, ..., cs_N$. Each station cs_i is defined by two parameters: a fixed location represented by $loc(cs_i)$ and an availability indicator. Conversely, the vehicle's location and SoC characterize each EV user request to charge. This problem integrates complexities reminiscent of warehouse optimization. It falls into the category of Integer Linear Programming (ILP) problems, where the decision maker (e.g., Charging Station Operator) must assign an incoming user to the most suitable CS, aiming to minimize the total waiting time, which encompasses both travel time to the station and waiting time until the station becomes available, as depicted in Figure 1. The discrete set of time steps is defined as $T = t_1, t_2, ..., t_k$. The dynamic availability of station $cs \in CS$ at time $t \in T$ is denoted by $A_{cs,t}$. It's obtained from a trained Deep Learning model [12], where $A_{cs,t} = 0$ indicates that the station is available and $A_{cs,t} = 1$ indicates otherwise.

The travel time of user $u \in U$ to station $cs \in CS$ is represented by $C_{u,cs}$. The decision variable is defined as:

$$X_{u,cs,t} = \begin{cases} 1 & \text{if user } u \text{ is assigned to station } cs \text{ at time } t, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

The objective is to minimise the total waiting time for all users, formalized as follows:

$$\min \sum_{u \in U} \sum_{cs \in CS} \sum_{t \in T} X_{u,cs,t} \cdot (C_{u,cs} + t) \quad (3)$$

The constraints for the assignment problem are:

- Each user is assigned to exactly one station at one time step.
$$\sum_{cs \in CS} \sum_{t \in T} X_{u,cs,t} = 1, \quad \forall u \in U \quad (4)$$
- A user can be assigned to a station at time t only if the station is available.
$$X_{u,cs,t} \leq 1 - A_{cs,t}, \quad \forall u \in U, cs \in CS, t \in T \quad (5)$$

IV. Experimental Setup and Results

This section outlines the experimental configuration and results of the two-stage framework. Initially, the dataset used and the feature engineering conducted are detailed. Following this, the model's configuration and training process are presented. Finally, a comprehensive performance analysis is conducted using various metrics, and the obtained results are compared with those of standard baseline methods.

A. Data Description

The evaluation dataset contains charging sessions recorded in Yonne, France, from January 1 to December 31, 2023. This dataset compromises 466,371 charging sessions from users at 136 charging points. There are three types of CSs based on their charging capacity: normal ($\leq$25 kW), rapid ($>$25 kW), and ultra-rapid ($\geq$100 kW) types. Specific attributes that characterize the users and the CSs are extracted from the dataset and utilized as node features (w_u and w_cs) within the bipartite graph, as detailed in Table II. The edge features $S(e)$ were based on four parameters: charging session duration, energy consumption, start time, and price. The dataset was split into 60% training, 20% testing, and 20% validation. The system uses the Google Maps API to calculate travel times to CSs for users, incorporating real-time traffic data.

TABLE I: Extracted data features.

User features	CS features
Location	Location
Average charging duration	Total energy consumption
Average charging consumption	Mean start time
Frequency of charging	Average charging duration
Preferred charging station	Average number of charging hourly
Most frequent charging time	Number of charging sessions
	Charging capacity
	Number of nearby Points of Interest

B. Model Training

BipartiteSAGE model is implemented using PyG library[1]. Initially, we re-implemented the existing SAGEConv class from the PyG library to incorporate crucial edge features. The model consists of four layers: a customized SAGEConv spatial convolution module, batch normalization, and a dropout layer, which generates node embeddings to capture complex node relationships. These embeddings are processed by a multi-layer perceptron (MLP) to predict user-station connections accurately. The model is trained in batches of 32 examples using an EarlyStopping mechanism to prevent overfitting. We optimize with the Adam optimizer at a learning rate of 0.001, balancing convergence speed and model accuracy. This approach ensures robust, detailed processing of bipartite graph data for efficient CS recommendations.

C. Performance Evaluation

Metrics such as accuracy, recall, precision, and the Area Under the Curve (AUC) [12] are computed to assess the effectiveness of BipartiteSAGE. These results are compared to those obtained using a GAT [13]. This analysis highlights each model's strengths and limitations in handling node interaction complexities.

In the second stage, the CSLP optimization model allocates users to recommended CSs, generating various scenarios with differing user numbers, locations, and EV battery levels. The efficiency of the optimization problem is validated by measuring the Mean Waiting Time (MWT) for all scenarios, defined as the sum of travel time to the station and waiting time until availability. Additionally, user satisfaction is assessed based on the accuracy of BipartiteSAGE recommendations. The model's performance is then benchmarked against three baseline approaches:

- **Genetic Algorithm:** A genetic algorithm [14] is implemented to solve this optimization problem.
- **Nearest Assignment:** A distance-based selection assumes drivers will choose the closest CS regardless of its current availability and user satisfaction.
- **Random Assignment:** Users are randomly assigned to CSs.

[1]PyG: https://pytorch-geometric.readthedocs.io/en/latest/

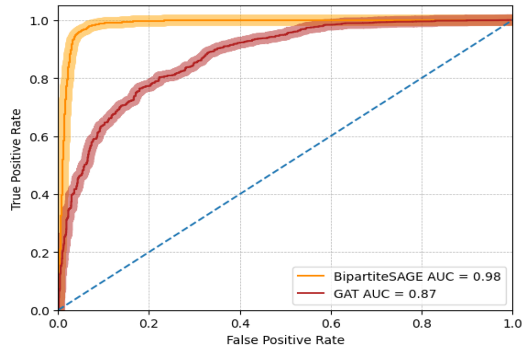

Fig. 3: ROC curve on the test dataset.

D. Results & Analysis

Table II comprehensively evaluates the proposed BipartiteSAGE and the baseline GAT across four metrics. BipartiteSAGE demonstrates superior performance in all metrics, achieving an accuracy of 95%, recall of 98.97%, precision of 93.84%, and an F1-score of 96.34%. BipartiteSAGE is particularly effective in accurately predicting user-station links, reflecting historical charging behaviors. In contrast, GAT, while still effective, shows lower scores with an accuracy of 77.69%, recall of 86.90%, precision of 77.78%, and an F1-score of 82.09%. These results indicate that GAT may struggle comparatively in precision and overall accuracy but maintains a reasonably high recall, which suggests effectiveness in identifying positive instances. Figure 3 presents the Receiver Operating Characteristic (ROC) curve analysis. BipartiteSAGE achieves an AUC of 98%, outperforming GAT, which has an AUC of 87%. BipartiteSAGE demonstrates higher TPR and lower FPR, indicating its superior performance in learning the underlying patterns of user behavior and station characteristics. The message-passing technique focuses on the most relevant local information around each node to predict the CSs a user would be interested in for charging his vehicle.

TABLE II: Evaluation metrics on the test dataset.

	Accuracy	Recall	Precision	F1-score
BipartiteSAGE	0.9557	0.9897	0.9384	0.9634
GAT	0.7769	0.8690	0.7778	0.8209

Figure 4 visually compares the MWT across various scenarios for four assignment strategies. It shows that CSLP outperforms with the lowest median MWT, and its mean closely mirrors the median, indicating a balanced distribution around the center and efficiency in optimization. Genetic follows as the second most effective, with a comparable median to CSLP but more variability. The Nearest method results in the highest MWT with less variability than Random, which, while not as extreme as Nearest, suffers from inconsistent results, suggesting significant variability and less predictability.

Overall, the results suggest that strategies like CSLP and Genetic, incorporating predicted station availability into their algorithms, are more effective in minimizing user waiting times. Given the system's small size, CSLP outperforms the

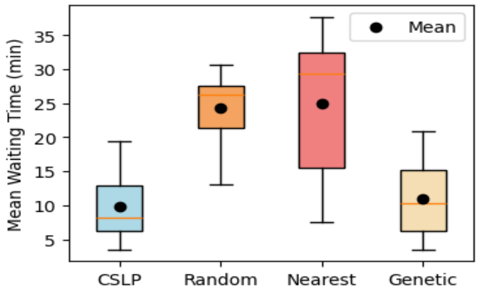

Fig. 4: Boxplot of MWT as a function of assignment strategy.

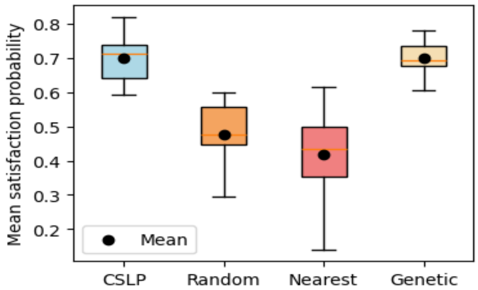

Fig. 5: Distribution of users satisfaction probabilities.

metaheuristic Genetic algorithm, offering optimal and consistent solutions with lower computational demand, making it the preferable choice for reliable user-to-CS assignments. This analytical insight highlights the importance of integrating predictive elements into assignment strategies to enhance the overall efficiency of CS utilization.

Figure 5 compares user satisfaction probabilities using the four methods derived from BipartiteSAGE scores. Among these methods, CSLP exhibits the highest and most consistent satisfaction rates, followed by genetics, which exhibits moderately high satisfaction. These results can be attributed to the BipartiteSAGE-based preferred station assignments in CSLP and Genetic methods, ensuring a better alignment with user preferences. In contrast, the Nearest and Random methods show lower and more varied satisfaction levels. Mainly, the Nearest method exhibits significant variability in satisfaction, indicating a potential misalignment with user preferences.

V. Conclusion

This paper introduces a cutting-edge CS recommendation framework based on GNN to identify optimal CSs for EVs. The proposed system offers finely tuned recommendations highly aligned with individual user needs with an accuracy of 94%, capturing the complex relationships and dependencies within user-station charging habits and strategically assigning users using the CSLP algorithm by considering the predicted availability of CSs and the real-time travel distances to these stations. This solution ensures an efficient allocation of users across available stations, substantially minimizing waiting times and thereby improving user satisfaction and the system's overall efficiency. This two-stage framework underscores the importance of advanced analytics in improving charging network efficiency and promoting EV adoption. Future work will refine these models to adapt to dynamic user behavior, station conditions, and traffic. Prioritizing renewable energy-powered CSs will help balance the electrical grid during off-peak hours. This approach supports sustainable development and fosters innovation in smart city initiatives.

Acknowledgment

This paper is supported by the OPEVA project that has received funding within the Chips Joint Undertaking (Chips JU) from the European Union's Horizon Europe Programme and the National Authorities (France, Czechia, Italy, Portugal, Turkey, Switzerland), under grant agreement 101097267. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or Chips JU. Neither the European Union nor the granting authority can be held responsible for them. This work was also supported by the SDEY (Syndicat Départemental d'Energies de l'Yonne).

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