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SIMULATION MODELLING OF ELECTRIC VEHICLE CHARGING RECOMMENDATIONS BASED ON Q-LEARNING

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Abstract
The adoption of electric vehicles (EVs) represents a pivotal shift towards sustainable mobility, yet the challenge of efficient charging station recommendations persists, influencing user convenience and EV uptake. This study introduces a novel approach utilizing Q-learning for simulating EV charging station recommendations, aiming to optimize the matching process between EVs and charging infrastructure. By integrating Markov decision processes with Q-learning algorithms, we dynamically adapt recommendations to user behaviours and preferences, significantly enhancing recommendation accuracy and personalization. The methodology involves constructing a simulation environment to model EV charging behaviour, evaluating the performance of the Q-learning based recommendation system under various scenarios. Results demonstrate the effectiveness of this approach in identifying optimal charging strategies, thus contributing to improved user satisfaction and charging station utilization. The findings underscore the importance of innovative technological integration for addressing the complexities of sustainable urban mobility.
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Key Words: Electric Vehicles, Q-Learning, Charging Station Recommendations, Simulation Modelling, Intelligent Transportation Systems, Sustainable Mobility

1. INTRODUCTION

The rapid development of electric vehicles (EVs) not only signifies innovation in the automotive industry but also marks an important step towards sustainable development. By adopting electric power instead of fossil fuels, EVs play a crucial role in reducing greenhouse gas emissions and air pollution, while their high energy efficiency and low operational costs bring substantial benefits to consumers. With continuous advancements in battery technology and the gradual improvement of charging infrastructure, the EV market has witnessed unprecedented growth. This growth not only demonstrates the power of technological innovation but also reflects the global pursuit of low-carbon, environmentally friendly transportation solutions [1-3].

However, the widespread adoption of EVs has encountered significant challenges, particularly in terms of insufficient charging infrastructure and low charging efficiency. The uneven distribution and limited number of charging stations, coupled with prolonged charging times, have led to "charging anxiety" among consumers, thereby affecting the acceptance and popularity of EVs. This predicament not only impedes the broad adoption of EVs but also highlights the urgent need for innovation in charging technology, improvements in the electrical grid, and policy support. Therefore, developing efficient, convenient charging solutions and constructing an extensive charging network have become critical tasks in this field [1-3].

Against this backdrop, the research and development of EV charging recommendation systems become particularly important, yet they face the dual challenges of processing complex user data and enhancing the accuracy of personalized recommendations. Recommendation systems need to accurately capture and respond to the diverse needs and preferences of users, while also efficiently analysing large datasets to make precise recommendations. The limitations of existing technologies have prevented recommendation accuracy and user satisfaction from reaching ideal levels, while the rapid evolution of the EV market demands that recommendation system algorithms and models must have the capability to continuously update and optimize to adapt to these changes [4, 5].

In response to these challenges, this study proposes a simulation method based on Markov processes and Q-learning, aimed at optimizing EV charging recommendation systems. By simulating the charging behaviour of EV users with Markov processes, this method can dynamically capture changes in user behaviour. Coupled with the Q-learning algorithm, it further learns and predicts user preferences, thereby enhancing the accuracy of recommendations while also achieving personalized recommendation optimization. The innovation of this method lies not only in its ability to efficiently process and adapt to complex user behaviour data but also in providing more accurate and personalized charging station recommendations, significantly improving user experience. Through extensive simulation analysis, we have verified the effectiveness and practicality of this recommendation system, demonstrating its potential to promote the wider adoption of EVs.

The contributions of this paper to the field of intelligent transportation systems and EV charging recommendations are manifold. Among these, three primary contributions stand out, each adding significant value to both academic research and practical applications in sustainable transportation technologies.

1) This study's foremost contribution lies in its innovative application of the Q-learning reinforcement learning algorithm to optimize EV charging station recommendations. By integrating Q-learning with Markov decision processes, the research demonstrates a novel approach to dynamically adapting charging station recommendations based on user behaviour and preferences. This methodological innovation not only showcases the potential of reinforcement learning algorithms in solving complex decision-making problems but also advances the development of intelligent, data-driven solutions for sustainable transportation challenges. The application of Q-learning in this context is a significant step forward in creating more efficient and user-friendly charging infrastructure for the growing EV market.

2) Through detailed simulation modelling and analysis, this paper contributes to a deeper understanding of EV user behaviour and charging patterns. By simulating various scenarios and analysing the algorithm's performance under different conditions, the study provides valuable insights into how EV users make charging station choices and how these choices can be optimized for better efficiency and satisfaction. This enhanced understanding is crucial for the development of more effective EV charging recommendation systems that can accurately reflect and respond to the real-world needs and preferences of EV users, thereby facilitating the broader adoption of EVs.

3) Lastly, this research lays a strong foundation for future exploration and development in the field of intelligent transportation systems and EV charging recommendations. By identifying the potential of Q-learning algorithms in this domain and highlighting the effectiveness of simulation-based evaluation, the study opens up new avenues for further research. Future studies can build on these findings to explore other reinforcement learning algorithms, incorporate more complex variables, and integrate real-time data for even more accurate and personalized recommendations. Additionally, this work underscores the importance of ongoing innovation in charging technology and infrastructure planning, contributing to the evolution of sustainable urban mobility solutions.

2. LITERATURE REVIEW

2.1 EV charging recommendation methods

In the research of EV charging recommendation systems, the development of innovative methods can be discussed from two dimensions: the utilization of data and the application of algorithms. Firstly, the introduction of Internet of Things (IoT) technology, as demonstrated by Savari et al. [6] and Cao et al. [7], signifies the crucial role of real-time data in charging recommendation systems. By monitoring the charging needs of EVs and the operational status of charging stations in real-time, these methods can provide timely and effective recommendations, ensuring that users find suitable charging stations, thereby enhancing the usage efficiency of charging stations and user satisfaction. The core of these methods lies in the full utilization of real-time data, achieving quick responses to the dynamic changes in EV charging demands through high data connectivity and real-time analysis.

Moreover, the integration of learning algorithms offers the potential for deep optimization of charging recommendation systems. Through the work of Zhang et al. [8], Teimoori et al. [9], and Xu et al. [10], we have witnessed the application of advanced algorithms such as reinforcement learning, federated learning, and graph reinforcement learning in EV charging recommendations. These methods, by analysing historical and real-time data, can not only accurately predict user charging needs but also optimize charging recommendation strategies, achieving personalized recommendations. Specifically, these learning algorithms can process and analyse complex datasets, learning from user behaviour and charging station status to dynamically adapt to user needs and optimize the allocation of charging resources.

2.2 Simulation-based recommendation systems

Research on simulation-based recommendation systems is becoming an important branch in the field of recommendation systems. This approach, by simulating real-world user behaviours and system operations, offers a unique perspective for exploring the design and optimization of recommendation systems. Recent studies have showcased the potential and advantages of simulation-based recommendation systems in understanding the dynamics of user behaviour, balancing consumer and business values, and enhancing recommendation performance. For instance, Ghanem et al. [11] revealed the importance of balancing consumer and business values when designing recommendation systems, emphasizing the necessity of considering the balance between user satisfaction and business objectives. Through simulating different recommendation strategies, they demonstrated the dual role of recommendation systems in enhancing user experience and promoting business success. Following that, Zhang et al. [12] explored the long-term dynamics of recommendation systems and their interaction with consumer behaviour and recommendation performance through an agent-based simulation framework, highlighting the importance of evaluating recommendation systems from a long-term perspective. Additionally, Bhaskaran and Marappan [13], by simulating an enhanced personalized recommendation system for public machine learning datasets, verified the applicability of simulation in evaluating and optimizing the performance of recommendation systems, especially effective in handling large-scale complex data. Zhao's et al. [14] development of the KuaiSim simulator represents the forefront of simulation-based recommendation system research, capable of comprehensively simulating all aspects of recommendation systems, including user behaviour, recommendation algorithms, and system environment, showcasing the potential of simulation to fully understand and optimize the operation mechanisms of recommendation systems. These studies collectively highlight the unique advantages of simulation-based methods in deeply understanding the complex interactions between recommendation systems and user behaviour, testing, and optimizing recommendation strategies without affecting real user experience, indicating a possible pathway to achieve business objectives while ensuring recommendation quality and user satisfaction.

Combining the results from the review of EV charging recommendation methods and simulation-based recommendation system research, this paper proposes a simulation method based on Markov processes and Q-learning [15], aimed at overcoming the limitations of existing recommendation systems in processing complex user data and providing personalized recommendations [16-19]. By leveraging the advantages of IoT technology in real-time data processing and the application of learning algorithms in data analysis and personalized recommendation optimization, this study further explores the potential of simulation technology in the EV charging recommendation system. Specifically, by simulating the charging behaviour and preference changes of EV users, coupled with the dynamic optimization capabilities of reinforcement learning, we propose a new method capable of processing large-scale complex data and achieving precise personalized recommendations. This method not only enhances the accuracy and user satisfaction of the recommendation system but also provides scientific decision support for the layout and operation of EV charging stations, thereby contributing to the wider adoption of EVs and the development of sustainable transportation systems.

3. METHODOLOGY

3.1 Preliminary

Before delving into the model of the EV charging recommendation problem, this study will detail the architecture of the EV charging recommendation system, which is essential for a comprehensive understanding of the role of charging recommendation algorithms in optimizing the EV usage experience. The EV charging recommendation system consists of four core components: the EVs that issue charging requests, the charging stations that perform the charging operations, the intelligent traffic system that provides real-time traffic information, and the charging navigation system that plans the charging route.

EVs: Within the system, EVs are not only the initiators of charging requests but also can detect and transmit their remaining battery information to the charging navigation system. When the battery level falls below a predetermined threshold or the driver initiates a charging request, the vehicle sends its detailed information (such as remaining battery level, current location, etc.) to the charging navigation system to seek recommendations for charging stations.

Charging Stations: In the system, charging stations are equipped with waiting areas for charging and can transmit real-time information about vehicles being charged and those waiting to be charged to the charging navigation system, facilitating more effective distribution of charging stations.

Intelligent Traffic System: This system monitors road conditions, such as traffic flow and average speed, and provides essential traffic information to the charging navigation system, aiding in optimizing the recommended route to the charging station.

Charging Navigation System: As the hub of the system, the charging navigation system exchanges information with EVs, charging stations, and the intelligent traffic system. Based on the collected real-time information, this system can predict waiting times for charging and accordingly recommend suitable charging stations to users.

In the entire charging recommendation system, information flow proceeds as follows: EVs issue charging requests to the charging navigation system and provide their current location information; the charging navigation system then collects relevant information from charging stations and the intelligent traffic system in real-time; taking into account the information provided by EVs, charging stations, and the intelligent traffic system, the charging navigation system recommends the best charging station to the requesting vehicle based on the principle of shortest anticipated waiting time; finally, the EV proceeds to the recommended charging station for charging based on the navigation system's recommendation.

The driving behaviour of EVs from issuing a charging request to heading to a charging station for charging can be viewed as a process of temporal change from a starting position to a destination. The initial position of the EV when issuing a charging request is considered the problem's initial position, with the EV acting as the agent executing actions. In this context, the EV's choice of a charging station for charging based on road path conditions can be abstracted into a discrete problem, breaking down the journey to the charging station into small, discrete path choice problems, well aligning with the characteristics of a Markov decision process.

At the initial position, the EV perceives its current location and remaining battery level, choosing from available paths the decision with the maximum anticipated cumulative reward and executing it. With each choice of path towards the charging station, the EV receives corresponding environmental feedback. Positive feedback is given for path choices that contribute to reducing waiting times for charging, while negative feedback penalizes choices that increase waiting times. This cycle continues, enabling the EV to complete a Markov decision process from the initial state to action, then to a new state and another action, until the final state is reached.

In reinforcement learning, the foundation of an effective model consists of states, actions, and rewards. For the EV charging recommendation task, states include the EV's location, remaining battery, and the location of charging stations; actions are defined as the EV's route choice, taken in a discrete form based on connected road nodes; rewards focus on the EV's location changes, travel time, and charging efficiency, aiming to optimize the charging process through immediate and cumulative rewards, thereby reducing waiting times. The essence of this approach is to guide the EV efficiently to the charging station through a reasonable reward-penalty mechanism, showcasing the potential and real value of reinforcement learning in the domain of EV charging recommendations.

3.2 Problem description

First, let's define the state s of the EV, which includes its position in the grid map, its battery level, and the surrounding environmental states. An action a represents the process of moving from the current state s to a new state s', that is, moving one grid up, down, left, or right in the grid. The reward r is the feedback obtained from the environment after performing action a, aiming to evaluate the effectiveness of the action.

The action space A is defined as the four basic movement actions that the EV can perform:

$$A = \{\text{up, down, left, right}\} \tag{1}$$

The change in state after performing an action can be represented by the transition function, transitioning from state s to state s':

$$s' = f(s, a) \tag{2}$$

The reward function $R(s, a)$ assesses the immediate reward received after moving from state s by performing action:

$$R(s, a) = r \tag{3}$$

The goal of reinforcement learning is to find a policy π that maximizes the total reward G obtained by performing a series of actions following the policy π from the initial state s. The total reward G is accumulated from a series of immediate rewards:

$$G = \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \tag{4}$$

where γ is the discount factor, indicating the present value of future rewards.

The optimal policy π^* can be found by updating the Q-value (action-value function), which represents the expected return of choosing action a in state s. The Q-value update formula is:

$$Q(s,a) = Q(s,a) + \alpha \left[R(s,a) + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \tag{5}$$

where α is the learning rate, γ is the discount factor, s' is the new state after performing action a, and $\max_{a'} Q(s',a')$ is the Q-value of the best possible action in the new state.

Through iterative updates of the Q-value, the algorithm can eventually learn the optimal path from the EV's initial position to the charging station, while minimizing the waiting time for charging, effectively solving the task of recommending charging stations for EVs.

3.3 Reinforcement learning algorithm

Given the enhancements made to the Q-table structure and the methodologies for action selection and reward setting, let us incorporate some extended mathematical formulas to illustrate these concepts further.

The update of the Q-value in the Q-learning algorithm is governed by the following formula:

$$Q(s,a) = Q(s,a) + \alpha \left[R(s,a) + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \tag{6}$$

where:

- $Q(s,a)$ is the current Q-value for state s and action a,
- α is the learning rate,
- $R(s,a)$ is the reward received after executing action a in state s,
- γ is the discount factor,
- $\max_{a'} Q(s',a')$ is the maximum predicted Q-value for the next state s', across all possible actions a',
- s' is the new state after action a is taken.

Greedy Strategy: the ε-greedy strategy for action selection can be mathematically expressed as:

$$\begin{cases} \arg\max_{a} Q(s,a) & \text{with probability } 1-\varepsilon \\ \text{a random action} & \text{with probability } \varepsilon \end{cases} \tag{7}$$

where $A(s)$ represents the action chosen based on the current state s, and ε is the exploration factor that decreases over time according to a predefined strategy, such as:

$$\varepsilon(t) = \varepsilon_0 e^{-\delta t} \tag{8}$$

In this equation, ε_0 is the initial exploration rate, δ is the rate of decay, and t is the iteration or time step.

This formulation ensures a balance between exploring new actions and exploiting known actions with high Q-values.

The dynamic adjustment of the exploration factor ε as the learning progresses can be represented by:

$$\varepsilon = \min\left(\varepsilon_0, \frac{\varepsilon_{\min}}{\sqrt{t+1}}\right) \tag{9}$$

where ε_0 is the starting value of ε, $\varepsilon_{\min}$ is the minimum value ε can take, and t is the current episode or iteration count.

This equation ensures that ε decreases over time but never falls below a minimum threshold $\varepsilon_{\min}$, allowing for continued exploration even as the algorithm converges.

The reward function, aiming to minimize waiting times while encouraging the EV to reach a charging station, can be articulated through an extended formulation incorporating different aspects of the EV's journey:

$$R(s,a) = R_{\text{reach}} + R_{\text{time}}(t) + R_{\text{collision}} + R_{\text{congestion}} + R_{\text{steps}} \tag{10}$$

where $R_{\text{reach}} = +20$ if the action leads to a charging station, $R_{\text{time}}(t) = -t \times 0.04$ applies a time penalty for each minute spent, $R_{\text{collision}} = -1$ applies for hitting a wall, $R_{\text{congestion}} = -0.2$

for encountering traffic, and $R_{\text{steps}} = -20$ if the EV has moved 50 steps without reaching a charging station.

These formulations embody the detailed mechanisms underlying the proposed EV charging station recommendation system, providing a mathematical basis for algorithmic decisions and behaviour.

4. SIMULATION ANALYSIS

4.1 Experimental data processing

Initially, the simulation experiment requires generating a grid map based on the location of charging stations and road paths in the Hongkou District of Shanghai. The location information of charging stations in Hongkou District, Shanghai, is as shown in Table I below.

Table I: Charging Station Location Information in Hongkou District, Shanghai

Charging Station Name	Longitude	Latitude
Shanghai North Bund White Magnolia Plaza	121.498540	31.248555
Shanghai Hongkou District Finance Street Helen Center	121.490398	31.259732
Huayuanfang Supercharger Station	121.474892	31.272042
Shangbin Life Plaza (Public)	121.504079	31.260338
Huayuanfang DC Fast Charger Station	121.474785	31.272713
Shanghai Hongkou District Library Charging Station	121.476386	31.296109

Using the latitude and longitude information of the charging stations, their locations are imported into LocaSpace Viewer software, displayed on the actual map, and marked as shown in Fig. 1.

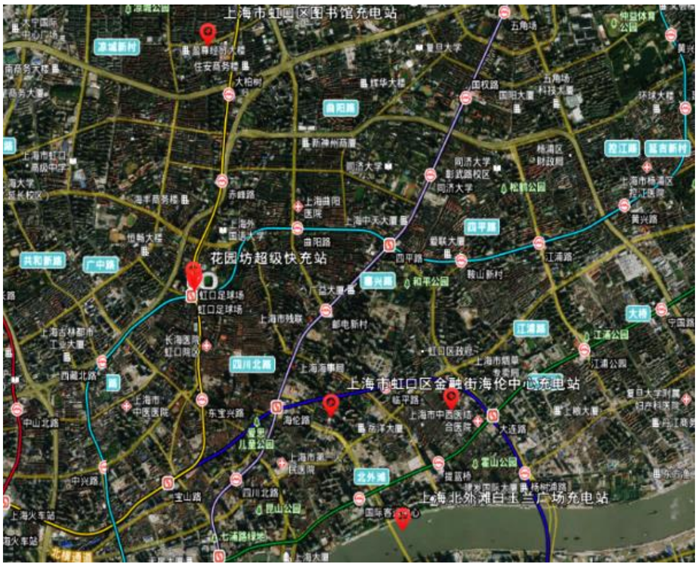

Figure 1: Charging Station Map Markings in Hongkou District, Shanghai (text in Chinese).

Furthermore, by utilizing the YoviSun toolkit to calculate based on the charging stations' latitude and longitude information, the average distance between two adjacent charging stations is approximately 3.8 kilometres.

With the information above, the location information of charging stations in Hongkou District, Shanghai, is abstracted into the grid map, preparing for subsequent algorithm experiments. The abstracted grid map is shown in Fig. 2.

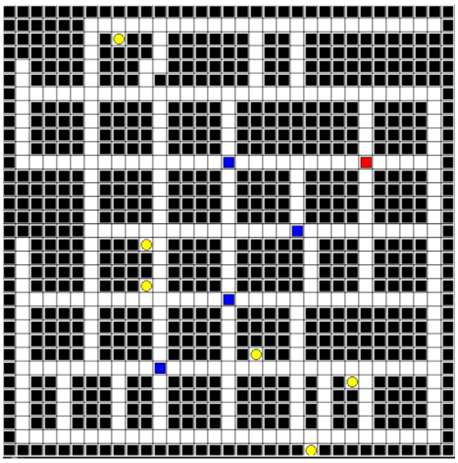

Figure 2: Simulation grid of charging stations in Hongkou District, Shanghai.

In this grid, yellow dots represent the locations of charging stations, blue dots represent pre-set traffic congestion points, and red dots represent the current location of the EV. Calculating based on the average distance of approximately 3.8 kilometres between two adjacent charging stations, each grid cell in this simulation network represents a distance of about 400 meters. According to the "2016 Smart Travel Big Data Report", the average driving speed in Shanghai is 24.5 kilometres per hour, equivalent to 400 meters per minute. Therefore, the experiment sets the time for EVs to pass through a white free cell as one minute, and the time to pass through a blue congestion cell as five minutes. Experiments are conducted based on this simulation grid.

4.2 Simulation results

Building upon the content of the previous section, this paper has provided a detailed introduction to the training process of the *Q*-learning reinforcement learning algorithm. In the specific simulation experiments, the algorithm's training was carried out on a 33×33 grid for 10,000 episodes. After completing the final episode, the algorithm utilized Python to call Matplotlib to output the convergence of the algorithm's reward values, assessing the algorithm's performance.

As shown in Fig. 3, the convergence of *Q*-values during the iterative process based on the *Q*-learning algorithm demonstrates the effectiveness of the algorithm.

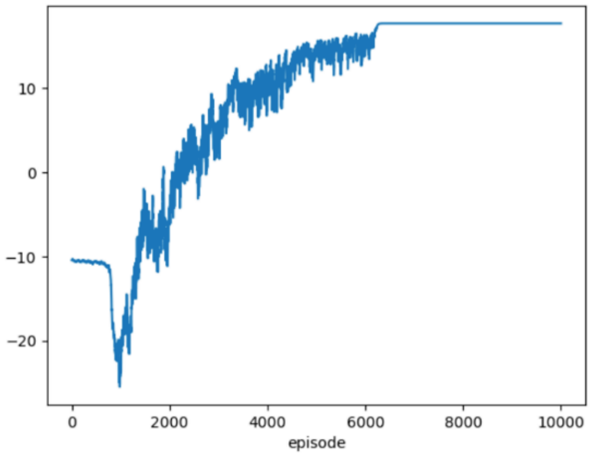

Figure 3: Convergence of *Q*-values during *Q*-learning algorithm training.

To verify the impact of the *Q*-table update method on *Q*-value convergence, as discussed in section 3, the Sarsa algorithm was also employed for recommending charging stations for EVs under the same environmental conditions. The convergence of Q-values during the iteration process of the Sarsa algorithm is illustrated in Fig. 4.

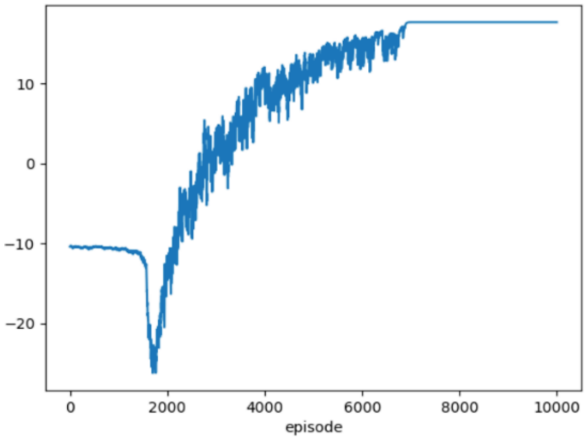

Figure 4: Convergence of Q-values during Sarsa algorithm training.

Comparing Figs. 3 and 4, it is evident that the experimental outcomes align with the predictions made in section 3. Both the Q-learning and Sarsa algorithms for EV charging station recommendation were able to achieve reward value convergence, i.e., finding the optimal strategy for charging station recommendation. Notably, the Q-learning algorithm reached Q-value convergence around 6,000 iterations, whereas the Sarsa algorithm achieved Q-value convergence after 7,000 iterations. Thus, the "bold" strategy of Q-learning is more conducive to Q-value convergence.

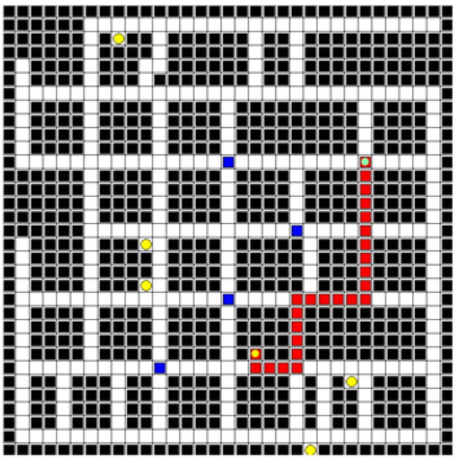

Figure 5: Optimal strategy.

Upon completing the algorithm training, the optimal strategy for EV charging station recommendation was obtained from the Q function, as depicted in Fig. 5. The strategy involves an EV departing from a green point and proceeding along the red cells to reach the charging station, which represents the action strategy that minimizes charging waiting time.

In expanding upon the initial description, this analysis showcases the practical application and effectiveness of reinforcement learning algorithms, particularly Q-learning and Sarsa, in navigating complex decision-making scenarios. By conducting extensive simulations over a sizable grid, the research highlights the algorithms' capacity to adaptively learn and improve upon the strategy for recommending the most efficient path to EV charging stations. This not only underscores the potential of such algorithms in optimizing real-world processes but also opens avenues for further exploration into enhancing algorithm efficiency and effectiveness in various applications beyond EV charging recommendations.

5. DISCUSSION

5.1 Theoretical insights

This study, through simulation modelling based on *Q*-learning, explored the optimization paths for EV charging recommendation systems, providing a new theoretical perspective for the field of intelligent transportation. Firstly, this paper demonstrated the effectiveness of reinforcement learning algorithms, especially *Q*-learning, in addressing and optimizing complex decision-making problems, such as the selection of charging stations for EVs. This finding emphasizes the potential of data-driven models in achieving sustainable transportation solutions, particularly in the face of the complexities of urban traffic and energy management.

Secondly, by integrating Markov decision processes with *Q*-learning, this study presented a method capable of dynamically adapting to changes in user behaviour and preferences. This not only enhanced the accuracy and personalization level of the charging recommendation system but also laid the groundwork for the future development of more efficient and responsive intelligent recommendation systems.

Furthermore, the results of this research also indicated that by precisely simulating and analysing the charging behaviour of EV users, it is possible to better understand user needs. This, in turn, enables more rational decisions in the design of charging infrastructure and the formulation of related policies, which is crucial for promoting the widespread adoption of EVs and achieving a low-carbon transformation of the transportation system.

Lastly, this study validated the applicability of simulation technology in optimizing the design and evaluation of recommendation systems through simulation analysis. This not only proved the efficiency of simulation methods in handling large-scale complex data and scenarios but also provided a platform for future research to further explore and validate new theories and methods.

5.2 Practical implications

This study's simulation modelling based on *Q*-learning offers significant practical guidance for the real-world application of EV charging recommendation systems. Key practical implications include:

1) Charging infrastructure planning and optimization: This research revealed the feasibility of optimizing EV charging recommendations using reinforcement learning algorithms, providing an effective tool for urban planners and policymakers to scientifically plan and optimize the layout of charging infrastructure. By simulating various charging station locations and traffic conditions, charging demand distribution can be predicted, guiding the rational placement of charging stations to reduce congestion and enhance charging efficiency.

2) Increasing charging station utilization: Precise simulation and analysis of EV user behaviour allow the charging recommendation system to dynamically adjust its strategies, matching user needs and charging station resources more accurately. This not only improves the charging experience for users but also helps increase the utilization and operational benefits of charging stations.

3) Promoting EV adoption: An optimized charging recommendation system effectively alleviates "charging anxiety" and enhances the attractiveness of EVs. Providing convenient and efficient charging solutions can motivate more consumers to choose EVs, supporting the widespread promotion of EVs and the development of sustainable transportation systems.

4) Integration with intelligent transportation systems: This study highlights the importance of intelligent transportation system information in enhancing the efficiency of charging recommendations. It suggests integrating the charging recommendation system with existing intelligent traffic management systems. By incorporating real-time traffic data, charging

recommendations can consider not only the status of charging stations but also current road conditions, further optimizing users' travel routes and charging plans.

5) Offering new directions for future research: The methods and findings of this study provide new research directions for further exploring EV charging recommendations and related intelligent transportation solutions. Especially in the context of ongoing advances in artificial intelligence and big data technologies, how to better integrate these technologies to enhance the performance and user experience of charging recommendation systems becomes a question worth exploring in depth.

6. CONCLUSION

The study utilized the *Q*-learning reinforcement learning algorithm, integrated with Markov decision processes, to model the decision-making process of EV charging station recommendations. This approach allowed for a dynamic adaptation to changes in user behaviour and preferences, demonstrating the efficacy of data-driven, intelligent systems in complex decision-making scenarios like selecting optimal charging stations. The utilization of simulation techniques enabled the detailed analysis and evaluation of the algorithm's performance under various conditions, providing a comprehensive understanding of its practical applicability.

The results showed that the *Q*-learning-based model successfully identified optimal strategies for EV charging recommendations, achieving significant convergence in reward values across numerous simulation episodes. This indicates not only the model's ability to learn and improve upon its strategies over time but also its potential to provide highly accurate and personalized recommendations for EV users. The comparison between *Q*-learning and Sarsa algorithms highlighted the former's advantage in terms of faster convergence, validating the choice of *Q*-learning for this application.

While the study has provided valuable insights, it also acknowledges certain limitations. The simulation was based on a predefined grid and set parameters, which, while effective for the study, may not encompass all real-world variables and complexities. Additionally, the integration of real-time traffic data and charging station statuses was simulated, pointing to the need for real-world data integration for more accurate and practical recommendations.

Future research directions include the exploration of other reinforcement learning algorithms and the integration of more complex variables, such as varying user preferences, different types of charging stations, and real-time data from intelligent transportation systems. The potential for incorporating machine learning techniques to predict user behaviour and charging needs more accurately is also an exciting avenue. Furthermore, the development of a more flexible and scalable model that can adapt to different urban layouts and charging infrastructure scenarios would enhance the applicability of the findings.

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