A User-Preference-Based Charging Station Recommendation for Electric Vehicles

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***Abstract*— The popularity of electric vehicles (EVs) is increasing, leading to higher demand for electric vehicle charging stations (EVCS). It is crucial to select an appropriate charging station based on user preferences; however, current selection solutions are limited and primarily focus on proximity or price. Such an approach neglects other significant factors of interest to EV users, namely charging time, waiting time, charging cost, and available facilities near the EVCS. To address this issue, this paper proposes a novel recommendation scheme, the User-Preferences based Charging Station Recommendation Scheme (UPCSRS), which integrates user preferences with Multiple Attribute Decision Making (MADM) theory to suggest the best available charging stations for EV users. UPCSRS consists of two parts: adopting Analytical Hierarchical Process (AHP) for weighting the importance of each selection criterion and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for ranking available charging stations. A mathematical model of the proposed scheme was developed, and then the effectiveness and accuracy were evaluated using MATLAB and a real dataset from the US Department of Energy website. Results showed that this proposed scheme provides more precise and personalized recommendations for users compared to current solutions that only consider the nearest or cheapest option. By enhancing the overall user experience through a more customized and efficient charging station selection process, this proposed scheme has the potential to contribute to more EVs adoption.**

***Index Terms*— Multi-attribute decision-making, recommendation scheme, electric vehicles.**

I. INTRODUCTION

GROWTH of the world economy, coupled with the growth of the automobile industry, is causing greater energy consumption and increased environmental pollution to cause more and more serious problems. Currently, the use of petroleum by automobiles accounts for 60% of total petroleum use [1]. New green energy automobiles are likely to be an effective way to reduce petroleum consumption and dependence, improve the status of environmental pollution, and overall be a trend in the development of the intelligent transportation systems. Thanks to this potential, many automotive factories have already begun to roll electric vehicles off their production lines [2]. Currently, there are more than 23,000 public charging stations in the US. There is expected to be many more added in the near future, as highway fast-charging stations become more popular [3].

EVs are considered to be part of the emerging future Intelligent Transportation Systems (ITS) [11], as they have been recognized as a promising solution to reduce CO2 emissions compared to traditional gasoline vehicles [4], [12]. However, compared to the time it takes to fill four gasoline-powered cars with gasoline, electric vehicles take much longer time to charge their batteries. So, selecting an appropriate EVCS to charge a given EV becomes a necessity. This is because each energy provider offers different prices and charging technology based on the current load, availability of energy, and waiting time [5]. The International Renewable Energy Agency believes that smart charging and user incentives, like dynamic pricing, will be key factors in unlocking the flexibility potential of EVs, which is necessary for successful grid integration of EVs and renewable energy in the future. There is a trend towards dynamic pricing among competing charging networks in making EV charging a viable business [6]. For example, in the United States, many charging station network operators (Electrify America, Tesla, Blink, ChargePoint, and eVgo) are entering the market with each offering different charging prices per minute or kilowatt hour (KWh).

Current state-of-the-art solutions proposed several centralized charging station selection approaches where EVCS and intermediary nodes select the charging station for EV users [7], [8], [9]. In other words, the decision has been taken by considering charging stations and the aggregators' requirements, while ignoring EV user preferences. For instance, the service requirements of some EV users are elastic, e.g., some users are willing to charge their EVs for a lower price with more waiting and traveling time, while others prefer short waiting times but with a higher charging price. Therefore, excluding EV users' context and preferences will lead to dissatisfaction with the provided quality of service facing long waiting times, high charging costs, long travel distances, etc.

This research sought to address EV users' challenges in selecting the most suitable EVCS to charge their electric cars. Individual EV users will be able to make an independent charging decision based on their preferences and other service requirements. The proposed recommendation scheme will increase EV user comfort with an optimized price and better quality of service (QoS) for EV users. Moreover, it will have an important and long-term impact on the viability of the EVCS network. The main aim of this work was to

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design a user preference-based charging station recommendation scheme (UPCSRS) that would suggest the best charging stations for EV users according to EV technical specifications as well as user needs.

Specifically, the following are the contributions of this research:

1) The system architecture for the recommendation scheme is presented, which takes into account user preferences as well as theoretical and technical considerations involved in its design and implementation (Section III).
2) A mathematical model was developed for the proposed recommendation scheme, namely UPCSRS, which considers the preferences of EV users. The Analytical Hierarchical Process (AHP) was employed to determine the weight of the selection criteria and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) to rank the available EVCS. This results in a careful recommendation of the best available charging station (Section IV).
3) An operational research quantitative analysis of the proposed scheme (Section V) is also provided, which is then evaluated to examine the performance by implementing the scheme in MATLAB, and tested using a real dataset. The results indicated that this proposed scheme outperforms previous solutions (Section VI).

II. Related Works

The global market for electric vehicle charging infrastructure is projected to reach $63.9 billion by 2025 [10]. However, the availability and selection of charging stations remain a major challenge for electric vehicle drivers [11]. Despite online directories and locators published by charging station providers, these methods may not effectively help EV drivers find and choose the charging station that best suits their needs. The reason for this is that information related to charging stations is typically vendor-specific and primarily intended to direct users toward the nearest available charging station. Other obstacles for EV drivers include long waiting times, long charging times, varying charging costs, poor charging and customer service, and issues related to safety and value for money. As such, an efficient charging station recommendation system that is based on user needs can assist EV drivers in finding and selecting the charging station that is most suitable for their dynamic requirements.

Previously, Danish et al. [8] proposed an efficient protocol for EVCS selection based on blockchain technology. A conceptual framework based on smart contracts was proposed, in which the architecture is composed of EV, EVCS, and Road Side Unit (RSU) that acts as a mediator between EV and EVCS. The selection protocol is based on defining a set of basic variables involved in the selection process, such as distance, arrival time, waiting time, and price, then converting all selection criteria into a cost to standardize the different units into one comparison unit (cost) to make them comparable. By considering that the total variables cost does not exceed the threshold that represents the budget determined by EV driver, the best price can finally be considered as the best option that is suggested to the user as shown in Fig. 1. All

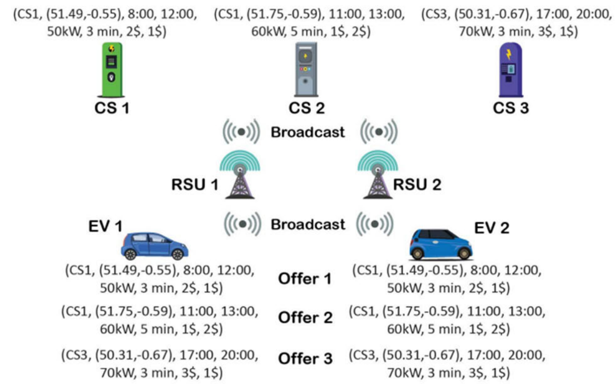


Fig. 1. BlockEV architecture [8].

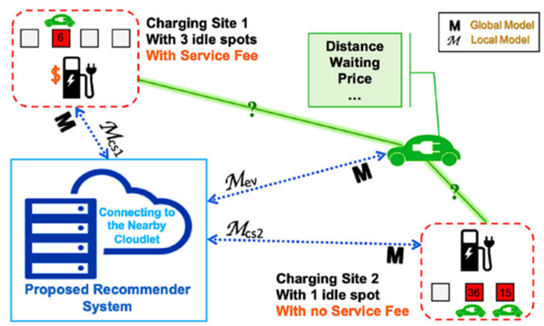


Fig. 2. Cloudlet-based EVCS recommendation system [12].

EVCSs must be registered with the nearby RSUs. These RSUs receive requests from EVs within their limited coverage area. They then execute the proposed selection protocol to identify the most suitable EVCS and subsequently suggest this option to the user. The use of RSU forces to suggest EVCSs that are within the coverage of RSU, which may lead to the omission of many better EVCSs outside the coverage area of the RSU. Furthermore, providing a range for each criterion does not accurately reflect user preference and the importance of each criterion.

Meanwhile, Teimoori et al. [12] presented an EVCS recommender model for EV based on a combination of cloud and federated learning. In this work, the architecture is based on integrating blockchain and cloudlet technologies with EV and EVCS, as shown in Fig.2. Several aggregators that collect data from vehicles and store them in the cloud are relied upon as an alternative to central structures to save time and effort in duplicate data entry operations. The selection process is done based on some variables such as the availability of EVCS charging spots, distance, remaining battery capacity, price, and time. The weights are calculated by dividing the parameters into EV and EVCS-related parameters and forming a vector of pairs representing the variables involved in the computation. The average of all EVCS variable values is assigned as a weight for that variable. Since the proposed model is assumed to recommend an EVCS in real-time, the latency can be notified in the selection process because of insufficient EV and EVCS sample size, which can affect the execution time and, consequently, the performance of the recommender system. Furthermore, the time needed for mining and verifying a new cloudlet inside a blockchain

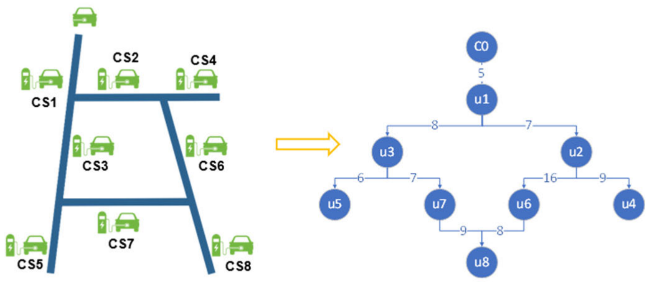


Fig. 3. Weighted spanning tree ST model [14].

network can be drastically affected by the size of the shared ledger. However, user preferences have not been taken into consideration while selecting the best EVCS. Moreover, the decision is made by the model, not the user, thus it may affect the quality of user experience.

In addressing issues of previous studies, Savari,et al. [13] proposed an application that monitors the operation of the vehicle and sends notifications to the driver to search for EVCS to save time and effort in searching for EVCS. The system architecture consists of EV, EVCS, and IoT devices that are employed to collect vehicle data, such as current location via GPS. In this proposed application, the nearest available charging station is searched that contains an available charging slot. The main purpose of this work is to suggest real-time EVCS to the EV driver as well as schedule charging in EVCS by reserving a charging slot in EVCS as per driver requirements. The traveling time is very important but other factors such as charging cost, charging status, and distance traveled are neglected in this selection model, hence, the decision is taken by the model, not the EV driver, who may have different perspectives.

Further work was done by Zhao and Zhang [14], who presented an algorithm to suggest charging stations to EV users based on variables that are related to the EVCS and not the driver himself. The architecture of this model includes EV, EVCS, IoT devices, and server. This algorithm combines charging power, charging cost, and charging time to optimize the algorithm of finding the EVCS. Moreover, some parameters such as EVCS power limitations, traffic in the area around the EV, and EV battery capacity are taken into consideration for selection. The spanning tree algorithm was used in the IoT to generate a topology for EVCSs. In this previous research, the main focus is on time, whereby the station that wastes the least time in terms of waiting and arrival, is chosen, and therefore it is considered the least expensive, that is, the different parameters are converted into time to compare them with each other and reach the best option by employing the spanning tree, as shown in Fig. 3. Weights are given based on the State of Charge (SoC) window which represents a threshold when reached and the nearest station is given high priority, otherwise charging time is given the utmost importance in the selection. The use of a Spanning Tree (ST) for selecting suitable EVCS may ignore some of the better EVCSs that will not be recommended based on this algorithm because of the selected path in ST.

Next, Sun et al. [15] introduced an online competitive algorithm designed to address the challenges of an online decision-making scenario. The algorithm focuses on recommending charging stations and their associated energy prices to sequential EV arrivals. It orchestrates the charging allocation in a way that maximizes the anticipated total revenue. The algorithm, known as the Online Competitive Algorithm for Recommendation (ORC) algorithm, is parameterized by a value function, allowing for tailored designs. User-related factors, such as arrival time, charging availability, and price, are harmonized into a unified price metric for comparability. The ultimate recommendations are then based on identifying the most favorable price. The algorithm strategically identifies four EVCSs for each EV, considering the city's geographical layout, and estimates the value of arrival time accordingly. The factors are limited and may affect the user preferences by considering different preferences for different users.

Meanwhile, Liu et al. [16] presented an innovative Urgency First Charging (UFC) charging scheduling policy, complemented by a reservation-based EVCS-Selection scheme embedded within the UFC charging scheduling framework. UFC evaluates charging urgency by considering the charging demand of EVs and their parking durations, using this urgency metric for prioritized scheduling. Higher charging urgency grants a preemptive charging privilege to the respective EV. Additionally, UFC introduces a reservation-based CS-Selection scheme based on total trip duration estimation, derived from the summation of time spent at EVCS and travel time to and from the EVCS. Notably, the time spent at EVCSs is estimated using the UFC scheduling policy. The EVCS-Selection is determined by real-time charging status at EVCSs. However, a limitation of this approach is its lack of consideration for various factors, relying on travel time estimation that could impact the accuracy of recommended EVCS. Moreover, it is not user-centric, as it does not allow users to express their preferences for consideration in the recommendation process.

In a different approach, Moradipari and Alizadeh [17] introduced a framework for the management of EVs within a public charging station network, emphasizing differentiated services. Their approach involves EVs selecting their energy demand and priority level from a customizable menu of options. This customization aims to optimize profit by strategically assigning EVs to suitable charging stations. The proposal takes into account user mobility patterns, distribution network constraints, and behind-the-meter solar generation. It employs an algorithm to discover a globally optimal solution for the Charging Network Operator (CNO) in scenarios with hard capacity constraints, addressing both social welfare and profit maximization. Despite the emphasis on power considerations and estimated travel distances, this framework has room for improvement by incorporating a broader range of user preferences crucial in selecting the most suitable EVCS for individual users.

Further investigation was also performed by Tang et al. [18], who presented a decentralized charging scheduling algorithm that empowers users to dynamically choose the optimal charging station. The algorithm focuses on maximizing social welfare, considering factors like varying electric vehicle (EV) demand, pricing, and balancing capacity, as well as congestion across different charging stations (CSs). The approach introduces both a centralized charging strategy (CCS) and a distributed charging strategy (DCS) to tackle this challenge. In CCS, the optimization problem is split into two segments. Initially, EVs are centrally distributed to CSs to balance congestion and minimize travel costs. Subsequently, charging capacities and power supply are optimized using a closed-form solution through the Lagrangian dual method. Meanwhile in DCS, a two-stage process is proposed. The first stage involves EVs obtaining real-time information from CSs and selecting the optimal CS to balance congestion and minimize travel distance. The second stage employs a distributed method to optimize charging demands. This work focuses on relying on charging demand and price in the weight calculation process and therefore neglects other factors that would directly affect the proposal of an appropriate EVCS.

Next, Mathioudaki et al. [19] introduced an effective algorithmic framework designed for real-time computation of a service-price menu catering to individual EVs. Each option in the menu offers distinct trip completion times and energy costs. EV users opt for the most preferable option that aligns with their budget and ensures the total duration (inclusive of the trip, waiting, and charging times) meets their set deadline. Essentially, the menu-based approach generates a diverse set of options, considering a broad spectrum of user preferences based on predefined criteria. Users then make selections, potentially influenced by criteria not explicitly visible to the system. Noteworthy is the model's reliance on total time as a primary metric for comparison among different EVCSs, but other preferences maybe overlooked. This model operates without requiring users to disclose their preferences, potentially impacting the precision of recommendations and the system's user-centricity.

Further investigation by Danish and Zhang [7] resulted in the introduction of an innovative decentralized blockchain-driven architecture for EV charging, revolutionizing the communication dynamics between electric vehicles (EVs) and charging stations (EVCSs). Unlike traditional setups, this architecture operates without the need for a centralized authority, fostering a decentralized exchange of information. The recommendation system within this framework incorporates key factors such as charging price, charging time, and waiting time. However, a critical consideration arises in the process of converting these diverse variables into a unified price metric for effective comparison. This conversion methodology, while effective in some contexts, proves less suitable for the nuanced realm of EVCS recommendation. The absence of normalization to standardize units across different variables might introduce inconsistencies, highlighting the importance of incorporating normalization techniques tailored to the specificities of EV charging station recommendations.

A detailed comparison of charging station selection/ recommendation solutions together with their key features is provided in Table I.

TABLE I
CRITICAL ANALYSIS OF THE STATE-OF-ART

Ref	**Technique**	**Selection criteria**	**1**	**2**	**3**	**4**
[8]	Blockchain	distance, remaining battery capacity, price, and time	✗	✔	✗	✔
[12]	Federated learning	Distance	✗	✔	✗	✗
[13]	Nearest	Distance	✗	✗	✗	✗
[14]	Spanning tree	Time	✗	✔	✗	✗
[7]	Blockchain-based decentralized selection	Price, charging time, waiting time	✗	✔	✗	✔
[15]	On-Arrival Commitment	Arrival time, charging availability, and price	✗	✔	✗	✗
[16]	A total trip duration estimation	Travelling Time	✗	✗	✗	✔
[17]	Energy demand user preferences	Energy and Travelling Distance	✔	✔	✗	✗
[18]	Centralized Charging Strategy (CCS) and Distributed Charging Strategy (DCS)	Charging demand, and price	✗	✔	✗	✗
[19]	Online Truthful Algorithm	Traveling Time, waiting time, and charging time	✗	✔	✗	✔
This research	MADM	Consider both technical and user preferences factors	✔	✔	✔	✔

1:User-Centric, 2:Multi-attributes, 3:Comprehensive evaluation, 4: Preserving user data

Novelty of This Work:

UPCSRS introduces novelty through its user-centric approach and the incorporation of advanced decision-making techniques namely AHP and TOPSIS. The system stands out by not only considering traditional technical factors but also prioritizing individual user preferences, thus offering more tailored recommendations. The inclusion of abnormality testing, where the top-ranked station is intentionally removed to assess system consistency, contributes to the robustness and reliability of the recommendation process. Additionally, the UPCSRS integrates diverse data sources, employs a real-world dataset, and ensures transparency in its recommendations, therefore it is further distinguished in the realm of charging station recommendation systems.

III. SYSTEM MODEL

In this section, the conceptual model of the recommendation scheme is presented. Specifically, the key components

TABLE II
CONVENTIONS OF SYMBOLS THROUGHOUT THE PAPER

Symbol	Description
$C_1 ... C_n$	Criteria 1 to n
$W_1 ... W_n$	Weights 1 to n
A1...An	Alternative 1 to n
A_{norm}	Normalized Matrix
C_I	Consistency Index
RI	Random Index
CR	Coherence Ratio
W_i	Weight
S_j^+	Positive Similarity Distance
S_j^-	Negative Similarity Distance
C_j^*	Fina Rank

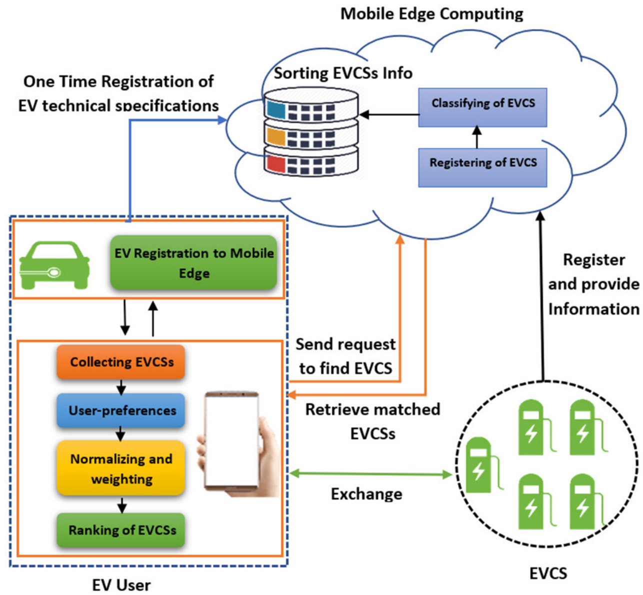


Fig. 4. System model for this study.

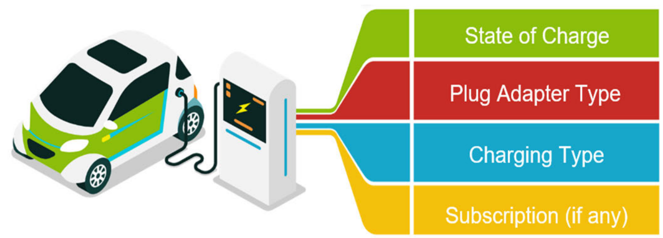


Fig. 5. Technical criteria.

and their interactions are outlined, as well as the technical considerations that were considered. The user preferences and primary factors that the system addresses are also discussed. Lastly, a brief explanation is provided regarding the multiple attributes decision-making theory, with a focus on AHP and TOPSIS, highlighting their key features and their relevance to the recommendation scheme. Table II displays the symbols used throughout the paper and their corresponding conventions.

Figure 4 depicts the primary components of the User-Preferences Based Charging Station Recommendation Scheme (UPCSRS), which includes EVCS, EV users, and mobile edge computing. The model is simplified for this paper. The EVCS first register themselves by providing their official registration ID to offer their services. The information provided will be verified and validated by the edge server, and acceptance or denial will be based on this evaluation. The edge server will receive information about the technical features of EVCS, its charging offers, and other related services through a one-time EV registration process.

EV users will register their EV's technical specifications, such as battery capacity, plug adapter type, and other charging-related technical aspects, locally. This information, along with the preferred geographical location for EV charging, will be sent to the edge server. The edge server will then retrieve a list of EVCS that can provide the required technical specifications for charging the EV and send it to the EV user. Subsequently, on the user's end, the recommendation scheme will be executed to rank the available EVCS and sort them based on the user's preferences. Finally, the user will select his preferred EVCS and contact it directly where they will exchange information about booking available time slot in real time for charging the EV.

A. Technical Criteria

The initial step in selecting an appropriate EVCS is to gather information about its technical specifications. Each EV has its unique set of specifications that must be present at the EVCS to proceed to the next stage. If any of these requirements are not met at a particular station, it will be excluded from consideration. Figure 5 illustrates the main technical specifications to screen EVCSs. These factors are mandatory to facilitate EV charging. For example, the most important factors are:

- **The state of charge (SoC):**This is a critical factor that must be considered. Charging becomes a necessity rather than a preference when the SoC is less than 10%. Therefore, it is necessary to check the SoC first to make an informed decision about whether charging is a preference or a necessity.
- **Plug Adapter Type:** Another technical factor that must be considered is the compatibility of the EV charging adapter type with the EVCS adapter type. Most EVs have separate ports for AC and DC quick charging inlets, and the type of charging connector varies depending on the country of manufacture and EV brand.
- **Charging Type:** Charging stations can be categorized as residential or non-residential, and they can support both slow charging (level 1 and level 2) and fast charging (level 3 and DC).
- Other technical factors could be considered as well in this proposed scheme, such as payment type, access type (public or private), service provider, etc.

B. User Preferences

When selecting a charging station for EVs, it is important to consider user preferences [20]. However, most current recommendation solutions are based on either centralized or charging station requirements, without taking into account the user's needs and desired quality of experience beyond proximity or cost. This study aims to shift decision-making power to the user, allowing them to choose an EV charging station based on their personal preferences. For example, a user may opt for a station further away with lower prices or one that allows them to start charging immediately rather than wait for 15 minutes at a closer station. By considering user preferences, it becomes possible to recommend the most suitable EV charging station and ensure a satisfactory quality of experience for the user.

A large number of criteria can cause a decline in system performance, while a smaller number may not result in a good decision. Therefore, to determine the appropriate range of criteria, a review was conducted, ranging from three [21], [22], [23] to ten, but according to the literature review, a cardinality of four [24], [25] is most used. These criteria have been carefully chosen through robust methodology. An extensive review of existing literature was conducted, identifying the most common and impactful factors influencing the selection of charging stations for EVs. These factors, namely distance, charging time, waiting time, and price, emerged as key determinants from a comprehensive analysis of prior works in the field. These criteria are the most significant according to user preferences. Therefore, they have been considered in this study. However, the selected criteria can be changed or adjusted to align with future preferences without affecting the operation of this proposed system. This flexibility adds another advantage to this scheme compared to other works. A brief definition of each selected criterion is provided below:

- **Travel Distance (TD)**criterion denotes the distance that must be traveled to reach a specific charging station and is measured in kilometers (km).
- **Waiting Time (WT)**criterion refers to the duration a driver must wait at the selected charging station before they can begin charging their vehicle and is measured in minutes (min).
- **Charging Time (CT)**criterion represents the amount of time required to fully charge the EV and is measured in minutes (min).
- **Price**criterion refers to the charging cost, which is denominated in US dollars (USD).

C. Multiple Attribute Decision Making (MADM)

MADM is a decision-making approach that involves evaluating and selecting the best alternative from a set of alternatives based on multiple criteria or attributes. This approach is particularly useful in situations where decision-makers need to consider various factors simultaneously to make an informed and comprehensive decision [26]. One common strategy in MADM is to use hierarchy approaches, which involve hierarchically **structuring** the decision problem. This hierarchy typically consists of levels, with the top level representing the overall objective and the lower levels representing the criteria or attributes that contribute to achieving that objective. Hierarchy approaches provide a systematic and organized framework for decision-makers to assess and prioritize different criteria [27]. The Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and Artificial Neural Networks (ANN) stand out as three commonly employed hierarchy approaches in decision-making and pattern recognition. Each approach offers unique features and is suited for specific types of problems, making them valuable tools in diverse fields. Table III provides a comparative overview, offering insights into the distinctive characteristics of these approaches for helping practitioners determine the most suitable methodology based on the nature of their decision or analysis requirements.

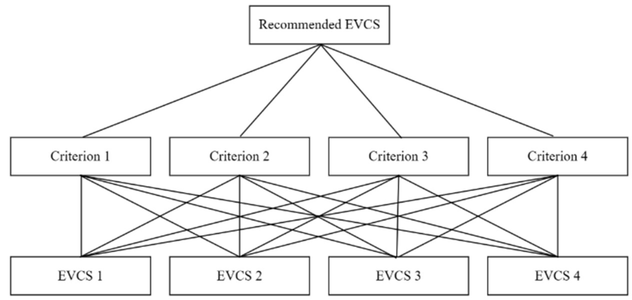


Fig. 6. AHP working procedure.

Selection approaches in decision-making encompass various methodologies aimed at identifying the most suitable alternative from a set of choices. Techniques like VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Simple Additive Weighting (SAW), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are notable in this domain. Among these, TOPSIS holds significance for UPC-SRS, as it is particularly effective in ranking alternatives based on their proximity to the ideal solution, which aligns well with the objective of UPCSRS to recommend charging stations that best match user preferences across multiple criteria.

1) AHP: Hierarchical approaches in decision-making involve organizing complex problems into a structured hierarchy of criteria, sub-criteria, and alternatives. These methodologies, such as AHP, ANP, and ANN, facilitate systematic analysis and prioritize elements based on their importance within the hierarchy. Upon comparing these approaches in Table III, AHP emerges as particularly advantageous for UPCSRS. AHP's strength lies in its ability to handle pairwise comparisons, making it well-suited for evaluating criteria concerning user preferences in a charging station selection context.

Additionally, AHP accommodates a straightforward way of capturing and incorporating user preferences into the decision-making process; a crucial aspect of personalized recommendations in UPCSRS. AHP starts by structuring the decision problem into a hierarchical tree with three main levels: goal, criteria, and alternatives, as shown in Fig. 6.

- The top level represents the overall goal or objective.
- The second level consists of criteria that contribute to achieving the goal.
- The bottom level includes the alternatives or options being evaluated.

TABLE III
COMPARISON OF HIERARCHY APPROACHES

Aspect	AHP	ANP	ANN
Advantages	• Hierarchical Structure: AHP accommodates complex problems in a structured manner, allowing decision-makers to break down decisions into manageable components. • Pairwise Comparisons: Enables intuitive and consistent comparisons, facilitating judgments for decision criteria. • Transparent Decision Process: Offers transparency by documenting decisions and justifying the ranking of alternatives. • Flexibility: Allows for the addition or modification of criteria and alternatives easily.	• Handling Complex Interactions: ANP accommodates the interactions and interdependencies between elements more effectively than AHP. • Adaptability to Complex Structures: More adaptable to complex decision-making scenarios with network-based structures. • Versatility: Applies to situations where factors influence each other.	• Non-linearity Modeling: Captures complex, non-linear relationships in data. • Pattern Recognition and Prediction: Proficient in recognizing patterns and predicting outcomes from data. • Adaptability: Can learn from data and adjust to new patterns without reprogramming.
Disadvantages	• Complexity in Large Decision Models: It can be challenging to manage and apply in large-scale decision models with numerous criteria and alternatives. • Expert Dependency: Heavily reliant on expert judgments, which might introduce biases. • Sensitivity to Subjectivity: Subjectivity in pairwise comparisons can influence final outcomes and may not reflect objective realities.	• Complexity: Similar to AHP, ANP can be complex, especially when dealing with interconnected structures and interdependencies. • Expert Dependency: Requires substantial expert input, which might lead to subjective biases.	• Computationally Intensive: Training and large-scale usage can be computationally demanding. • Black Box Nature: Interpretability might be limited, making it hard to understand the reasoning behind specific decisions. • Overfitting and Generalization: May overfit to the training data and struggle to generalize to new, unseen data.

The core of AHP involves making pairwise comparisons between elements at each level of the hierarchy. This is done using a scale of preference. The scale typically ranges from 1 to 9, where 1 indicates equal importance, 3 indicates a weak preference, 5 indicates a moderate preference, 7 indicates a strong preference, and 9 indicates an extreme preference. Reciprocal values are used for comparisons in the opposite direction (e.g., if A is preferred over B by a factor of 3, then B is considered less preferable than A by a factor of 1/3). The pairwise comparisons are used to create a square matrix for each level of the hierarchy. Diagonal elements are always 1 (indicating that an element is perfectly equal to itself), and the elements below the diagonal are reciprocals of those above (maintaining consistency).

2) TOPSIS: The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) which was developed by Hwang and Yoon in the 1980s, is the second multi-criteria decision-making method that is widely used in various fields of research and industry [28]. The key feature of TOPSIS is that it can help decision-makers select the best alternative by considering multiple criteria simultaneously. The TOPSIS process involves identifying the criteria, establishing the weight of each criterion, and normalizing the decision matrix. Once the decision matrix is normalized, the ideal and negative ideal solutions are identified. Then, the distance between each alternative and the ideal and negative ideal solutions is calculated, and ultimately a relative closeness coefficient is determined. Based on the relative closeness coefficient, the alternatives are ranked, and the best alternative is selected. The advantages of TOPSIS include its ability to handle both qualitative and quantitative criteria, to provide a flexible and transparent approach to decision-making, and to allow for sensitivity analysis. TOPSIS has been successfully applied in various fields, such as engineering, management, and environmental studies. In conclusion, TOPSIS is a powerful multi-criteria decision-making method that can help decision-makers select the best alternative by considering multiple criteria simultaneously [29], [30]. The method's ability to handle complex decision matrices and generate a well-ordered preference ranking makes it a valuable tool for the selection phase in UPCSRS. Operating in several steps, TOPSIS begins with the formulation of a decision matrix representing the performance of each alternative against different criteria. The next steps involve normalizing the matrix, determining the weighted normalized values, and then identifying the positive and negative ideal solutions. Distances from each alternative to these ideal solutions are calculated, and the final step involves determining the relative closeness of each alternative to the positive ideal solution. The alternative with the highest closeness coefficient is considered the most favorable. TOPSIS combines elements of similarity and distance metrics to offer a systematic approach for decision-making in diverse fields, including the charging station recommendation context of the UPCSRS.

D. Dataset

This research utilized actual data acquired from the website of the US Department of Energy [31]. This dataset contained data on EVCSs located in all states of the USA, but for this research, the dataset was filtered for EVCSs located in New York and related information was gathered, including their location, identification number, and pricing data. Basic elements such as Facility Type, EV Level, EV Other Info, Owner dataset, EV Connector Types, Access Code, EV Pricing, EV On-Site Renewable Source, and Estimated Charging time were also obtained. The dataset was pre-processed to be suitable for use in UPCSRS. The experiments were carried out by testing different scenarios where the EV was within a range of 2 to 50 charging stations, and the location of the vehicle on a map was also randomly selected. The travel time to each charging station was calculated based on an average speed of 60 km/h. The experiments were conducted 100 times, and the outcomes were averaged.

IV. Design of Upcsrs Recommendation Scheme

The proposed recommendation scheme incorporates a hybrid methodology of user preferences and MDAM algorithms. Specifically, it utilized AHP to determine the importance of selection criteria based on user preferences and TOPSIS to rank the available EVCSs. A detailed description of the recommended scheme is provided in the following subsections.

A. User Preference

In UPCSRS, the process of aligning user preferences with AHP is seamlessly integrated into an intuitive graphical user interface (GUI). The journey begins as users handpick their preferred criteria, such as TD, WT, CT, P, and more. Within the GUI, users are guided to assign the importance of each pair of selected criteria using an interactive slider mechanism. For instance, the user will be able to assign the importance of (Travel distance to Waiting Time), (Travel distance to Charging Time), (Travel distance to Price), (Waiting Time to Charging Time), etc. This dynamic feature empowers users to finely calibrate the relative significance of one criterion in comparison to another, providing a nuanced expression of their preferences. Following this, the system diligently computes the weights for each selected criterion, leveraging the assigned importance values, which will be explained later. This inherently user-centric methodology ensures the precise capture and translation of individual preferences into actionable weights, thereby enriching the personalized recommendation of charging stations that seamlessly align with the unique priorities of each user as shown in Fig. 7.

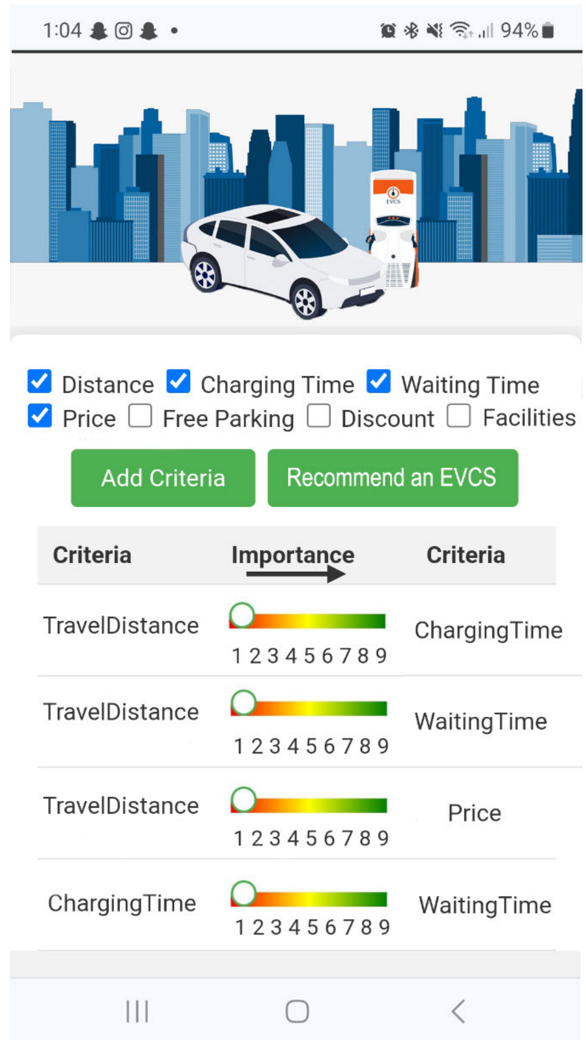


Fig. 7. User preferences mapping to AHP.

B. Weighting Process Based on User Preferences

AHP was utilized to determine the weights of the selection criteria of charging stations. The user selects the desired criteria to be included in the comparison as shown in Fig. 7. According to the selected criteria, pairs of criteria will be created to assign the importance value by the user. For instance, the user will assign the importance of the first selected criterion to the second selected criterion, and then the importance of the first to the third, etc. The process for adopting AHP to assess weightings involves the following sequential steps:

Step 1: Create the pairwise comparison matrix

Assume that the user selected a set of criteria C = [Ci; i = 1, 2,…, n] to be evaluated for recommending the most appropriate charging station based on user preferences, then these criteria are compared with each other creating an even pairwise comparison matrix of dimensions (n * n), denoted by A [i,j = 1, 2,…, n]. In this matrix, each element a_{ij} depicts the relative importance of the i^{th} criterion concerning j^{th} criterion. This value is determined by the user according to preferences by using Saaty's 1 to 9 scale, which is utilized to show the significance of each criterion in contrast

TABLE IV
THE SCALE OF IMPORTANCE FROM SAATY [27]

Intensity of importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values

to other criterion, as shown in Table IV. In the matrix A, $a_{ij} = 1$ when i = j and $a_{ij} = 1/\,a_{ij}$, as depicted in equation (1).

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{21} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \quad \text{where, } a_{ii}{=}\,1, \;\; a = \frac{1}{a_{ij}} \tag{1}$$

Step 2: Compute the normalized weight.

Comparing criteria can be challenging due to the varying units used to measure them. To improve accuracy, it is necessary to standardize the units and equalize the values. Therefore, the normalization of the pairwise comparison matrix is accomplished by dividing each entry in a column by the sum of column entries of matrix A. The normalized matrix called A_{norm} is constructed from Equation 1, which is produced by dividing each element by the sum of the elements of the same column in Equation 1, as shown below:

$$A_{norm} = \begin{bmatrix} \frac{a_{11}}{\sum a_{i1}} & \frac{a_{12}}{\sum a_{i2}} & \cdots & \frac{a_{1n}}{\sum a_{in}} \\ \frac{a_{21}}{\sum a_{i1}} & \frac{a_{22}}{\sum a_{i2}} & \cdots & \frac{a_{2n}}{\sum a_{in}} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{a_{n1}}{\sum a_{i1}} & \frac{a_{n2}}{\sum a_{i2}} & \cdots & \frac{a_{nn}}{\sum a_{in}} \end{bmatrix} \; where, i = 1, \ldots n \tag{2}$$

The normalized matrix is used for evaluating the normalized relative weight of the matrix elements by taking the average of each row element. The normalized weight (Wi) of each element is calculated using Equation 3. The sum of all values in the matrix W must be 1 to obtain the desired consistency in calculating the weights. Otherwise, there is a need to revise the pairwise matrix until the attainment of consistency.

$$W = \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} \; where, Wi = \frac{\sum_n^{j=1} a_{ij}}{n} \tag{3}$$

Step 3: Evaluate the Consistency Ratio (CR)

Consistency can be checked by calculating the value of CR. CR is a measure used in AHP to assess the consistency of the pairwise comparison matrices. It quantifies the acceptable level of inconsistency in the decision-making process. The selection of a CR threshold is often context-dependent. In general, a CR of 0.1 or less is acceptable, which indicates a reasonable perspective of the decision-makers in allocating the relative importance/weight of criteria. This assumes that, in real-world decision-making, achieving perfect consistency is challenging, and a slight degree of inconsistency is tolerable. CR is calculated by dividing the Consistency Index (CI) by the Random Index (RI), which is a measure of the level of inconsistency in the matrix of pairwise comparisons. A lower CI indicates better consistency. Generally, a CI of 0 implies perfect consistency, and higher values indicate increasing inconsistency. However, the CI needs to be interpreted alongside the Random Index (RI). CR is calculated as follows:

TABLE V
RANDOM INDEX (RI) VALUES

Criteria	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

$$CR = \frac{CI}{RI} \tag{4}$$

The Random Index (RI) value is chosen based on the number of criteria used as shown in Table V. Four criteria were selected in this study; hence the RI value will be 0.9. AHP often involves iterative refinement, where decision-makers revisit their judgments to improve consistency. This iterative process is practical for achieving a balance between reasonable consistency and timely decision-making.

Using a sample size of 500, Saaty [27] displayed the average of the random index (RI) value for matrices of order 1 to 10. Similar to Table V, an acceptable value is 0.1 or less; if the value exceeds this threshold, the evaluation needs to be redeveloped or recalculated.

The Consistency Index (CI) is determined as follows:

$$\lambda = \frac{A * W}{W} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \end{bmatrix} \tag{5}$$

$$\lambda_{max} = \frac{\lambda_1 + \lambda_2 + \cdots + \lambda_n}{n} \tag{6}$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{7}$$

C. Recommendation Process

TOPSIS is a widely used technique for preferential decision-making. It is based on the Multiple Attribute Decision Making (MADM) theory, which uses Euclidean distance as its foundation. The ideal solution is used as a reference point, with the solution being as close as possible to the ideal solution and as far as possible from the negative ideal solution. TOPSIS methodology employs a decision matrix and a normalized decision matrix to calculate the numerical scores for each alternative based on the selected criteria. The positive and negative ideal charging stations are determined based on the characteristics of the criteria. The order of preference for the alternative charging stations is then finalized based on the closeness distance coefficient of each alternative. This assists users in making informed decisions based on their preferences.

TOPSIS is adopted in this work for its advantages such as ease of use, easy interpretation, and easy to understand results. The sequential steps for applying TOPSIS in this study are shown below:

Step 1: Develop the decision matrix

The decision matrix D is formed by the coordinated mapping of alternatives (charging stations) to the shortlisted proposed criteria of this research. Each element is the intersection of the alternative A with the respective criteria C, i.e., $A_i C_i$ where i =1, ..., the total number of available charging stations and j = 1, ..., total number of selected criteria.

$$D = \begin{bmatrix} A_1C_1 & \cdots & \cdots & A_1C_n \\ \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ A_mC_1 & \cdots & \cdots & A_mC_n \end{bmatrix} \tag{8}$$

Step 2: Develop the normalized decision matrix

The normalization process of the decision matrix is performed and the normalized decision matrix is obtained as per Equation 9.

$$Rij = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d^2 ij}} \tag{9}$$

where d_{ij} is the original and R_{ij} is the normalized element of the decision matrix.

Step 3: Develop the weighted normalized decision matrix.

The weighted normalized decision matrix is developed as a product of the weights W_j of selection criteria and the normalized decision matrix R_{ij}. The inputs of the V_{ij} matrix will be the same as the weights obtained in the previous weighting process using the AHP technique.

$$V_{ij} = R_{ij} * W_j \tag{10}$$

where W_j is weights of the criteria and $\sum_{j=1}^{n} W_j = 1$

Step 4: Determine the positive and negative solutions $A^+ and A^-$

$$A^+ = V_1^+, \cdots, V_m^+$$
$$A^- = V_1^-, \cdots, V_m^- \tag{11}$$

For the desired criteria:

$$V_1^+ = maxV_{ij}, j = 1, \ldots, n \tag{12}$$
$$V_1^- = minV_{ij}, j = 1, \ldots, n \tag{13}$$

For the undesired criteria:

$$V_1^+ = minV_{ij}, j = 1, \ldots, n \tag{14}$$
$$V_1^- = maxV_{ij}, j = 1, \ldots, n \tag{15}$$

Step 5: Determining the separation measure

There are two measures of separation in TOPSIS and these are the positive ideal distinction S_i^+ and the negative ideal distinction S_i^-. The Euclidean distance approach is used to calculate the separation criteria as shown in Equations 16 and 17.

$$S_j^+ = \sqrt{\sum\nolimits_{j=1}^{n} \left(V_i^+ - V_{ij}\right)^2} \quad where,\ j = 1, \ldots, n \tag{16}$$
$$S_j^- = \sqrt{\sum\nolimits_{j=1}^{n} \left(V_{ij} - V_i^-\right)^2} \quad where,\ j = 1, \ldots, n \tag{17}$$

Step 6: Once the positive and negative ideal solutions are obtained, the final rank vector C is computed as in Equation 18. The rank vector determines the ranking order of CSs among the available ones. The best CS from the vector is chosen in descending order of ranking. The one with the highest rank is the best charging station according to user preferences.

$$C_j^* = \frac{S_j^-}{S_j^+ + S_j^-} \tag{18}$$

For a better understanding of this proposed scheme, a demonstration of the numerical analysis is presented in section V using real data.

In the proposed UPCSRS, the decision-making process combines standard methodologies with tailored adaptations to address the CS selection problem. The foundation steps involve the application of AHP for the weighing process and TOPSIS for the ranking process. These methods, recognized as standard in decision-making procedures, provide a systematic approach for evaluating and prioritizing preferences. However, unique adaptations are introduced to accommodate the specific challenges of CS selection. For instance, a normalization process is integrated to handle diverse preferences measured in different units, thus ensuring fair comparisons. Additionally, the system is designed to be user-centric, acknowledging the individuality of user preferences in the EVCS context. This adaptation is crucial in aligning the decision-making process with the dynamic and personalized nature of user preferences in the CS domain. The integration of AHP and TOPSIS in this work for recommending CSs for EVs is among the early efforts in this research direction that paves the way for further research in this area.

V. Numerical Analysis

This section presents a numerical analysis of the proposed recommendation scheme that considers CSs from various service providers. Figure 4 depicts the proposed recommendation model for EVCSs, starting with the collection of offers and technical information from EVCSs. These are then filtered based on technical factors that align with EV technical requirements. The proposed scheme, which incorporates user preferences, is then applied, and the best EVCS is recommended based on the resulting ranking as shown in the steps of Fig.9. The experiments were executed on 11th Gen Intel(R) Core (TM) i7-11800H @ 2.30GHz Processor with 16 GB RAM, and implemented using MATLAB.

The following scenario assumes that the user selects the criteria: [C1=TD, C2=WT, C3=CT, C4=P] and the alternatives are [A1=EVCS1, A2=EVCS2, A3=EVCS3, A4=EVCS4]. As mentioned above, the user depends on Saaty's Table to

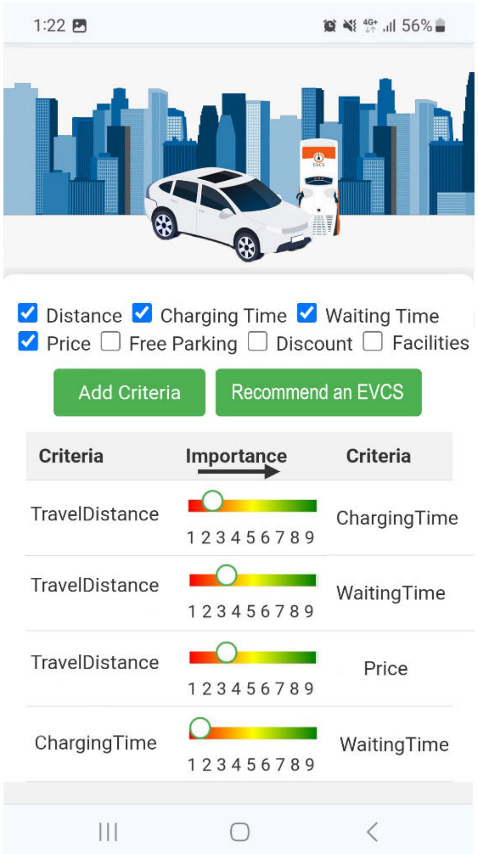


Fig. 8. Assigning the importance value for each pair of selected criteria by the user.

construct the pairwise matrix as shown in Equation 1 by assigning the importance of each criterion to the others. In this example, it is assumed that the user assigns the relative importance between criteria, for instance, assigning the importance of TD to WT as 3, the importance of TD to CT as 2, and the importance of TD to P as 3, while the importance of WT to TD is 1/3, the importance of CT to TD is 1/2, etc., as shown in Fig. 8.

$$A = \begin{array}{|l|l|l|l|l|}\hline \text{Criteria} & \text{TD} & \text{WT} & \text{CT} & \text{P} \\ \hline \text{TD} & 1.00 & 3.00 & 2.00 & 3.00 \\ \hline \text{WT} & 0.33 & 1.00 & 1.00 & 3.00 \\ \hline \text{CT} & 0.50 & 1.00 & 1.00 & 2.00 \\ \hline \text{P} & 0.33 & 0.33 & 0.50 & 1.00 \\ \hline \end{array}$$

The next step is calculating the A_{norm} matrix. Thus, first, the calculation of the summation of columns is needed, as follows;

$$\text{SumofColumns} = \begin{bmatrix} 2.16 & 5.33 & 4.50 & 9.00 \end{bmatrix}$$

$$A_{norm} = \begin{bmatrix} 0.462963 & 0.562852 & 0.444444 & 0.333333 \\ 0.152778 & 0.187617 & 0.222222 & 0.333333 \\ 0.231481 & 0.187617 & 0.222222 & 0.222222 \\ 0.152778 & 0.061914 & 0.111111 & 0.111111 \end{bmatrix}$$

Then, the normalized weight (Wi) of each criterion is calculated using Equation 3.

$$W = \begin{bmatrix} 0.450898 & 0.223987 & 0.215885 & 0.109228 \end{bmatrix}$$

where W = [$W_1, \ldots, W_4$].

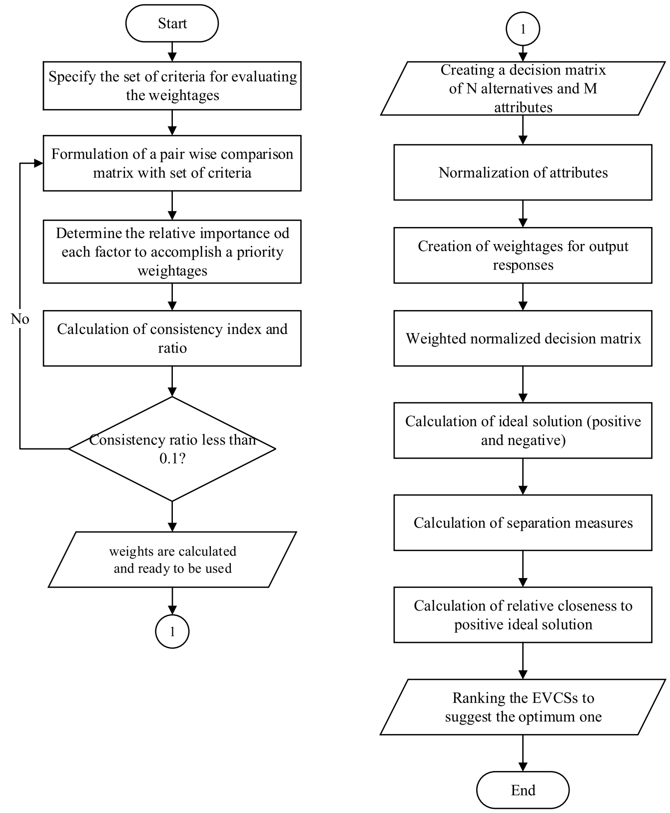


Fig. 9. Flow chart of the proposed EVCS selection scheme.

TABLE VI
SELECTION CRITERIA AND EXPECTED VALUES

	Travel Distance (TD) km	**Waiting Time (WT) min**	**Charging Time (CT) min**	**Price (P) USD**
EVCS	10	0-60	30-270	0-67.5$

To check the consistency of the calculated weight, λ_{max} is calculated based on Equations 5 and 6 ($\lambda_{max} = 5.027$). Then, the Consistency Index (CI) is computed by applying the Equation 7 (CI = 0.007). Finally, the consistency Ratio (CR), is calculated by Equation 4 (CR = 0.006). The CR value (0.006) is below the range of the upper limit acceptable for consistency. Hence, this has implicitly accredited the AHP consistency requirement.

The values in the decision matrix D are generated from selection criteria values, as shown in Table VI. The normalized matrix R_{ij} is calculated based on Equation 9, while Vij values are computed using Equation 10. Similarly, the ranking vector C is calculated based on the Equations 11 to 18. Alternatives [A1=EVCS1, A2=EVCS2, A3=EVCS3, A4=EVCS4] and Criteria [C1=TD, C2=WT, C3=CT, C4=P] are considered in forming the decision matrix D, where these values are retrieved from the dataset based for all alternatives (EVCSs).

$$D = \begin{bmatrix} 10 & 10 & 202.5 & 30 \\ 7 & 15 & 197.1 & 32.85 \\ 3 & 1 & 191.7 & 26.98 \\ 5 & 15 & 194.4 & 28.8 \end{bmatrix}$$

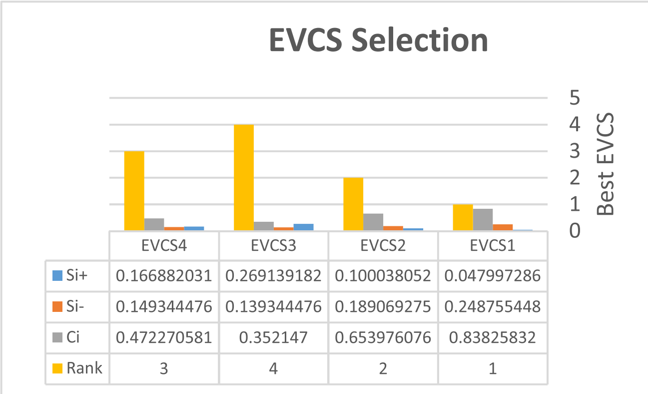


Fig. 10. Ranking of available EVCSs.

$$R_{ij} = \begin{bmatrix} 0.7392 & 0.4260 & 0.5154 & 0.5045 \\ 0.5175 & 0.6390 & 0.5016 & 0.5524 \\ 0.2218 & 0.0426 & 0.4879 & 0.4537 \\ 0.3696 & 0.6390 & 0.4947 & 0.4843 \end{bmatrix}$$

$$V_{ij} = \begin{bmatrix} 0.3333 & 0.0954 & 0.1113 & 0.0551 \\ 0.2333 & 0.1431 & 0.1083 & 0.0603 \\ 0.1000 & 0.0095 & 0.1053 & 0.0496 \\ 0.1667 & 0.1431 & 0.1068 & 0.0529 \end{bmatrix}$$

$$C_i^* = \begin{bmatrix} 0.838258 \\ 0.653976 \\ 0.352147 \\ 0.472271 \end{bmatrix}$$

According to the obtained results, ranks are assigned to all CSs depending on the values of vector C. As shown in Fig. 10, EVCS1, which represents alternative A1 has the highest rank among the four charging stations, which indicates that it is the best choice among the available alternatives. This is followed by EVCS2, EVCS4, and EVCS3 respectively.

Following the validation of this proposed recommendation scheme, Section VI delves into the assessment of its performance and discussion of the obtained results.

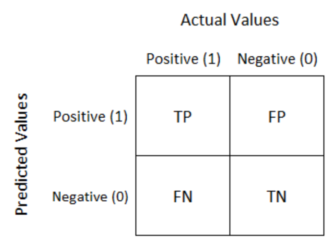
VI. Performance Evaluation

The proposed recommendation scheme's performance is evaluated through MATLAB simulation. Table VI presents the criteria used to rank available charging stations, considering their significance to user preference. These criteria can be easily modified or expanded based on user requirements. The analysis was conducted at a hundred decision points. In each simulation iteration, a random location for an EV is generated within the selected city, and the measurement of each criterion for the available charging stations within the EV's coverage is obtained from a real dataset described in section III-C.1.

A performance comparison was conducted between this proposed recommendation scheme and three other notable and closely related works. The first method recommends CSs based on best price. The second method by Savari [24] focused on selecting the station closest to the driver based on location (latitude and longitude). The third method is called "BlockEV" as presented by Danish and Zhang [7], where it determines the best CS by converting all variables into cost and selecting the station with the lowest charging price.

The experiment involved three distinct scenarios: travel distance, best price, and random preference. Each scenario represented a different user preference. In the first scenario, the distance to the charging station was considered the most important factor for EV users. In the second scenario, charging cost held the highest priority, while the third scenario encompassed random preferences. For each scenario, the experiment was conducted 100 times to ensure the robustness and reliability of the results. Subsequently, two primary performance metrics were calculated to evaluate the outcomes of the experiments as follows:

- **Recommendation accuracy** measures how effectively the recommendation system suggests relevant and useful CSs to EV users. This is typically evaluated by comparing the system's recommendations with the actual preferences of EV users. The accuracy and error rate are calculated according to Equations 19 and 20, respectively.



TP= $True\ positive\ value$
FP= False $positive\ value$
FN= $False\ negative\ value$
TN= $True\ negative\ value$
N= $Total\ number\ of\ values$

Accuracy is an intuitive and straightforward metric, representing the overall correctness of the system's recommendations. In the context of UPCSRS, a high accuracy would imply that most recommendations align with the user's preferences.

$$Accuracy\ rate = \frac{(TP + TN)}{N} \tag{19}$$

The error rate is the complement of accuracy and represents the proportion of incorrect recommendations. Like accuracy, it provides a clear, interpretable measure of how well UPCSRS is performing in terms of recommendation correctness.

$$Error\ rate = \frac{(FP + FN)}{N} \tag{20}$$

Precision is valuable when the cost of false positives is high. In the context of UPCSRS, high precision would mean that the recommended charging stations are more likely to meet the user's preferences. This is crucial for ensuring a positive user experience and encouraging user trust in the recommendations.

$$Precision = \frac{TP}{TP + FP} \tag{21}$$

Recall is important in scenarios where missing relevant recommendations (false negatives) is costly. For UPCSRS, high recall would indicate that the system is effective in not missing suitable charging stations according to the user's preferences. This is crucial for providing comprehensive recommendations.

$$Recall = \frac{TP}{TP + FN} \tag{22}$$

TABLE VII
COMPARISON OF THE RECOMMENDED EVCS OF OUR MODEL WITH THE DIFFERENT MECHANISMS

Scenario	Test	EVCS Selection Mechanism			
		Best Price	Nearest Mechanism [13]	BlockEv mechanism [7]	The Model of this Study
Travel Distance	Accuracy	57%	89%	75%	96%
	Error rate	43%	11%	25%	4%
	Precision	0.5525	0.8045	0.7201	0.95
	Recall	0.5969	0.8486	0.7523	0.9127
	F1-Score	0.5738	0.8259	0.7358	0.93097
Best Price	Accuracy	82%	62%	86%	94%
	Error rate	18%	38%	14%	6%
	Precision	0.7046	0.6326	0.7898	0.94
	Recall	0.7263	0.6521	0.8202	0.9008
	F1-Score	0.7152	0.6422	0.8047	0.91998
Random Preferences	Accuracy	72%	68%	73%	95%
	Error rate	28%	32%	27%	5%
	Precision	0.6971	0.8	0.7012	0.95
	Recall	0.7682	0.6667	0.7314	0.9091
	F1-Score	0.7309	0.7272	0.7159	0.9291

F1-score is a balanced metric that considers both false positives and false negatives. In the case of UPCSRS, where both precision and recall are important, the F1-score provides a comprehensive measure of the system's overall performance. It is especially useful when there is an uneven distribution between relevant and non-relevant recommendations.

$$F1 - Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{23}$$

- **Ranking abnormality** refers to any deviation or anomaly in the order or arrangement of CSs within a recommended list. An abnormality occurs when the inclusion or exclusion of a single station disrupts the expected or typical order of items in the ranking. Ranking abnormality depends on several steps, as in the following:
    1. **Initial Ranking:**Rank EVCSs based on the defined criteria for UPCSRS. This establishes a baseline ranking.
    2. **Best Station Identification:**This EVCS will intentionally be removed.
    3. **Abnormality Introduction:**Remove the best recommended EVCS from the data set.
    4. **Recommendation System Run:** Run UPCSRS on the modified shortlisted EVCS (without the best station).
    5. **Data Analysis:** Analyze the results of the recommendation system. Note any changes in the recommendations compared to the initial run.
    6. **Evaluation:** Evaluate the consistency of recommendations. If the removal of the best station significantly changes the recommended stations, it indicates a potential inconsistency or dependency on specific data.

A. Accuracy Evaluation

Table VII provides an overview of the results obtained from the proposed model, as well as the best price, nearest station, and BlockEV methods in three different scenarios. For all scenarios the criteria are determined by the user, as shown in Fig.8, then the user assigns a different importance value for each pair of selected criteria based on preferences. For instance, the user assigns the biggest value for the importance of TD to the other criteria, that means, the user considers TD as the most important criterion in this scenario. Meanwhile, assigning the biggest value for the importance of P to the other criteria means that the user considers price as the most important criterion in this scenario.

1) Travel Distance Use Case: In this scenario, previous research showed that the Nearest Mechanism algorithm [23] yielded the best results. This algorithm selects the nearest charging station, aligning with user preferences and requirements. Consequently, other algorithms such as the price or BlockEV algorithm exhibited lower accuracy compared to the Nearest Mechanism algorithm. However, the proposed algorithm in this research outperforms them all, achieving an impressive accuracy rate of up to 96%. This is attributed to the comprehensive consideration of all relevant factors.

While users typically prefer the nearest charging station, there may be drawbacks, such as long waiting times or high costs associated with such stations. This proposed model takes this into account and assigns utmost importance to proximity while also considering other factors. By assigning different weights to these factors, the proposed model would recommend the most suitable station that aligns with the user's preferences. This ensures the optimal charging option for the user, based on predetermined criteria.

2) Best Price Use Case: As for the best price scenario, there is convergence in the results of some previous works, but the best result was obtained using the BlockEv mechanism [7] because it depends on converting all variables into a price and

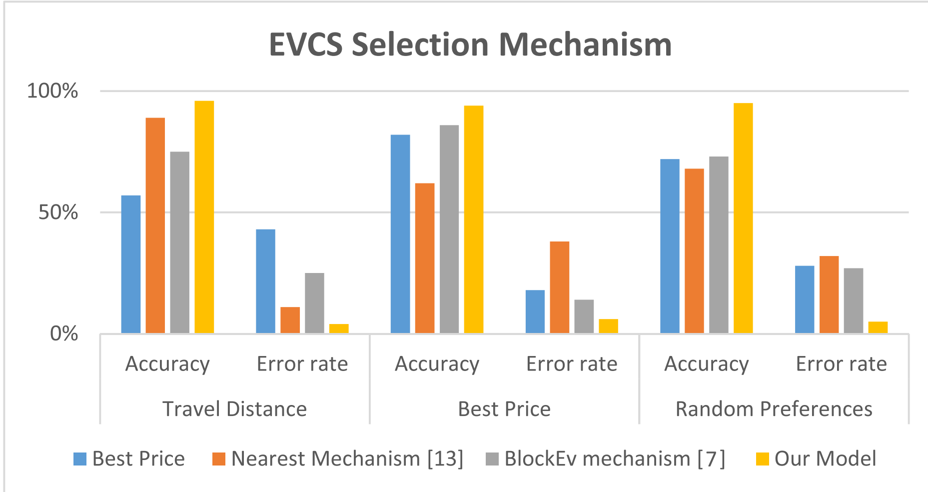


Fig. 11. Performance evaluation of different selection mechanisms.

then choosing the best price among the stations. Therefore, it is obvious that the results of this algorithm would be close to the most appropriate price algorithm. Moreover, this explains the weakness of the results using the distance traveled algorithm compared to this algorithm, because it depends on the nearest station, regardless of the price, whether it is appropriate or exaggerated. Despite this, it was revealed that there is a significant superiority of this study's proposed algorithm, which is evident by achieving an accuracy of up to 94% when tested on the preferences of a user who sets the price as a priority, while not eliminating the rest of the factors, but setting different weights for waiting time, distance traveled and charging time. This is the main reason that led to this better performance in the results, as the user may prefer the most appropriate price because he or she may want to go to a station that provides direct charging without the need to wait. Therefore, taking all factors into consideration is an ideal solution that meets all desires.

3) Random Use Case: The third scenario plays a pivotal role in evaluating algorithm performance due to the varying orientations and preferences of users. Some users prioritize traveling a longer distance to access direct charging without waiting, while also considering a suitable price. On the other hand, certain individuals may opt for a nearby station that may not be the closest, but ensures a charging period of not more than an hour, indicating a preference for fast charging. These divergent user preferences render algorithms relying on a single factor ineffective in suggesting an appropriate charging station. For instance, an algorithm may recommend the nearest station, but the user might prefer a more distant station with lower prices, or vice versa.

This underscores the significance of employing methods that consider multiple factors and assigning them different weights based on user preferences, rather than at random. Such an approach is essential in obtaining an optimal charging station that aligns with the user's desires. When evaluating this study's proposed algorithm, an impressive accuracy rate of 95% was observed, surpassing the performances of all other algorithms. This success can be attributed to the algorithm's comprehensiveness and integration of various factors, enabling it to cater to a wide range of user preferences more effectively.

For each scenario, a comparison has been performed among the existing selection mechanisms that were mention to be state-of-the-art. As shown in Fig 11, the proposed mechanism shows a superior performance in terms of accuracy and best error rate.

B. Ranking Abnormality

In evaluating charging station selection algorithms, it is essential to assess the ranking abnormality across different scenarios: travel distance, price, and random scenario. Ranking abnormality refers to the inconsistency in the suggested station rankings compared to the user's preferences. For the travel distance scenario, abnormality can occur if the algorithm fails to prioritize the nearest station, disregarding the user's preference for proximity. In the price scenario, abnormality arises when the algorithm suggests a higher-priced station despite the user's preference for lower prices. In the random scenario, abnormality is observed when the algorithm generates inconsistent rankings without clear correlation to user preferences. Measuring and minimizing such abnormality is crucial for algorithm effectiveness and user satisfaction.

1) Travel Distance Use Case: In the travel distance scenario, ranking abnormality is assessed by considering the user's preference for travel distance as a priority. The experiment was conducted 100 times to calculate the accuracy and error rate. Abnormality occurs when the algorithm fails to rank the nearest charging station as the top choice according to user preferences. The accuracy measurement determines the percentage of times the algorithm correctly ranks the nearest station as the preferred option. Conversely, the error rate quantifies the frequency of incorrect rankings, where a higher error rate indicates a higher degree of abnormality. Table VIII shows a comparison between the normal and abnormal tests on the same user preferences of this study's proposed mechanism.

2) Best Price Use Case: Table IX shows the results of performing the abnormality ranking test on the lowest price

TABLE VIII
ABNORMALITY RANKING ORDER OF EVCSs

Normal Ranking			Abnormal Ranking		
EVCS	C_i^*	**Rank**	**EVCS**	C_i^*	**Rank**
EVCS1	0.838258	1	EVCS2	0.625869	1
EVCS2	0.653976	2	EVCS3	0.412987	3
EVCS3	0.352147	4	EVCS4	0.536991	2
EVCS4	0.472271	3			

TABLE IX
ABNORMALITY RANKING ORDER OF EVCSs

Normal Ranking			Abnormal Ranking		
EVCS	C_i^*	**Rank**	**EVCS**	C_i^*	**Rank**
EVCS1	0.775325	1	EVCS2	0.323692	3
EVCS2	0.231645	4	EVCS3	0.586987	1
EVCS3	0.614258	2	EVCS4	0.423254	2
EVCS4	0.371452	3			

scenario. The results indicated that the outcomes are not affected by deleting one of the stations on the proposed station order based on the preferences set by the user.

3) Random Preferences Use Case: In the random preferences scenario, ranking abnormality is assessed by introducing random user preferences for charging station selection. The experiment was repeated 100 times to calculate the accuracy and error rate. Abnormality occurs when the algorithm generates inconsistent rankings that do not align with the random user preferences. The accuracy measurement quantifies the percentage of times the algorithm correctly ranks the preferred charging station according to the random preferences. Conversely, the error rate indicates the frequency of incorrect rankings, reflecting the extent of abnormality. Evaluating ranking abnormality in the random preferences scenario provides insights into the algorithm's robustness and its ability to adapt to diverse user preferences. The proposed algorithm demonstrated success in maintaining consistent results across different scenarios, indicating its reliability and effectiveness in charging station arrangement. Table X shows a comparison between the results of implementing the proposed method in the two cases (ranking normal and abnormal). The results indicated that the outcome of the proposed arrangement of charging stations is not affected when one of these stations is deleted. This indicates the success of this proposed algorithm in this test by re-executing the test on different scenarios and many times.

The ranking abnormality test involved comparing the results of the proposed mechanism with other scenarios. The experiment was repeated 100 times to calculate accuracy and error rates. Abnormality in ranking occurs when the proposed mechanism deviates from the expected rankings based on user preferences. The accuracy measurement determines the percentage of times the proposed mechanism correctly ranks the preferred charging station, while the error rate quantifies the frequency of incorrect rankings. By conducting multiple iterations of the experiment, the study evaluated the consistency and reliability of the proposed mechanism in minimizing ranking abnormality. These results provide insights into the effectiveness and robustness of the proposed mechanism compared to other scenarios as shown in Fig.12.

The proposed approach demonstrates scalability across varying problem sizes, making it adaptable to a spectrum of scenarios. This adaptability is particularly advantageous in the context of electric vehicle charging station recommendation systems. Whether the dataset involves a small number of users and criteria or scales up to encompass a larger user base and more intricate criteria sets, the approach remains robust. Its efficiency in handling diverse problem sizes underscores its practical utility for real-world applications. This flexibility ensures that the UPCSRS can seamlessly accommodate both current and potential future expansions in data and user interactions, making it a versatile and scalable solution.

VII. CHALLENGES AND LIMITATIONS

The successful implementation of UPCSRS confronts several challenges and considerations. Foremost among these challenges is the pivotal issue of data availability, system scalability, and real-time updates.

1. Data Availability and Quality:

Challenge: The success of UPCSRS critically depends on the availability and quality of data. In regions where comprehensive charging station data is lacking or inconsistently updated, the reliability of recommendations may be compromised.

Technical Considerations: Academic research should focus on data augmentation techniques, employing machine learning algorithms to improve the collection procedure. Techniques such as transfer learning can enhance data quality by leveraging information from more robust datasets. Additionally, the implementation of data validation and cleaning algorithms is crucial to ensure the accuracy of the input data.

TABLE X
MALITY RANKING ORDER OF EVCSS

Normal Ranking			Abnormal Ranking		
EVCS	C_i^*	**Rank**	**EVCS**	C_i^*	**Rank**
EVCS1	0.354236	4	EVCS1	0.257839	3
EVCS2	0.647215	1	EVCS3	0.645532	1
EVCS3	0.485218	2	EVCS4	0.458932	2
EVCS4	0.412587	3			

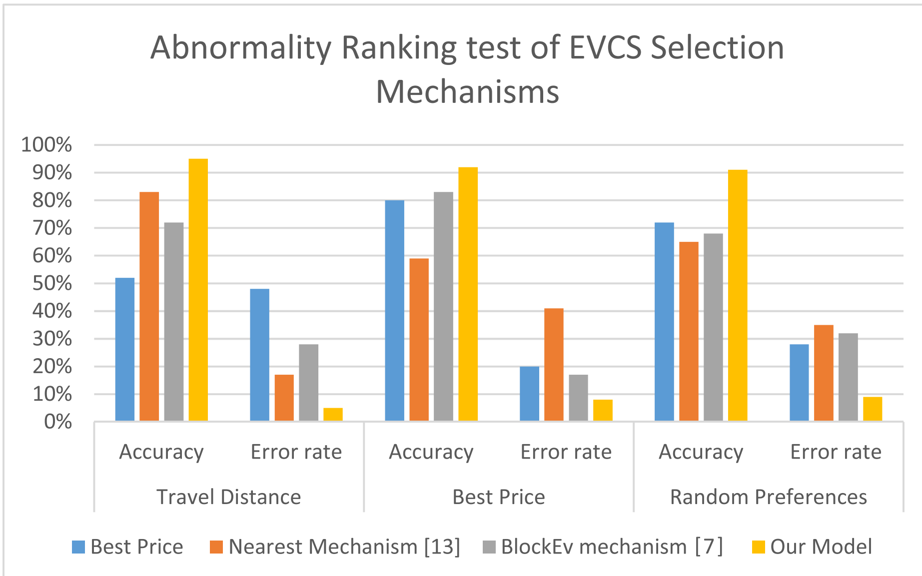


Fig. 12. Performance evaluation of different selection mechanisms.

2. System Scalability:

Challenge: As the UPCSRS user and charging station databases grow, ensuring the scalability of the system becomes paramount. This involves addressing computational efficiency and response time to maintain real-time recommendation capabilities.

Technical Considerations: Academically, researchers can delve into advanced algorithms with lower time and space complexity. The exploration of parallel and distributed computing paradigms, possibly leveraging cloud computing resources, is imperative.

3. Real-time Updates:

Challenge: Achieving synchronicity between UPCSRS and the real-time state of charging stations is a complex technical challenge. Real-time updates are crucial to adapt the system promptly to changing conditions.

Technical Considerations: Research efforts should be directed toward developing event-driven architectures that can handle real-time data streams effectively. Implementing streaming analytics and exploring technologies like Apache Kafka for real-time data ingestion can contribute to the technical underpinnings of UPCSRS.

4. Interdisciplinary Approaches:

Challenge: The multifaceted nature of the challenges requires an interdisciplinary approach, integrating principles from data science, machine learning, and system architecture.

Technical Considerations: Academia can foster collaboration across disciplines, encouraging joint research initiatives. Cross-disciplinary research teams can explore hybrid models that integrate advanced machine learning techniques with principles from distributed systems and database management. This holistic approach is vital for developing a technically robust UPCSRS that can withstand the challenges associated with data, scalability, and real-time requirements.

VIII. CONCLUSION AND FUTURE DIRECTION

The electric vehicle industry is receiving the most attention at the level of the automobile industries at the present time due to its environmental protection, lower costs, and the preservation of energy sources. One of the most important challenges facing this industry is the mechanism of choosing EVCS among the many available charging stations, as most technologies tend to choose the nearest or cheapest charging station. In this research, the EVCS selection mechanism was presented based on the user's desire, by actually taking user preferences into consideration. In this study, EVCS selection is a technique based on MADM approaches and preferences awareness. This proposed mechanism is based on two parts, the first part is the preference-aware analytical hierarchy process (AHP), while the second part is the use of the preference-aware technique of system preference by analogy with the ideal solution (TOPSIS). These two techniques were used to choose alternatives, compare them and then make a decision to recommend an appropriate EVCS based on user preferences.

This UPCSRS was explicitly designed as a user-centric scheme to accommodate the diverse and subjective nature of user preferences in the context of EV charging. The justification lies in the understanding that user preferences can vary significantly based on individual needs, priorities, and contextual factors. The CS selection process is inherently subjective, influenced by factors such as distance, waiting time, pricing, and additional amenities. In UPCSRS, the system is tailored to consider a comprehensive set of criteria that encompass various aspects of user preferences. By integrating methodologies like AHP and TOPSIS, this system allows users to express their preferences on different criteria. This user-centric approach acknowledges that there is no universally correct or rational decision when it comes to charging stations, as these choices are inherently personal and context-dependent. By providing users with a platform to input and weigh their preferences, UPCSRS respects the individuality of user choices. It embraces the idea that what may be a rational decision for one user might not be for another, and thus, there are no wrong preferences. The system's goal is to empower users to make decisions aligned with their unique priorities, ensuring a personalized and user-centric charging station recommendation experience.

The results were evaluated according to the principle of abnormality ranking, where it was found that the proposed mechanism significantly reduces the effects of abnormal arrangement, as deleting one of the alternatives does not affect the order of the other alternatives at all. Moreover, the results of the proposed EVCS were compared with state-of-art methods to test and highlight the performance of the proposed model. The results indicated a clear performance superiority of EVCS in the ability to make a decision based on user preferences and not influenced by the abnormality ranking.

All factors are very important to be taken into consideration. Therefore, the proposed model shows a high accuracy in comparison with the other mechanisms. This paper supposes two scenarios based on different users and different preferences. The first one supposes the user prefers to select an EVCS by giving distance the greatest importance then the waiting time, charging time, and the lowest importance for price. In this scenario, the results have been compared with the nearest mechanism that was proposed by [23] and showed marked superiority with 96% accuracy and 4% error rate, while it indicated to 89% accuracy and 4% error rate by using the nearest mechanism. The second scenario supposes the user prefers to select an EVCS by giving price the greatest importance then charging time, waiting time, and the lowest importance for distance. In this scenario, the results have been compared with the BlockEV mechanism that was proposed by [7] and showed a marked superiority with 94% accuracy and 6% error rate, while it indicates to 86% accuracy and 14% error rate for the BlockEV mechanism. The next focus and direction for this research journey shall be on recommending an enhanced EVCS by combining this proposed mechanism with a context, so as to create a context-aware EVCS selection (CEVCSS) system.

References

[1] J. Ping, S. Chen, Z. Yan, H. Wang, L. Yao, and M. Qian, "EV charging coordination via blockchain-based charging power quota trading," in *Proc. IEEE PES Innov. Smart Grid Technologies Asia (ISGT)*, no. 51707116, 2019, pp. 4362–4367, doi: 10.1109/ISGT-Asia.2019.8881070.

[2] M. Khodari, A. Rawat, M. Asplund, and A. Gurtov, "Decentralized firmware attestation for in-vehicle networks," in *Proc. 5th Cyber-Physical Syst. Secur. Workshop*, Jul. 2019, pp. 47–56.

[3] M. H. Au, J. K. Liu, J. Fang, Z. L. Jiang, W. Susilo, and J. Zhou, "A new payment system for enhancing location privacy of electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 63, no. 1, pp. 3–18, Jan. 2014.

[4] M. E. Özdağ and N. A. Atasoy, "Analysis of highway traffic using deep learning techniques/derin Öğrenme teknikleri kullanılarak anayol trafik analizi," in *Proc. 4th Int. Symp. Innov. Approaches Eng. Natural Sci. Proc.*, Jul. 2019, pp. 384–390, doi: 10.36287/setsci.4.6.098.

[5] F. Knirsch, A. Unterweger, and D. Engel, "Privacy-preserving blockchain-based electric vehicle charging with dynamic tariff decisions," *Comput. Sci. Res. Develop.*, vol. 33, nos. 1–2, pp. 71–79, Feb. 2018.

[6] Y. Yu, T. Song, C. Su, X. Tang, and Z. Han, "Hierarchical game for electric vehicle public charging market," in *Proc. IEEE Int. Conf. Commun., Control, Comput. Technol. Smart Grids (SmartGridComm)*, Oct. 2019, pp. 1–6.

[7] S. M. Danish, K. Zhang, H.-A. Jacobsen, N. Ashraf, and H. K. Qureshi, "BlockEV: Efficient and secure charging station selection for electric vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 7, pp. 4194–4211, Jul. 2021.

[8] M. Pustišek, A. Kos, and U. Sedlar, "Blockchain based autonomous selection of electric vehicle charging station," in *Proc. Int. Conf. Identificat., Inf. Knowl. Internet Things (IIKI)*, Oct. 2016, pp. 217–222, doi: 10.1109/IIKI.2016.60.

[9] S. M. Danish, K. Zhang, and H.-A. Jacobsen, "A blockchain-based privacy-preserving intelligent charging station selection for electric vehicles," in *Proc. IEEE Int. Conf. Blockchain Cryptocurrency (ICBC)*, Toronto, ON, Canada, May 2020, pp. 1–3, doi: 10.1109/ICBC48266.2020.9169419.

[10] A. Gupta. (2019). *63.9 Bn Electric Vehicle Charging Infrastructure Market 2019-2025*. Eqmagpro. Accessed: Nov. 29, 2023. [Online]. Available: https://www.eqmagpro.com/63-9-bn-electric-vehicle-charging-infrastructure-market-2019-2025/

[11] F. Alanazi, "Electric vehicles: Benefits, challenges, and potential solutions for widespread adaptation," *Appl. Sci.*, vol. 13, no. 10, p. 6016, May 2023, doi: 10.3390/app13106016.

[12] Z. Teimoori, A. Yassine, and M. S. Hossain, "A secure cloudlet-based charging station recommendation for electric vehicles empowered by federated learning," *IEEE Trans. Ind. Informat.*, vol. 18, no. 9, pp. 6464–6473, Sep. 2022.

[13] G. F. Savari, V. Krishnasamy, J. Sathik, Z. M. Ali, and S. H. E. A. Aleem, "Internet of Things based real-time electric vehicle load forecasting and charging station recommendation," *ISA Trans.*, vol. 97, pp. 431–447, Feb. 2020, doi: 10.1016/j.isatra.2019.08.011.

[14] Y. Zhao, C. Song, K. Zhang, X. Wang, and C. Zhang, "Method for finding the best charging station in the power Internet of Things," in *Proc. IEEE/IAS Ind. Commercial Power Syst. Asia (ICPS Asia)*, Jul. 2020, pp. 1720–1726.

[15] B. Sun, T. Li, S. H. Low, and D. H. K. Tsang, "ORC: An online competitive algorithm for recommendation and charging schedule in electric vehicle charging network," in *Proc. 11th ACM Int. Conf. Future Energy Syst.* New York, NY, USA: Association for Computing Machinery, Jun. 2020, pp. 144–155, doi: 10.1145/3396851.3397727.

[16] S. Liu, X. Xia, Y. Cao, Q. Ni, X. Zhang, and L. Xu, "Reservation-based EV charging recommendation concerning charging urgency policy," *Sustain. Cities Soc.*, vol. 74, Nov. 2021, Art. no. 103150, doi: 10.1016/j.scs.2021.103150.

[17] A. Moradipari and M. Alizadeh, "Pricing and routing mechanisms for differentiated services in an electric vehicle public charging station network," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1489–1499, Mar. 2020, doi: 10.1109/TSG.2019.2938960.

[18] Q. Tang, K. Wang, K. Yang, and Y.-S. Luo, "Congestion-balanced and welfare-maximized charging strategies for electric vehicles," *IEEE Trans. Parallel Distrib. Syst.*, vol. 31, no. 12, pp. 2882–2895, Dec. 2020, doi: 10.1109/TPDS.2020.3003270.

[19] A. Mathioudaki, G. Tsaousoglou, E. Varvarigos, and D. Fotakis, "An online truthful algorithm for menu-based scheduling in electric vehicle charging networks," in *Proc. Int. Conf. Smart Energy Syst. Technol. (SEST)*, Sep. 2022, pp. 1–6, doi: 10.1109/SEST53650.2022.9898146.

[20] S. Balasubramaniam and J. Indulska, "Vertical handover supporting pervasive computing in future wireless networks," *Comput. Commun.*, vol. 27, no. 8, pp. 708–719, May 2004.

[21] R. Tawil, G. Pujolle, and O. Salazar, "A vertical handoff decision scheme in heterogeneous wireless systems," in *Proc. IEEE Veh. Technol. Conf. (VTC)*, 2008, pp. 2626–2630.

[22] M. Pink, M. Sprejz, and H. Koenig, "A coordinated group decision for vertical handovers in heterogeneous wireless networks," in *Proc. Int. Conf. MOBILe Wireless MiddleWARE, Operating Syst., Appl.*, Nov. 2013, pp. 130–137.

[23] S.-M. Liu, S. Pan, Z.-K. Mi, Q.-M. Meng, and M.-H. Xu, "A simple additive weighting vertical handoff algorithm based on SINR and AHP for heterogeneous wireless networks," in *Proc. Int. Conf. Intell. Comput. Technol. Autom.*, vol. 1, May 2010, pp. 347–350.

[24] O. Markaki, D. Charilas, and D. Nikitopoulos, "Enhancing quality of experience in next generation networks through network selection mechanisms," in *Proc. IEEE 18th Int. Symp. Pers., Indoor Mobile Radio Commun.*, 2007, pp. 1–5.

[25] D. Zhang, Y. Zhang, N. Lv, and Y. He, "An access selection algorithm based on GRA integrated with FAHP and entropy weight in hybrid wireless environment," in *Proc. 7th Int. Conf. Appl. Inf. Commun. Technol.*, Oct. 2013, pp. 1–5.

[26] C.-L. Hwang and K. Yoon, *Multiple Attribute Decision Making: Methods and Applications a State-of-the-art Survey*, vol. 186. Berlin, Germany: Springer, 2012.

[27] T. L. Saaty, "How to make a decision: The analytic hierarchy process," *Eur. J. Oper. Res.*, vol. 48, no. 1, pp. 9–26, 1990.

[28] L. Ekiz et al., "Potential of cooperative information for vertical handover decision algorithms," in *Proc. 16th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2013, pp. 455–460, doi: 10.1109/ITSC.2013.6728273.

[29] T. L. Saaty and L. G. Vargas, *Models, Methods, Concepts & Applications of the Analytic Hierarchy Process*, vol. 175. New York, NY, USA: springer, 2012.

[30] D. R. Dange, S. Dutta, T. Chakraborty, and M. Majumder, "Identification of priority parameters for representation of desertification by using AHP-VIKOR method," in *Proc. IEEE Delhi Sect. Conf. (DELCON)*, Feb. 2022, pp. 1–4, doi: 10.1109/DELCON54057.2022.9752995.

[31] US Department of Energy. *Electric Vehicle Charging Station Locations*. Accessed: Nov. 24, 2023. [Online]. Available: https://afdc.energy.gov/fuels/electricity_locations.html

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