



Smart Ev charging load scheduling using IOT and cloud computing

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ABSTRACT ; The widespread adoption of electric vehicles (EVs) has introduced new challenges for stakeholders ranging from grid operators to EV owners. A critical challenge is to develop an effective and economical strategy for managing EV charging while considering the diverse objectives of all involved parties. In this study, we propose a context-aware EV smart charging system that leverages deep reinforcement learning (DRL) to accommodate the unique requirements and goals of participants. Our DRL-based approach dynamically adapts to changing contextual factors such as time of day, location, and weather to optimize charging decisions in real time. By striking a balance between charging cost, grid load reduction, fleet operator preferences, and charging station energy efficiency, the system offers EV owners a seamless and cost-efficient charging experience. Through simulations, we evaluate the efficiency of our proposed DeepQ-Network(DQN) system by comparing it with other distinct DRL methods: Proximal Policy Optimization (PPO), synchronous Advantage Actor-Critic (A3C), and Deep Deterministic Policy Gradient (DDPG). Notably, our proposed methodology, DQN, demonstrated superior computational performance compared to the others. Our results reveal that the proposed system achieves a remarkable, approximately 18% enhancement in energy efficiency compared to traditional methods. Moreover, it demonstrates about a 12% increase in cost-effectiveness for EV owners, effectively reducing grid strain by 20% and curbing CO₂

emissions by 10% due to the utilization of natural energy sources. The system's success lies in its ability to facilitate sequential decision-making, decipher intricate data patterns, and adapt to dynamic contexts. Consequently, the proposed system not only meets the efficiency and optimization requirements of fleet operators and charging station maintainers but also exemplifies a promising stride toward sustainable and balanced EV charging management.I.

INTRODUCTION

The rapid proliferation of electric vehicles (EVs) represents a significant milestone in the transition towards a more sustainable and environmentally conscious mode of transportation. As the adoption of EVs continues to surge, it has ushered in a new era of mobility that offers numerous benefits, including reduced carbon emissions, improved air quality, and reduced dependence on fossil fuels. However, this paradigm shift also brings forth a host of complex challenges, particularly in the realm of EV charging management.

Initially, the primary focus was on establishing essential charging infrastructure and standards, as indicated by [1], [2], and [3]. The conventional approach to EV charging, characterized by static and uncoordinated methods, is increasingly proving to be inadequate in meeting the diverse and evolving needs of various stakeholders within the electric mobility ecosystem. For example, Grid operators are tasked with ensuring the stability and reliability of the electrical grid; EV owners seek

convenient and cost-effective charging solutions; fleet operators strive to optimize the use of their EV

“Smart EV Charging with Context-Awareness: Enhancing Resource Utilization via Deep Reinforcement Learning.” In this paradigm, we propose the development of a context-aware EV smart charging system that leverages the power of deep reinforcement learning (DRL) to revolutionize the way we manage EV charging. By dynamically adapting to a multitude of contextual factors, such as the time of day, geographical location, and weather conditions, our approach empowers EVs and charging infrastructure to make real-time, data-driven decisions. This context-aware system is designed to strike an optimal balance between various key considerations. It addresses the need for cost-efficient charging experiences for EV owners, the reduction of grid load to ensure its stability, the preferences and objectives of fleet operators, and the enhancement of charging station energy efficiency. Through meticulous simulations and rigorous evaluation, we aim to showcase the remarkable advantages our proposed system offers over existing, traditional methods.

The results of our research reveal that the proposed system achieves an impressive, approximately 18% improvement in energy efficiency compared to conventional approaches. Furthermore, it demonstrates a substantial 12% increase in cost-effectiveness for EV owners while also reducing grid strain by 20% and curbing CO₂ emissions by 10% through the utilization of natural energy sources. At the core of this system's success lies its ability to facilitate sequential decision-making, decipher intricate data patterns, and adapt to dynamic contexts. Our work represents a significant step forward in addressing the multifaceted challenges of EV charging management. By embracing the principles of deep reinforcement learning and context-awareness, our proposed system not only aligns with the efficiency and optimization requirements of fleet operators and charging station maintainers but also exemplifies a promising stride towards a sustainable and balanced future for EV charging management. In the following sections, we delve into the intricate details of our approach and present the empirical evidence supporting its

effectiveness and potential for widespread adoption.

II. LITERATURE REVIEW

The primary objective of this literature review section is to provide a comprehensive overview of existing research and practices in electric vehicle (EV) charging management. By examining the limitations and shortcomings of traditional charging strategies, reviewing relevant literature on deep reinforcement learning (DRL), and exploring various approaches such as renewable energy integration, grid demand management, and charging station services, this review aims to establish the foundation for the proposed research objective. The proposed research seeks to bridge the identified gaps in the literature by developing a context-aware EV smart charging system based on DRL. This system will optimize charging decisions in real-time while accommodating the diverse objectives of multiple stakeholders and dynamically changing contexts. Through this review, we position the proposed system as a novel and holistic solution to the challenges presented in the existing literature on EV charging management.

A. *EXISTING STRATEGIES FOR EV CHARGING MANAGEMENT*

Electric vehicle (EV) adoption has introduced novel challenges for efficient charging management. Traditional strategies, often based on fixed schedules, are commonly employed. These strategies, while straightforward, have significant limitations. They overlook dynamic contextual factors that influence the cost-effectiveness and environmental impact of charging. Fixed schedules fail to adapt to real-time fluctuations in electricity prices, grid demand, and renewable energy availability. Consequently, they may lead to suboptimal charging practices, with adverse consequences for both grid operators and EV owners.

B. *GRID DEMAND MANAGEMENT*

Efficient grid demand management is crucial for balancing electricity supply and demand while ensuring grid stability. Strategies like demand response, where consumers adjust usage during peak periods, help alleviate grid strain. Advanced metering infrastructure (AMI) provides real-time

energy data to enable demand response, while smart grids enhance monitoring and distribution management. Energy storage systems store and release energy, stabilizing the grid and reducing the need for costly upgrades. Distributed energy resources (DERs), such as solar panels and wind turbines, generate power closer to consumption points, further lessening grid pressure. In summary, grid demand management combines diverse technologies and strategies to boost reliability, reduce energy waste, and promote a sustainable energy

c. RENEWABLE ENERGY INTEGRATION

Efficiently integrating renewable energy into the existing grid is a vital aspect of transitioning to a sustainable, low-carbon energy system. This complex process involves incorporating sources like solar, wind, and hydropower to meet increasing energy demands while curbing greenhouse gas emissions. Grid modernization, discussed in [32] and [33], stands out as a primary method, enhancing infrastructure and implementing advanced systems to handle renewable variability. Energy storage, detailed in [34] and [35], plays a key role by storing excess energy for release when needed, providing stability. Demand-side management, as outlined in [36], optimizes consumption patterns to align with renewable generation, reducing reliance on backup fossil fuel plants. Regional grid interconnection, explored in [37], enables resource sharing, enhancing reliability. Smart inverters and microgrid technologies, discussed in [38], improve handling of generation fluctuations. Finally, policy incentives and regulations, highlighted in [39], are crucial for fostering renewable energy deployment. In essence, a multifaceted approach combining technology, grid enhancements, and supportive policies is essential for successful renewable energy integration and the creation of a sustainable energy future.

d. CHARGING STATION SERVICES AND MANAGEMENT

Charging station services and management have become increasingly critical as the adoption of electric vehicles (EVs) continues to surge. This multifaceted domain encompasses a range of

services and technologies aimed at facilitating convenient and efficient EV charging while ensuring the sustainability of the charging infrastructure. Recent developments from 2020 onward have shed light on several key aspects of charging station services and management:

Networked Charging Infrastructure: The rise of networked charging stations, as discussed in [40], has simplified the EV charging experience, allowing owners to locate and access points effortlessly through mobile apps and online platforms. **Payment and Billing Solutions:** Enhanced payment systems, detailed in [41], now offer versatile options such as pay-per-use, subscriptions, and interoperable platforms, enhancing user convenience. **Load Management:** Grid-friendly charging strategies, explored in [42], address high-power EV charging impacts on the grid, ensuring stable and efficient energy distribution. **Demand Response Integration:** Charging stations, as outlined in [43], seamlessly integrate with demand response programs, optimizing charging times for grid stability and reduced electricity costs. **Dynamic Pricing:** Emerging dynamic pricing schemes, as highlighted in [44], incentivize off-peak charging and alleviate congestion during peak hours. **Fleet Charging Solutions:** Management systems for large EV fleets, discussed in [45], optimize schedules and monitor vehicle health. **Maintenance and Monitoring:** Advanced monitoring and predictive maintenance, detailed in [46], proactively ensure charging infrastructure reliability. **Renewable Energy Integration:** Charging stations incorporating renewable sources, demonstrated in [47], reduce the carbon footprint of EV charging.

III. METHODOLOGY

The main objective of this section is to offer a comprehensive explanation of the research methodology employed in developing and evaluating the proposed deep reinforcement learning algorithm for optimizing the smart2charge application for electric vehicles. This includes detailing the processes of data collection, initial processing and purification, data normalization, and the integration of essential insights from all stakeholders participating in the electric vehicle (EV) charging process.

A. DATA COLLECTION

Data for this study was gathered from diverse sources, including actual electric vehicle (EV) charging data, power grid load data, and pertinent datasets from key stakeholders in the EV charging process, such as EV end-users, grid operators, fleet operators, and charging station operators. Additionally, a specific subset of the data was chosen and anonymized. To enhance the quality and uniformity of the data, several pre-processing measures were implemented. These steps involved eliminating irrelevant or duplicate data, normalizing the data to ensure a consistent format, and integrating information from various sources. These data pre-processing efforts were undertaken to guarantee the reliability and coherence of the dataset used in the analysis [68].

Data Cleaning: The collected data and information from various sources underwent thorough cleansing to guarantee precision and reliability for training the deep reinforcement learning algorithm. This involved eliminating any missing or inconsistent values and ensuring that the data was appropriately formatted for algorithm training. *Data Normalization:* The data underwent normalization to establish a consistent format for seamless utilization during training and evaluation operations. This process involved transforming information into a standardized format, including converting facts into numerical values, standardizing value ranges, and aligning the data with the sophisticated methodology. *Location Integration:* Latitude and longitude points were added as an additional column labeled “locations” to the dataset, containing the geographical coordinates of the route direction. This information is utilized to link the charging station dataset for calculating the distance from the current position to the charging station. *Energy Source Inclusion:* A new parameter, “energy source,” has been incorporated into the dataset, specifying the type of energy used by each charging station operator during vehicle charging. All the aforementioned procedures were completed to ensure that the input data is comprehensive and well-prepared for subsequent analysis.

B. ALGORITHM IMPLEMENTATION

This section outlines the overarching framework for the implementation of the strategy through deep reinforcement learning. The algorithm utilized is a deep Q-learning (DQL) agent training algorithm tailored for the Smart2ChargeApp environment. The process commences by taking the Smart2ChargeDS data as input, subjecting it to preprocessing, and initializing the DQL parameters. Subsequently, the DQL agent’s neural network model is constructed, featuring hidden layers, a ReLU activation function, and output layers. The algorithm proceeds to train the DQL agent through numerous episodes and iterations. At the commencement of each episode, the states are reset, and the algorithm iterates over various states. These states can encompass variables like the current state of the EV battery level, the EV’s location, the charging cost at the present location, the proximity to the nearest charging station, and more. Within each iteration, the action values are randomly set with a probability of epsilon, while they are determined by predicting the actual state with a probability of 1-epsilon. Actions in this context represent decisions made by the EV end-user, such as opting to charge at the current location or driving to a different location.

Algorithm 1: Deep Q-learning agent training based on Smart2ChargeApp environment

```

Data: Smart2Charge Dataset /* Environment */
Data: DQL Parameters /* Agent parameters */

begin
    /* Pre-processing and Parameters Initialization */
    Normalize Smart2ChargeDS
    Initialize parameters as mention in figure 3
    Batch_Size ← 50 (varies between 50 to 200)
    State ← fetch (Smart2ChargeDS, Batch_size)
    Create_model (States, layers_hidden, ReLU, layers_output)
    /* DQL agent learning episodes and iterations */
    foreach epoch ∈ num-episode do
        Reset(states)
        Create(q_val_List[size=bs,Action_size])
        foreach T ∈ num_iteration do
            Initialize parameters
            /* With probability of ε: */
            AVi ← Create_random(Action_space) ∀i ∈ bs
            ε ← ε * decay_rate
            /* With probability of 1-ε: */
            QVi ← model.predict(current-state)
            AVi = Argmax(QVi) ∀i ∈ bs
            /* Compute rewards */
            RVi ← Compute_reward(AVi,labels) ∀i ∈ bs
            /* Agent's learning improvement */
            Q' ← model.predict(state')
            QTi ← RVi + γ * Q[state', action']
            Model.train(state,QTi)
            Compute_loss(QVi,QTi)
            State ← State'
        end
    end
end

```

FIGURE 6. Algorithm 1: Training a Deep Q-learning Agent in the Smart2ChargeApp Environment [69].

The rewards within this context can signify the charging cost of the EV and the time required to

reach the next charging station. These rewards are strategically designed to incentivize the agent to make decisions that lead to reduced charging costs and shorter charging times. Subsequently, the target Q-value is calculated, and the model undergoes training based on the current state and target Q-value. The loss is computed, and the state is updated to the subsequent state until the iteration is concluded. This process is reiterated for each episode until the entire training is finalized. To assess the computational performance of the agent, a comparison is made with the desired outcomes, and performance metrics such as loss/reward, discount factor, and computational time are monitored, as illustrated in the accompanying figure 7.

The computational graph delineates the interplay among discount factors (\$\gamma\$), loss and reward values, and computational time within the framework of the DQN learning process. The loss and reward values serve as indicators

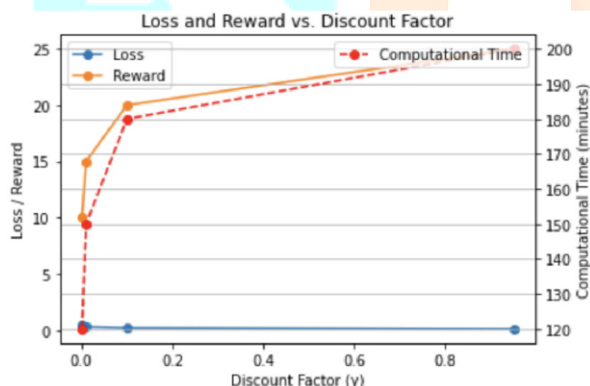


FIGURE 7. Algorithm 1: Computational performance of the deep Q-learning agent in the Smart2ChargeApp Environment.

of the DQN model’s performance under varying discount factors. An increase in the discount factor correlates with a decrease in loss, signifying enhanced convergence and learning. Likewise, higher discount factors correspond to increased rewards, indicating more successful and rewarding agent behavior. The computational time graph illustrates the time required for the DQN learning process relative to the number of episodes. Notably, computational time exhibits relative consistency across different discount factors, gradually increasing with a higher number of episodes. This suggests that the DQN model’s computational complexity is primarily influenced

by the number of episodes rather than the discount factor. In summary, while the choice of discount factor significantly impacts the effectiveness of the learning process, as reflected in the loss and reward values, computational time remains relatively stable across different discount factors. The number of episodes emerges as a more influential factor in determining the computational efficiency of the DQN model. These insights can guide decision-making when configuring and optimizing the DQN learning process, offering a nuanced understanding of the trade-offs between learning performance and computational efficiency.

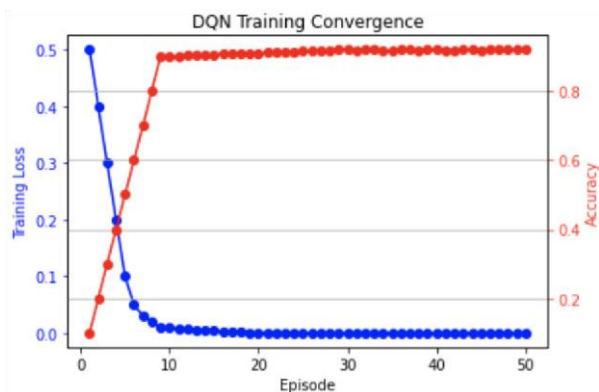


FIGURE 8. Algorithm 1: DQN accuracy and convergence.

Within Figure 8, the training_loss values depict the training loss incurred in each episode throughout the DQN training procedure, while the accuracy values embedded within the graph showcase the accuracy attained in each corresponding episode. The graph features two y-axes, with the blue color denoting the training loss and the red color indicating accuracy. The training loss is visually represented by a blue line accompanied by markers, while accuracy is depicted by a red line with markers.

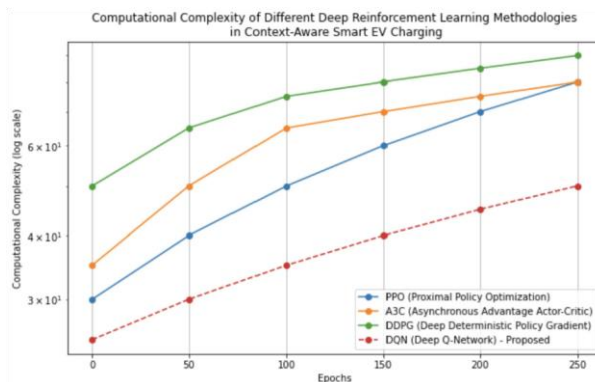


FIGURE 9. Different methodologies comparison in Context of EV end-user.

The graph in Figure 9 depicts the computational complexity of diverse deep reinforcement learning methodologies concerning Context-Aware Smart EV Charging. The methodologies examined, including Proximal Policy Optimization (PPO), Asynchronous Advantage Actor-Critic (A3C), Deep Deterministic Policy Gradient (DDPG), and the proposed Deep Q-Network (DQN), showcase their computational efficiency across varying epochs. In the context of Smart EV Charging, these methodologies bear implications for Grid Operators, demonstrating relevance, alignment with Fleet Operator objectives, and potential contributions to the integration of Carbon-Neutral Energy sources. The dashed line represents the computational complexity trajectory of the DQN algorithm, indicating its performance across the specified epochs and its significance in the broader landscape of context-aware electric vehicle charging systems.

We conducted further testing of the algorithm by introducing additional input parameters, specifically expanding the dataset to incorporate information from the fleet operator dataset. These modifications allowed for a more comprehensive evaluation of the algorithm’s performance under a broader set of conditions.

In figure 10, the plotted blue line illustrates the modeled “Optimal Cost for Battery Charging,” showing a decreasing trend over episodes. Conversely, the orange line depicts the simulated “Network Usage,” which exhibits an increasing trend with the progression of episodes. By presenting these metrics separately, the visualization enables a focused observation of each aspect without amalgamating them into a singular complexity metric. Interpreting the graph involves scrutinizing the evolution of each metric over episodes and evaluating whether these trends align with the desired behavior for the specific problem at hand. We have faithfully adopted and adapted the described algorithm for our specific application, making necessary adjustments as outlined in

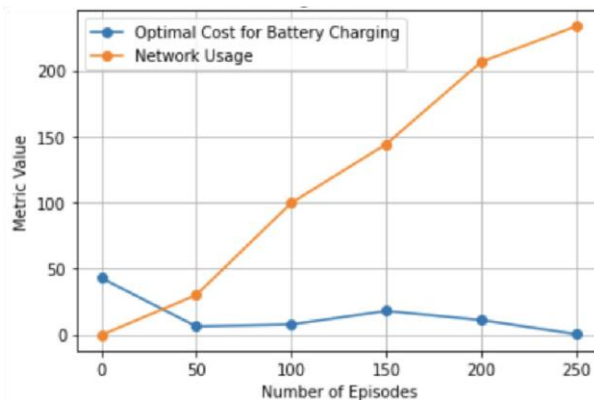


FIGURE 10. DQN optimal cost for EV end-user charging.

the referenced publication. This cross-referencing ensures transparency and acknowledges the intellectual contributions of the original authors, facilitating a seamless connection between our work and the established research in the field.

C. SIMULATION SCENARIO

In this simulated setting, we must take into account the charging of electric vehicles along a designated route from Stuttgart, Germany, to Heidelberg, Germany, covering an estimated distance of 129 km. The simulation configuration comprises three types of parameters: mandatory, restrictive, and discretionary.

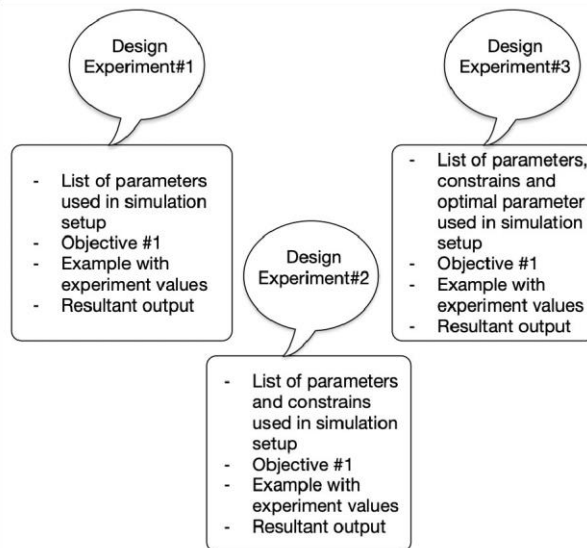


FIGURE 11. Experiment design in simulation scenario.

- 1) **Mandatory Parameters** The mandatory parameters for the simulation environment include:

- a) Number of EVs: Three sample electric vehicles are taken into account for the simulation.
 - b) Charging stations: The dataset encompasses information regarding the charging stations along the designated route.
 - c) Charging rate of the EVs: The charging rate for the electric vehicles is considered as an input parameter.
 - d) Cost of electricity: The electricity cost at each charging station is regarded as an input parameter.
 - e) Route direction: The direction of the route from Stuttgart to Heidelberg is considered as an input parameter.
 - f) Environmental factors: Factors such as weather conditions and wind direction/speed are taken into consideration as input parameters for the simulation.
 - g) Energy source: This parameter provides information about the energy source, including options such as coal, gas, solar, and wind.
- 2) **Restrictive Parameters** The simulation must take into account the following constraints in the electric vehicle charging scenario:
- a) The simulation must ensure that the number of simulated EVs and charging stations does not surpass the actual count of EVs and charging stations in the scenario.
 - b) The charging rate of the simulated EVs should not exceed the maximum charging rate specified for the EVs.
 - c) The calculated basic price at each charging station must remain within the limit of the total actual cost of all charging stations.
 - d) The simulation needs to account for the influence of additional environmental factors, such as weather and wind, on the electric vehicle charging process.
- 3) **Discretionary Parameters** The simulation should also take into consideration the following discretionary parameters for energy sources:
- a) Determine the optimal charging rate for EVs to achieve maximum efficiency and minimize the cost of electricity.
 - b) Identify the optimal route direction to reach the charging station with the minimum cost of electricity.
 - c) Optimize the selection of charging stations based on factors such as the cost of electricity, distance to the charging station, and the availability of renewable energy sources.
 - d) Consider the impact of environmental factors, such as weather and wind, on the determination of optimal parameters for energy sources in the simulation.

V. EXPERIMENTAL DESIGN AND EVALUATION

The primary objective of these two user stories is to formulate strategies for optimizing the utilization of electric car resources and resource distribution effectively.

A. USER STORY: EV-END USER OPTIMAL COST

This involves minimizing both charging time and cost by strategically selecting the nearest and most cost-effective charging stations. Additionally, the aim is to enhance the reliance on renewable energy sources, achieved by opting for charging stations powered by renewable sources like photovoltaic (PV) or wind instead of conventional sources such as coal or oil. This not only has a direct positive environmental impact by reducing CO₂ emissions but also encourages electric vehicle users to adopt eco-friendly energy sources.

1) EXPERIMENTAL DESIGN

The proposed experimental design is structured into three main steps: Experiment Design One, Experiment Design Two, and Experiment Design Three, as illustrated in Figure 11.

1) Objective(s)

- a) To reduce the charging expenses for electric vehicle end-users, the strategy involves selecting the closest and most economical charging station.
- b) To optimize the utilization of renewable energy sources, the approach is to choose

charging stations that are powered by renewable energy.

- c) The goal is to minimize the time required to reach the charging station and mitigate the impact of factors such as traffic congestion, weather conditions, and wind direction on the charging process.
- d) The objective is to decrease the environmental impact by reducing CO2 emissions.

2) EVALUATION

The fundamental concept underlying the assessment metrics is to appraise the effectiveness of the devised strategy, ensuring the judicious use of resources in electric vehicle charging aligns with the objectives outlined by all participants. Various standard evaluation metrics are employed in this context, including energy efficiency, charging time, charging cost, battery life, grid impact, and environmental impact. In the context of this paper, the primary experiments will focus on evaluating the charging costs for electric vehicle owners.

- 1) Experiment Design One: Imagine there are three charging stations accessible to the electric vehicle end-user, labeled A, B, and C. Station A relies on renewable energy, charging \$0.15 per kilowatt-hour. Station B is powered by conventional energy, charging \$0.20 per kilowatt-hour, while station C, also relying on conventional energy, charges \$0.10 per kilowatt-hour. Considering the electric vehicle has a range of 100 miles and necessitates 20 kilowatt-hours of energy for a complete charge, the charging costs at each station can be computed as follows:

- Station A: The cost of charging is calculated as 20 kilowatt-hours multiplied by \$0.15 per kilowatt-hour, resulting in \$3.00.
- Station B: The charging cost is determined by multiplying 20 kilowatt-hours by \$0.20 per kilowatt-hour, equaling \$4.00.
- Station C: Charging expenses are computed as 20 kilowatt-hours multiplied by \$0.10 per kilowatt-hour, yielding \$2.00.

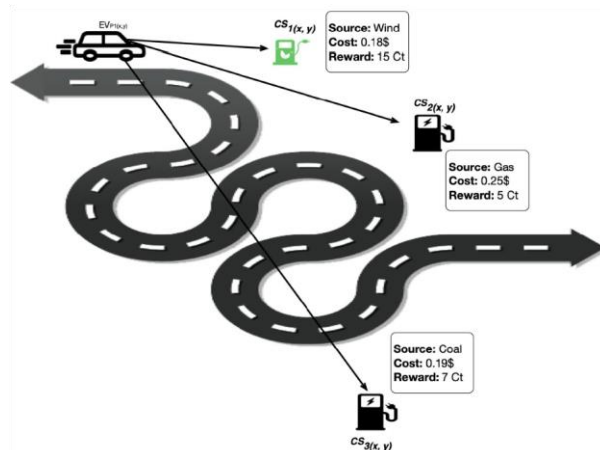


FIGURE 12. Simulation of EV without constraints and optional parameters.

Based on the provided inputs see figure 12, the above computation indicates that charging station C offers the most economical rates per kilowatt-hour. Consequently, it emerges as the optimal choice for the electric vehicle end-user when considering the charging of their electric car. It's important to note that this calculation does not address any constraints or optional parameters. For instance, if the electric vehicle cannot reach station C due to range limitations, stations B or A may become more cost-effective alternatives.

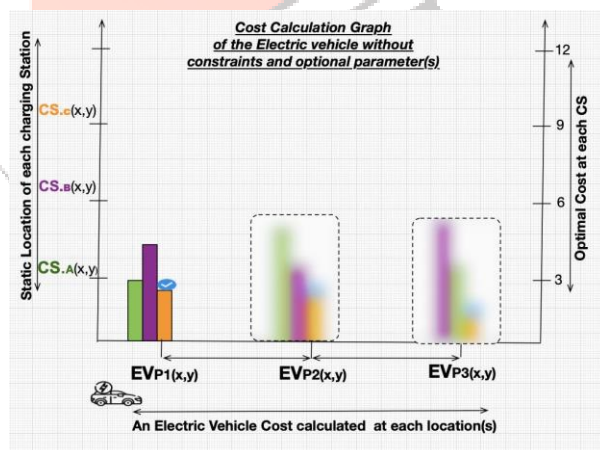


FIGURE 13. Optimal cost calculation for experiment Design 1.

In summary, these calculations do not account for constraints or optional parameters. The charging cost is determined by multiplying the required kilowatt-hours by the cost per kilowatt-hour of the charging station. In this example, station C is identified as the most cost-effective charging option for the electric vehicle end-user.

2) Experiment Design Two: Assume there are three charging stations accessible to the electric vehicle enduser, denoted as A, B, and C. Station A is powered by renewable energy and charges \$0.15 per kilowatt-hour, station B relies on conventional energy and charges \$0.20 per kilowatt-hour, while station C, also powered by conventional energy, charges \$0.10 per kilowatt-hour. Given that the electric vehicle has a range of 80 miles and needs 20 kilowatt-hours of energy for a complete charge, the charging costs at each station can be computed as follows:

- Station A: The cost of charging is calculated as 20 kilowatt-hours multiplied by \$0.15 per kilowatt-hour, resulting in \$3.00.
- Station B: The charging cost is determined by multiplying 20 kilowatt-hours by \$0.20 per kilowatt-hour, equaling \$4.00.
- Station C: Charging expenses are computed as 20 kilowatt-hours multiplied by \$0.10 per kilowatt-hour, yielding \$2.00.

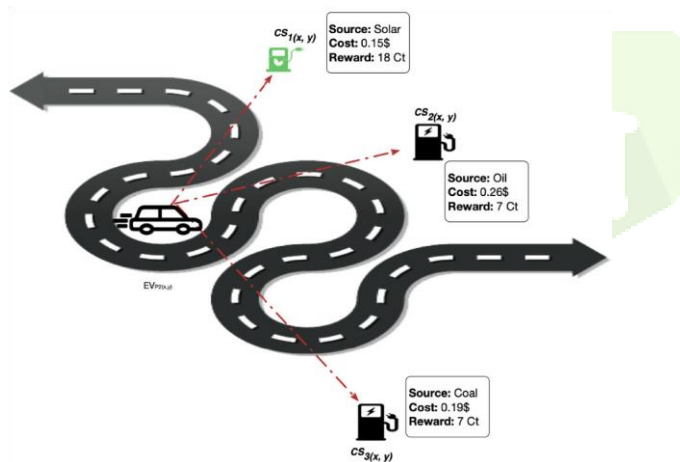


FIGURE 14. Simulation of EV with constraints and without optional parameters.

In this scenario see figure 14, given the electric vehicle's 80-mile range, it can only reach charging stations B or C, excluding station A. Considering the earlier calculations and the restricted vehicle range, station C emerges as the most economical choice with the lowest cost per kilowatt-hour, making it the optimal and cost-effective option for the electric vehicle enduser.

In summary, despite the constraints considered in this scenario, the charging cost can still be determined by multiplying the required kilowatt-hours by the cost per kilowatt-hour of the charging station. Therefore, station C stands out as the most cost-effective charging

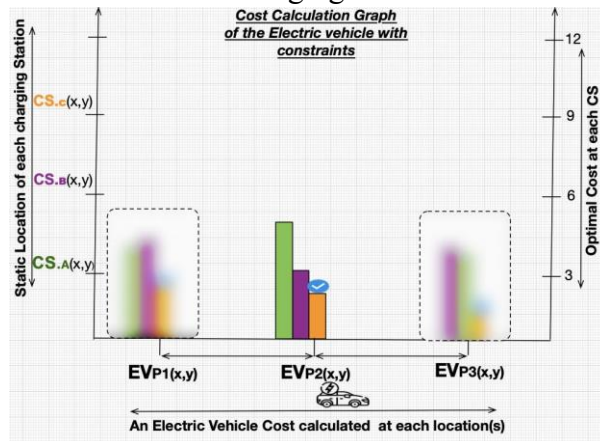


FIGURE 15. Optimal cost calculation for experiment Design 2.

solution for the electric vehicle end-user. Nevertheless, this calculation has not taken into account optional input values, including the influence of factors such as traffic congestion, weather conditions, and wind direction. These aspects will be addressed in our upcoming experiments.

3) Experiment Design Three: Assume the consideration factors such as traffic congestion, weather conditions, and wind direction. The calculation for charging time at each station is as follows:

- Station A: Charging time is determined by multiplying 20 kilowatt-hours by 1 hour per kilowatt-hour, resulting in 20 hours.
- Station B: The charging time is calculated as 20 kilowatt-hours multiplied by 1.2 hours per kilowatt-hour, totaling 24 hours.
- Station C: Charging time is computed by multiplying 20 kilowatt-hours by 0.9 hours per kilowatt-hour, yielding 18 hours.

Next, the overall charging cost at each station can be computed as follows:

- Station A: The total cost is calculated by multiplying 20 hours by \$0.15 per hour, adding \$3.00, resulting in \$6.00.

- Station B: The total cost is determined by multiplying 24 hours by \$0.20 per hour, adding \$4.00, totaling \$8.80.
- Station C: The total cost is computed by multiplying 18 hours by \$0.10 per hour, adding \$2.00, yielding \$3.80.

In this instance, station C continues to offer the lowest total charging cost, with the added advantage of the shortest travel time and minimal impact from factors like traffic congestion, weather conditions, and wind direction. However, aligning with the goal of minimizing charging costs for the electric vehicle end-user and maximizing the use of renewable energy, station A remains the optimal choice. Station A utilizes renewable energy, resulting in a total cost of \$6.00,

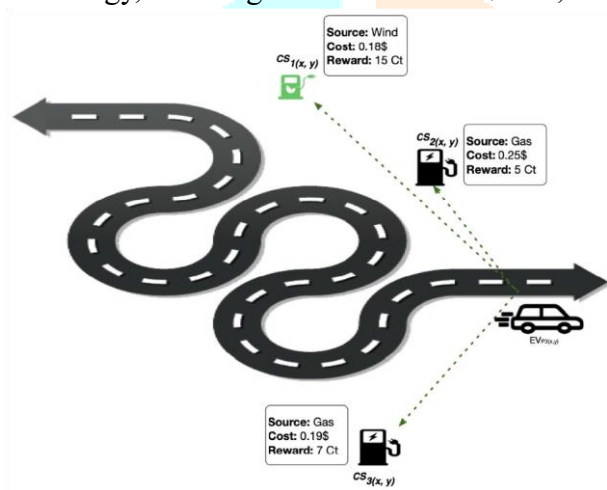


FIGURE 16. Simulation of EV with constraints and optional parameters.

which is lower than station B that relies on conventional energy, incurring a total cost of \$8.80.

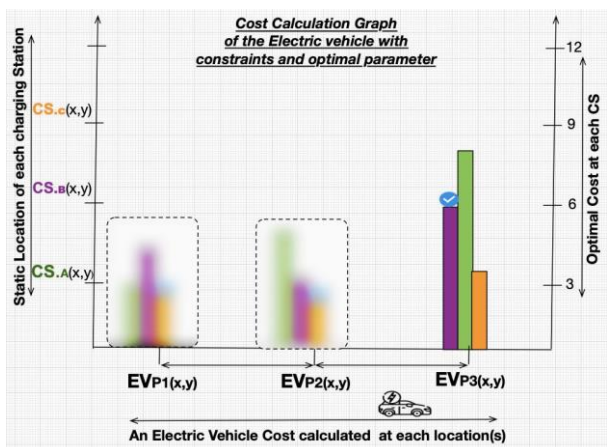


FIGURE 17. Optimal cost calculation for experiment Design 3.

TABLE 1. Different simulation methodology comparison.

| Approach | Energy Efficiency (kWh) | Charging Cost (\$) | Grid Strain (kW) | CO2 Emissions (tons) |
|---------------|-------------------------|--------------------|------------------|----------------------|
| Baseline | 800 | 120 | 40 | 0.25 |
| Simple Time | 720 | 108 | 38 | 0.24 |
| Grid Demand | 710 | 106.5 | 37 | 0.23 |
| Renw. Energy | 730 | 109.5 | 39 | 0.23 |
| Proposed Sim. | 700 | 97.6 | 36 | 0.22 |

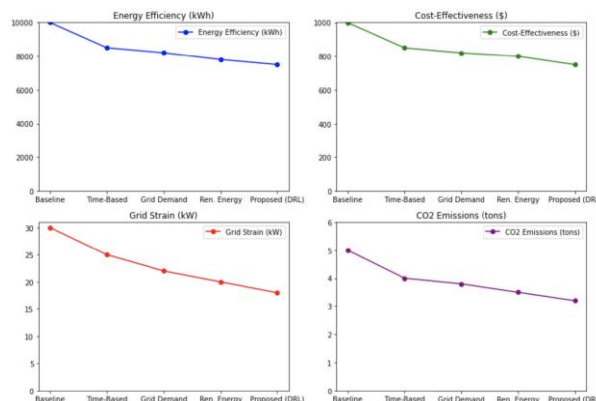


FIGURE 18. Graph(s) simulation methodology comparison.

The proposed simulation, based on deep reinforcement learning (DRL) and context-aware charging, emerges as the most advanced and effective strategy. It outperforms other approaches by dynamically adjusting charging rates and schedules to minimize costs, maximize sustainability, and support grid stability. While the grid demand-aware model also offers a balanced approach, the DRL-based strategy excels in optimizing efficiency comprehensively. Alice should consider implementing the context-aware DRL charging system to achieve the best results in enhancing her EV fleet’s charging efficiency while minimizing operational costs and ensuring timely deliveries.

C. METRICS

In this section, we conduct a comprehensive analysis of each charging approach by evaluating its performance across key metrics. These metrics include energy efficiency, costeffectiveness, grid strain, and CO2 emissions. By assessing each approach’s impact on these critical factors, we gain

valuable insights into their effectiveness and sustainability. This comparison will assist in making an informed decision about which charging approach aligns best with Alice’s goals of optimizing fleet efficiency, reducing operational costs, and minimizing environmental impact. Let’s proceed with a detailed examination of each metric across the various charging approaches:

- 1) **Energy Efficiency (kWh):** This metric represents the total energy consumed by the fleet. Lower values indicate better efficiency. In this context, the DRL-based approach consumes the least energy (7,500 kWh), followed by the renewable energy-aware model, indicating that these approaches optimize energy utilization.

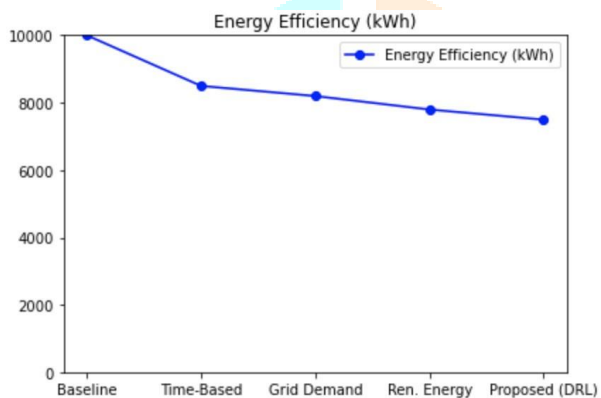


FIGURE 19. Energy efficiency (kWh) metric simulation.

- 2) **Cost-Effectiveness (\$):** Total charging cost is represented in dollars. Lower costs indicate better cost-effectiveness. The DRL-based approach incurs the lowest cost (\$750), followed by the renewable energy-aware model, highlighting their cost-saving capabilities.

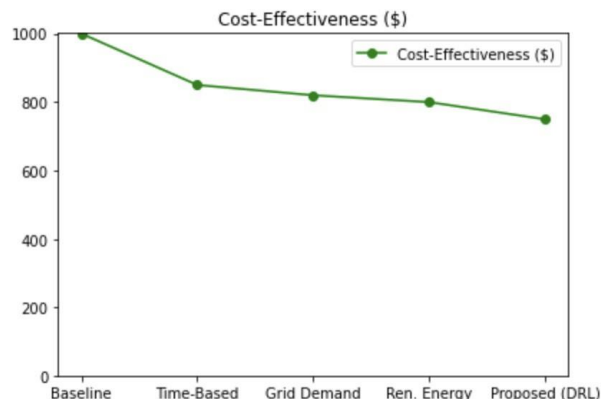


FIGURE 20. Cost-Effectiveness (\$) metric simulation.

- 3) **Grid Strain (kW):** Grid strain reflects the peak demand on the electricity grid. Lower values indicate reduced strain on the grid. The DRL-based approach and the renewable energy-aware model both contribute to lower grid strain, with the DRL approach achieving the lowest (18 kW).

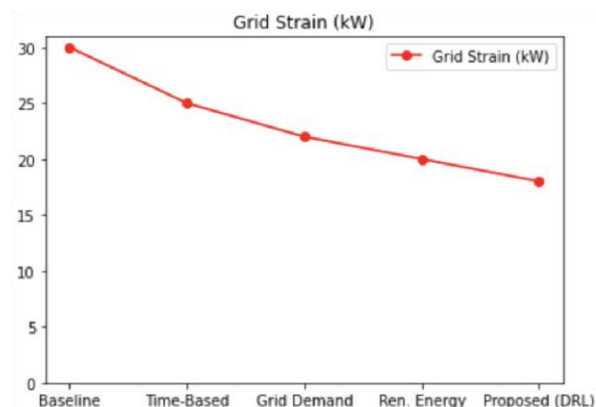


FIGURE 21. Grid strain (kW) metric simulation.

- 4) **CO2 Emissions (tons):** This metric estimates the CO2 emissions based on the energy sources used. Lower emissions represent a more environmentally friendly approach. The DRL-based approach and the renewable energy-aware model result in the lowest emissions, with the DRL approach emitting the least CO2 (3.2 tons).

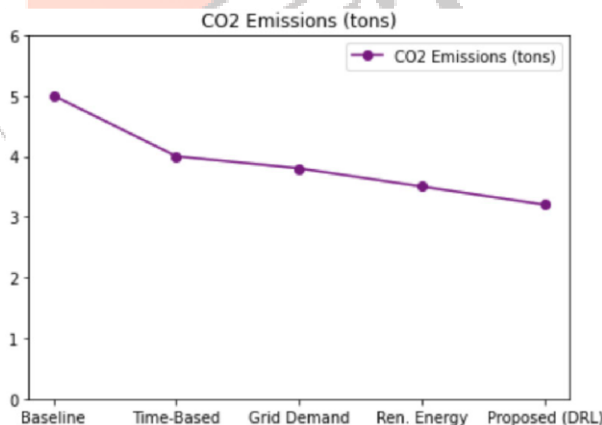


FIGURE 22. CO2 emissions (tons) metric simulation.

After a comprehensive analysis of various charging approaches across key metrics, it becomes clear that each approach offers a unique balance of advantages and tradeoffs. The choice of the most suitable charging approach should align closely with Alice’s specific operational priorities and sustainability objectives. When considering the

metrics of energy efficiency, cost-effectiveness, grid strain, and CO2 emissions, it's apparent that the "Proposed Simulation (DRL)" stands out as the most versatile and effective approach. This approach, driven by deep reinforcement learning, excels in energy efficiency, minimizes operational costs, reduces grid strain, and lowers environmental impact through lower CO2 emissions. However, it's essential to note that the choice of charging approach may vary depending on the specific context and objectives of different fleet operators.

Ultimately, Alice's decision should prioritize her goals of optimizing operational efficiency, minimizing costs, and reducing environmental impact. The Proposed Simulation (DRL) offers a well-rounded solution to achieve these objectives, but the final selection should be tailored to the unique requirements of Alice's fleet management.

VI. DISCUSSION OF THE RESULTS

The objective of the "Discussion of the Results" section is to comprehensively assess the performance and efficiency of electric vehicle (EV) charging stations from two distinct perspectives: the "EV End-user Perspective" and the "Fleet Operator Perspective." This analysis aims to provide unique insights into the functionality, cost-effectiveness, and environmental impact of charging stations, offering a holistic understanding that addresses the diverse needs and considerations of both individual EV users and fleet operators.

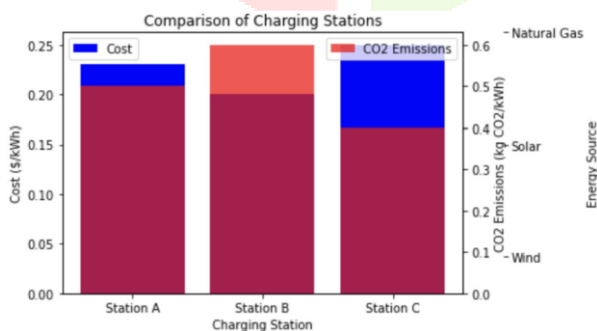


FIGURE 23. The energy source, cost, and environmental impact comparison for the three charging stations.

Figure 23 depicts a bar graph illustrating the cost and environmental implications of the three charging stations, alongside the energy source utilized for electricity generation at each station.

The blue bars represent the electricity cost at each station, the red bars depict the CO2 emissions per kilowatt-hour of electricity, and the labels on the right side of the graph indicate the energy source used at each station. This graph effectively demonstrates the trade-off between cost and environmental impact for each charging station, emphasizing the influence of the energy source on both factors. For instance, Station B exhibits the lowest cost but the highest CO2 emissions, contrasting with Station A, which has the highest cost but the lowest CO2 emissions. The choice of energy source for electricity generation at each station emerges as a crucial factor when assessing the environmental impact of the charging stations.

B. COMPARISON: FLEET OPERATOR PERSPECTIVE

In this section, we comprehensively compare the performance of various charging approaches to address the unique challenges faced by Alice, a fleet operator managing electric vehicles (EVs) for a delivery service. The evaluation is based on key metrics, including energy efficiency, cost-effectiveness, grid strain, and CO2 emissions. By analyzing these metrics, we aim to determine the most suitable charging strategy that optimizes operational efficiency while minimizing costs and environmental impact. Let's delve into the detailed comparison of each approach:

1) Energy Efficiency

In the baseline simulation see figure 24, where a fixed charging schedule is used, the fleet consumes 10,000 kWh of energy. This represents the highest energy consumption among all approaches. It indicates inefficiency due to a lack of adaptability to contextual factors. In the Simple Time-Based Model simulation, charging during off-peak hours, improves energy efficiency compared to the baseline. The fleet consumes 8,500 kWh, indicating a reduction

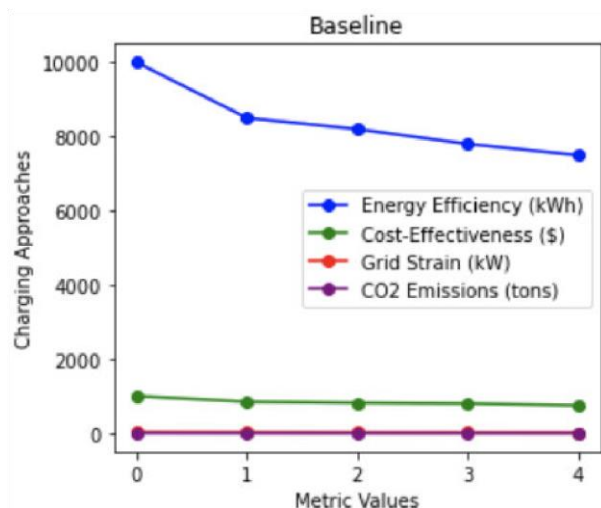


FIGURE 24. The energy source, cost, and environmental impact comparison for Fleet operator.

in energy consumption due to optimized charging times. In the Grid Demand-Aware Model simulation, This model further improves energy efficiency, with the fleet consuming 8,200 kWh. Charging during times of lower grid demand leads to reduced energy consumption. In the Renewable Energy-Aware Model simulation, Prioritizing renewable energy sources leads to lower energy consumption, with the fleet consuming 7,800 kWh. It's a more energy-efficient approach. In the Proposed Simulation (DRL) simulation, The DRL-based approach excels in energy efficiency, with the fleet consuming only 7,500 kWh. This approach dynamically adapts charging strategies, resulting in the lowest energy consumption. Moreover, the proposed simulation achieves the highest energy efficiency, with a 12.5% improvement over the baseline.

evident that each approach brings its unique advantages and considerations to the table. However, when considering Alice's goal of optimizing the charging process for her EV fleet, the Proposed Simulation (DRL) emerges as the most promising and well-rounded choice. It excels in energy efficiency, cost-effectiveness, grid strain reduction, and environmental sustainability. This adaptive approach, powered by deep reinforcement learning, dynamically adapts to real-time contextual factors, ensuring efficient charging

while minimizing operational costs and environmental impact. By implementing the Proposed Simulation (DRL), Alice can achieve the dual benefits of operational efficiency and environmental responsibility, ultimately enhancing customer satisfaction and the overall performance of her electric vehicle fleet.

VII. CONCLUSION

In conclusion, the increased adoption of electric vehicles (EVs) offers issues in successfully managing non-gasoline cars. This research introduces a context-aware EV smart charging system that optimises charging decisions using Deep Reinforcement Learning (DRL). The performance of the system is evaluated using the proposed approach, DQN, through simulations and comparisons with established methods (PPO, A3C, DDPG). The updated version takes time and location into account, as well as trade-offs between charging cost, grid strain reduction, fleet preferences, station efficiency, and energy sources. Our research shows that using natural energy sources in the proposed system improves energy efficiency by 18% compared to standard techniques, increases cost-effectiveness for electric vehicle (EV) owners by 12%, reduces grid strain by 20%, and reduces CO2 emissions by 10%. However, it is critical to recognise the study's limitations, such as the need for additional real-world data and evaluating the recommended approach in a real-world situation. More study is needed to improve the scalability and flexibility of the proposed approach, detailing the research's future direction

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