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RESEARCH ARTICLE

Smart EV Charging With Context-Awareness: Enhancing Resource Utilization via Deep Reinforcement Learning

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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 Deep Q-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.

INDEX TERMS Electric vehicles, smart charging, deep reinforcement learning, context-awareness, energy efficiency, cost-effectiveness, grid strain reduction, CO2 emissions reduction.

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.

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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 fleets; and charging station maintainers aim to enhance energy efficiency. However, in recent years, attention has shifted towards the creation of sophisticated charging systems capable of achieving optimal trade-offs across various objectives, such as minimizing the strain on the grid and reducing environmental impact, which is a formidable task, as highlighted by [4], [5], [6], [7], [8], [9], and [10]. The prevalent adoption of electric vehicles (EVs) represents a significant trend in the transportation sector, fueled by concerns surrounding energy security, climate change, and air pollution [11]. In response to these challenges, researchers have proposed a multitude of solutions. These include the implementation of time-of-use pricing schemes [12], [13], [14], [15], dynamic load management [16], [17], and the application of intelligent charging algorithms, such as the stochastic game approach [18], vehicle-to-grid (V2G) optimization [19], Pareto optimal solutions in multi-objective optimization [20], real-time energy management systems [21], and blockchain-based charging systems [22], [23], [24]. However, the integration of EVs into the electricity grid poses additional challenges for grid operators, fleet operators, charging station operators, and EV owners. The primary issue revolves around striking a balance between various objectives, such as reducing EV charging costs, alleviating the load on the power grid, optimizing fleet management, and enhancing energy efficiency at charging stations [25], [26].

One critical challenge in implementing the proposed context-aware EV smart charging system is the dynamic adaptation to rapidly changing contextual factors. Ensuring the system's ability to accurately assess and respond to real-time variations in time of day, location, and weather is crucial for optimal charging decisions. Moreover, maintaining the balance between different objectives, such as cost-effectiveness for EV owners and grid load reduction, while considering fleet operator preferences and station energy efficiency, requires a robust and adaptable algorithm within the deep reinforcement learning framework. To address this pressing challenge, our research endeavors to introduce a novel paradigm: "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 CO_2 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 future (cf. [27], [28], [29], [30], [31]).

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. **Regulatory Framework**: Evolving regulatory frameworks, highlighted in [48], ensure safety standards, interoperability, and equitable access. In conclusion, charging station services and management, driven by technology and regulation, have evolved significantly, supporting widespread EV adoption and fostering a sustainable and accessible transportation ecosystem.

E. REVIEW OF DEEP REINFORCEMENT LEARNING (DRL)

Deep reinforcement learning (DRL) algorithms, like Proximal Policy Optimization [49], Asynchronous Advantage Actor-Critic (A3C) [50], Deep Deterministic Policy Gradient [51], and Deep Q-Network [52], have garnered notable attention for solving intricate tasks across diverse domains, including gaming, robotics, and resource optimization for electric vehicles. Specifically in the realm of electric vehicle (EV) charging and resource optimality, DRL has proven promising. These algorithms, powered by neural networks, exhibit excellence in discerning complex data patterns and adjusting behavior based on environmental cues. DRL's capability to learn and optimize policies in dynamic environments aligns seamlessly with the variable nature of EV charging, making it a valuable tool for concurrently optimizing cost, grid strain, and environmental impact.

Recent studies, such as [53], showcase the application of Deep Reinforcement Learning (DRL) to formulate algorithms for optimizing charging schedules at stations. DRL agents skillfully balance user demand, grid limitations, and dynamic pricing, efficiently allocating charging resources to minimize grid stress and reduce costs for EV owners. In the domain of load management, as demonstrated in [54], DRL is utilized to control charging station loads, aligning them with grid capacity to ensure stable operations and prevent overloads during peak times. Explored in [55], DRL-based solutions facilitate effective participation in demand response programs, optimizing charging times based on grid signals and alleviating strain. Intelligent charging strategies tied to dynamic pricing, exemplified in [56], involve DRL agents learning to predict price fluctuations and adjusting charging patterns for optimal cost savings. Furthermore, fleet charging management, depicted in [57], leverages DRL to optimize schedules for companies with electric vehicle fleets, considering operational needs and minimizing downtime. Demonstrated in [58], DRL models enhance the reliability of charging station infrastructure through predictive maintenance, where agents monitor components and predict maintenance needs, thereby reducing downtime. This personalized approach is highlighted in [59], where DRL-driven personalization enhances the user experience at charging stations by learning user preferences and habits, recommending optimal charging times and locations for improved convenience. At the end, DRL techniques have emerged as powerful tools for optimizing charging station services and management in the electric vehicle ecosystem. By leveraging these advanced AI-driven approaches, the EV charging industry can enhance efficiency, reduce operational costs, and contribute to the sustainable integration of electric vehicles into the energy grid.

F. IDENTIFYING GAPS IN THE LITERATURE

While extensive literature exists on EV charging management, the proposed system targets notable gaps. Current studies often concentrate on singular objectives like cost minimization or grid load reduction in isolation. Few approaches systematically consider the multiple, sometimes conflicting, objectives of various stakeholders, including grid operators, fleet managers, charging station operators, and EV owners. Additionally, existing context-aware charging strategies, though present, lack the adaptability and sophistication inherent in DRL-based systems. A holistic approach is needed, leveraging DRL's power to optimize EV charging in real-time while accommodating diverse objectives and dynamically changing contexts (Reference from research gate save list).

In the domain of electric vehicle (EV) charging station services and management, it is imperative to address critical gaps related to resource optimality and context awareness, particularly within the framework of achieving carbon neutrality. Concerning resource optimality, challenges encompass scalability and effective resource allocation amid a growing EV market. The scalability of Deep Reinforcement Learning (DRL) models in charging station management must be addressed to accommodate an increasing number of stations and EVs. Exploring multi-objective optimization within DRL algorithms, balancing user convenience, grid stability, operational costs, and carbon neutrality objectives, is crucial. Enhancing energy efficiency in line with carbon neutrality goals involves optimizing energy consumption patterns and minimizing environmental impact using advanced DRL methodologies [60], [61], [62]. On the front of context awareness, persistent gaps involve ensuring multi-stakeholder context awareness and dynamic contextual adaptation for carbon neutrality. Integrating the interests and constraints of stakeholders, including utilities, charging station operators, and policymakers, is vital for sustainable development. The dynamic context, especially concerning carbon neutrality objectives, requires real-time adaptability of DRL models to evolving grid conditions, traffic patterns, and user preferences while minimizing environmental impact [63]. Collaborative learning strategies within a multi-stakeholder environment should be contextually informed, engaging participants like EV owners, charging station operators, and utilities. Facilitated by DRL models, collaborative learning aligns objectives with the overarching goal of achieving carbon neutrality. Bridging these gaps in resource optimality and context awareness within a carbon-neutral context is pivotal for advancing the efficiency, sustainability, and inclusivity of EV charging systems. This section aims to fill gaps in current literature by introducing a context-aware EV smart charging system powered by Deep Reinforcement Learning (DRL). This system will dynamically optimize charging decisions in real-time, accommodating diverse stakeholder objectives and adapting to changing contexts. The goal is to position our proposed system as an innovative and comprehensive solution, addressing challenges identified in prior research on EV charging management.

III. PROPOSED CONTEXT-AWARE EV SMART CHARGING SYSTEM

The heart of our research lies in the architecture of the context-aware EV smart charging system, a meticulously crafted framework comprising an intelligent agent, a dynamic environment, a reward function, and a neural network. We expound upon each component's functionality, highlighting their synergy in refining charging decisions, all the while embracing the ever-shifting contextual factors like time of day, location, and weather.

Artificial intelligence (AI) represents a vast domain within computer science, instrumental in the development of intelligent systems and computers capable of performing tasks that traditionally required human intelligence. These AI-powered machines not only excel in problem-solving but also contribute to better decision-making processes, effectively taking on responsibilities previously reserved for humans [64] and [65]. Within the expansive field of AI, Machine Learning (ML) emerges as a crucial subset. ML relies on data-driven approaches and the training of algorithms using data. Notably, ML models possess the remarkable ability to unearth patterns and insights from the data they ingest, without the need for explicit human intervention. ML employs a diverse range of algorithmic techniques to decipher data, enabling it to make predictions, improve itself, and elucidate complex data structures. These models can be trained through various strategies, including supervised, unsupervised, semi-supervised, and reinforcement learning. Among the multifaceted methodologies within ML, Deep Learning stands out as a subset characterized by its utilization of artificial neural networks. These neural networks, composed of multiple layers, exhibit self-learning capabilities through exposure to data, enabling them to accomplish a wide array of tasks, such as image recognition and speech recognition [66].

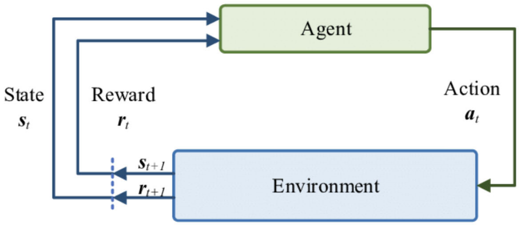

FIGURE 1. Reinforcement learning model.

Reinforcement Learning (RL) represents the science of decision-making within the realm of machine learning. In RL, a computer program assumes the role of an intelligent agent, engaging with its environment and acquiring the ability to make informed decisions based on its interactions. For instance, consider the scenario of a robotic agent mastering the intricacies of foot movement in order to excel in a game of football; this exemplifies the essence of reinforcement learning [64]. At the core of RL lies a fundamental model where an agent actively interacts with its environment, striving to learn an optimal policy for making decisions across varying states. At each discrete time step, denoted as t, the agent observes the current state, represented as St, of the environment and proceeds to select an action, denoted as Ai, based on its pre-defined policy. Subsequently, the environment transitions to a new state, St+1, and the agent receives a reward, Rt, corresponding to the action it undertook in state St. The overarching objective for the agent is to acquire knowledge and refine its policy to maximize the expected cumulative reward over time. The value of a state-action pair, represented as (St, Ai), encapsulates the anticipated cumulative reward commencing from state St, executing action Ai, and then adhering to the optimal policy thereafter. This value is formally denoted as Q(St, Ai).

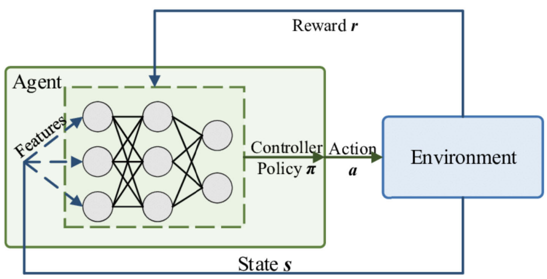

FIGURE 2. Deep reinforcement learning model with policy DNN.

In Figure 2, the agent is depicted as the primary learner and decision-maker, while the environment serves as the interface through which the agent interacts with its objectives. The environment, in response to the agent's actions, continually presents new scenarios and offers rewards, which are numerical values the agent strives to maximize over time through its chosen activities. The agent's overarching purpose is succinctly encapsulated in a unique signal known as the reward, transmitted from the environment to the agent at each time step. This reward is a straightforward scalar value, denoted as R_t that belonging to the set of real numbers, R. The informal objective of the agent revolves around the maximization of the cumulative reward it accrues over time. This entails optimizing not just for immediate rewards but also considering the long-term perspective. The concept of return encapsulates the agent's aspiration to maximize future benefits, typically expressed in terms of expected value. The specific definition of return varies based on the nature of the task at hand and whether delayed rewards are a part of the equation. For tasks that naturally break down into discrete episodes, an undiscounted formulation of return is suitable. Conversely, continuous tasks that do not naturally have episodic breaks benefit from a discounted formulation of return, which extends indefinitely. Our goal is to elucidate the concept of return for both episodic and ongoing scenarios, presenting a unified framework that can be applied across both paradigms. By solving the Bellman optimal equations, which serve as consistency conditions for optimal value functions, we can systematically derive an optimal policy based on these functions. This process allows us to navigate the intricate landscape of reinforcement learning, ultimately leading to informed decision-making within various environments and tasks.

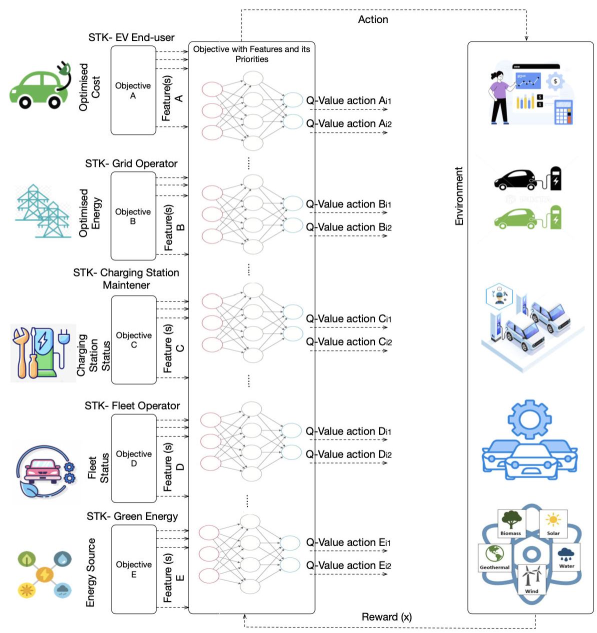

FIGURE 3. Proposed context-aware EV smart charging system using DRL.

We have conducted a comprehensive review of various research initiatives undertaken by distinct organizations, each functioning effectively within its domain. However, a recurring issue has been the inefficient utilization of resources due to a lack of collaboration and coordination among these entities. To illustrate this challenge, let's consider the scenario depicted in Figure 3. In this scenario, we have five primary stakeholders: Stakeholder 'A' whose objective is to get the optimised cost, Stakeholder 'B' whose objective is to get the optimised energy, and Stakeholder 'E' whose primary objective is to motivate EV-enduser to use Environmental-friendly source of energy to charge their vehicle that has directly less impact on the environment. For example, The first participants denoted as EV-end users primary interest lies in finding an optimal charging point during their journey from 'location X' to 'location Y.' Their objectives are to minimize both charging time and cost. Secondly, The grid operator is tasked with generating and supplying electricity to meet the demands of the region's charging point efficiently. However, they often lack precise information about the specific electricity needs of the EV charging stations in their area. Thirdly, The last stakeholder, offers demands of users related to promote Environmental friendly resources such as energy from wind, PV, etc. Historically, these stakeholders have operated independently, with limited awareness of the real-time demands and requirements of other vendors. This lack of synchronization often resulted in resource inefficiencies and suboptimal outcomes. However, the state-of-the-art methodology proposed in this paper addresses these challenges effectively. It introduces a realistic approach that integrates the preferred demands and requirements of various stakeholders, enabling more efficient resource allocation and utilization. This collaborative framework promises to usher in a new era of resource management, fostering synergy among stakeholders and ultimately enhancing the overall effectiveness of EV charging systems.

The following part explains thoroughly the manner in which the suggested architecture works. We demonstrate how the algorithm makes use of contextual data to determine the win-win requirement for each stakeholder. We define three different sets of stakeholders as an example in the efficient transportation eco-system including **Stakeholder-X**, **Stakeholder-Y**, and **Stakeholder-Z** renounce in figure as STK-X, STK-Y and STK-Z respectively.

1) **Stakeholder-A: EV end-users:** The EV end-user is encouraged to share their travel itinerary, including details such as the starting point and destination of their journey. Additionally, the end-user will receive routing suggestions, from which they can choose the most suitable path. The technical specifications of the vehicle, such as battery type, are also determined by the EV end-user. Subsequently, the algorithm generates a set of optimal route options based on these inputs, taking into account key performance indicators such as pricing and the availability of charging stations. The EV end-user can then select the routing option that aligns with their specific needs and preferences, making an informed decision based on both their immediate surroundings and the recommendations provided by the algorithm.
2) **Stakeholder-B: Grid-Operator:** The Grid operator plays a crucial role by furnishing data pertaining to feeder and transformer loads, which encompasses aspects like charging activities and electric supply reservations. This information significantly contributes to and influences the efficient and grid-friendly utilization of charging stations. Typically, the grid operator can employ advanced distribution network modeling technologies to forecast feeder and transformer loading for the next twenty-four hours with a high degree of accuracy.
3) **Stakeholder-C: Charging Stations Maintainer:** The role of the charging station maintainer is to ensure the continuous functionality of the charging station, guaranteeing it meets the demands of end-users and provides reliable services, even in the event of unforeseen disruptions. In cases where the cost of renewable energy experiences a decline, the charging station's owner may proactively notify customers, enabling them to charge their vehicles at a lower cost. Additionally, prior to their visit, end-users have the option to reserve a charging station for their specific fleet.
4) **Stakeholder-D: Fleet Operator** The central responsibility of the fleet operator revolves around monitoring the fleet's availability for booking and ascertaining the energy source it relies on (e.g., hydrogen, gas, gasoline, or electric). Additionally, the fleet manager will have access to vital battery usage information, including discharge rates, which can aid in diagnosing problems and scheduling necessary repairs. Furthermore, the fleet operator handles requests for specific fleet types, considering their associated costs and ensuring that they align with the load requirements specified by customers.
5) **Stakeholder-E: (CO2-Based Energy Provider)** The responsibility of this stakeholder is to supply energy derived from environmentally sustainable sources, including wind, photovoltaic, biomass, and water. Additionally, they serve as an informed resource provider to entities like charging station maintainers, facilitating the utilization of energy at more cost-effective rates compared to conventional gasoline resources like oil, gas, and coal.

The information gathered from individual stakeholders is represented as a set ($A_i -> A_n$, $B_i -> B_n$, $C_i -> C_n$, …, $Z_i -> Z_n$), each associated with its respective initial rewards. These parameters serve as the states, as depicted in the left section of Figure 3, and are subsequently provided as inputs to the model with associated objectives respectively. This data is then subjected to a cutting-edge approach rooted in deep reinforcement learning (DRL). Within this framework, the computer learns the weights of DRL parameters from these input sets, recommended domains, and their corresponding constraints, as well as associated priorities. Upon reaching the expected threshold, the precise results are generated, as illustrated on the middle of Figure 3 which represents the Q-value of action $A_{i1} -> A_{in}$ for Objective A, the Q-value of action $B_{i1} -> B_{in}$ for Objective B, and so on. In this output, tailored information is presented for specific stakeholders. For instance, "EV end-users" receive personalized scheduling and routing options tailored to their vehicle's battery needs and environmental considerations. "Grid Operators" obtain insights into anticipated power demands for a given region based on charging station reservations, facilitating the management of electric fluctuations, among other benefits. Furthermore, it's important to note that the system continuously refines its understanding of its surroundings by dynamically adjusting weights and other relevant parameters to optimize its performance and achieve the maximum reward to fulfill its task efficiently. Now, let's define the total reward i.e. R_t, as the sum of individual rewards such as R_{ev} is sum of individual reward of electric vehicle end-user, R_{grid} is sum of individual reward of Grid-Operator, and so on:

$$R_t = R_{ev} + R_{grid} + R_{cs} + R_{fleet} + R_{co2} \tag{1}$$

The goal is to learn a policy π that maximizes the expected total reward:

$$\pi_* = argMax_{\pi} \sum_{n=1}^{\infty} r^t R_t \tag{2}$$

We begin by introducing an objective function as shown in equation 2, for reinforcement learning and delineating its purpose. Our computation revolves around a reward function, denoted as 'r,' which operates across different time steps, symbolized as 't.' Utilizing this objective function, we can systematically accumulate all the rewards. At each specific time step, a 'state' is denoted by 'x,' while the action taken within that state is represented by 'a.' The 'reward,' denoted as 'r,' encapsulates the computed outcome based on both the state 'x' and the action 'a' taken within it. It's worth noting that each task aims to maximize a discounted sum of its rewards, incorporating a discount factor 'γ' across particular time steps [67].

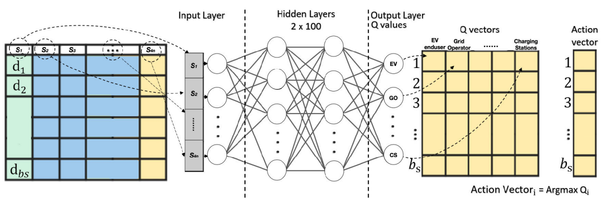

FIGURE 4. DQN model prediction using states and deep neural networks, the outputs are Q-values, and actions are computed based on Argmax Q_i for the current state.

As depicted in Figure 4, the DQN agent is supplied with input states originating from five distinct stakeholders: EV end users, Grid Operators, Charging Station Maintainers, Fleet Operators, and source of energy. These input states encompass a total of 16 features, denoted as X_1 to X_{20} in Figure 3. The DQN agent employs a batch size ranging from d_1 to d_{bs} for each of these input-feature states, designated as S_1, S_2, and so forth in Figure 4. For each state, the DQN agent retrieves a batch of records from memory, with batch sizes varying between 50 and 250, and processes them within a batch table. The Deep Neural Network (DNN) utilized by the DQN agent comprises sixteen input features and incorporates two hidden layers, each housing a multitude of interconnected nodes. The DNN outputs four distinct states, sequentially numbered from 1 to b_s, aligning with the number of participants involved in the system.

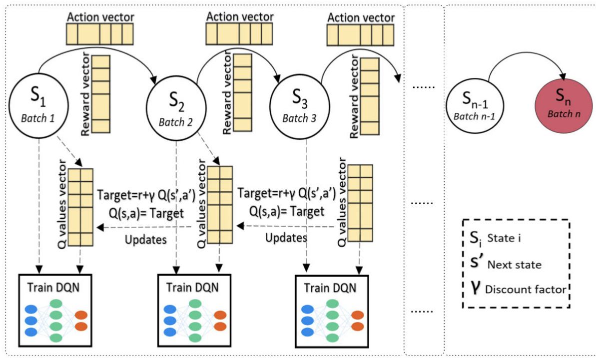

FIGURE 5. Based on training and prediction of the current and subsequent states, the DQN agent state transition Markov diagram illustrates the learning process.

The four output states serve as representations of the Q-values associated with each action for individual participants. These Q-values play a pivotal role in determining the optimal action for each participant within the given state. The action vector, as depicted in Figure 5, mirrors this format. In this context, an action signifies the decision made by the agent following its assessment of the environment during a predefined time window. The network agent compiles a list of actions in the form of an action vector by combining the input from the neural network with its respective features. These resulting Q-values are subsequently utilized to assess the effectiveness of information acquisition. The agent proceeds by providing the current DQN with the state vector using the designated batch size. It then evaluates the DQN's output, leveraging threshold rates and Q-values, to determine the Q-threshold value, which aids in the classification of stakeholders. Overall, the DQN agent harnesses input states from stakeholders to learn the optimal policy for orchestrating the charging of electric vehicles in a decentralized manner. This process is elaborated upon in the forthcoming methodology section and is further elucidated through an illustrative example. The core functionality has been encapsulated within a software package that facilitates interactions among users across diverse sectors through our platform. To streamline this interaction, we've developed middleware as a service component. This enhancement empowers us to showcase the model's utility even at the urban scale, capable of handling high computing demands, extensive datasets, and model scalability.

IV. 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:  */
          AV_i ← Create_random(Action_space) ∀i ∈ bs
          ϵ ← ϵ ∗ decoy_rate
           /* With probability of 1−ϵ:  */
          QV_i ← model.predict(current-state)
          AV_i = Argmax(QV_i) ∀i ∈ bs
           /* Compute rewards */
          RV_i ← Compute_reward(AV,labels) ∀i ∈ bs
           /* Agent's learning improvement */
          Q′← model.predict(state′)
          QT_i←RV_i+γ ∗ Q[state′, action′]
          Model.train(state,QT_i)
          Compute_loss(QV_i,QT_i)
          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 ($$), 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.

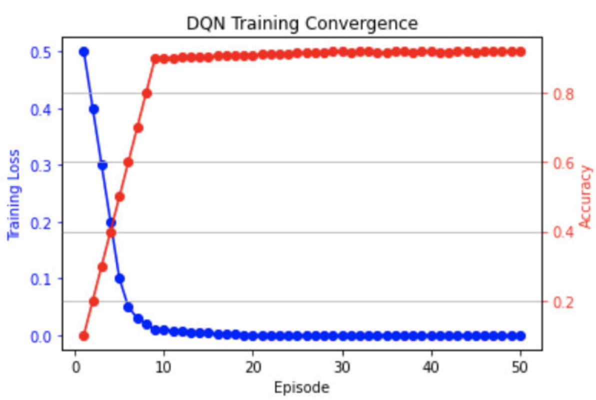

FIGURE 8. Algorithm 1: DQN accuracy and convergence.

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.

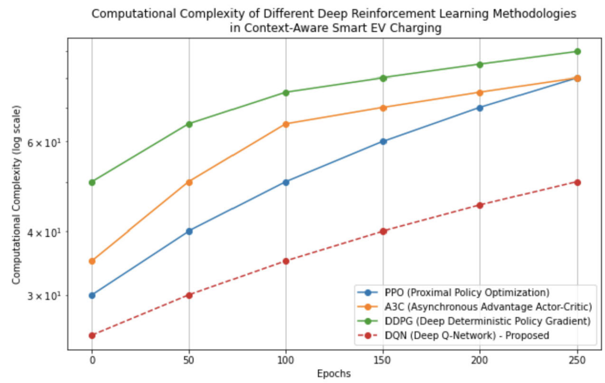

FIGURE 9. Different methodologies comparison in Context of EV end-user.

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

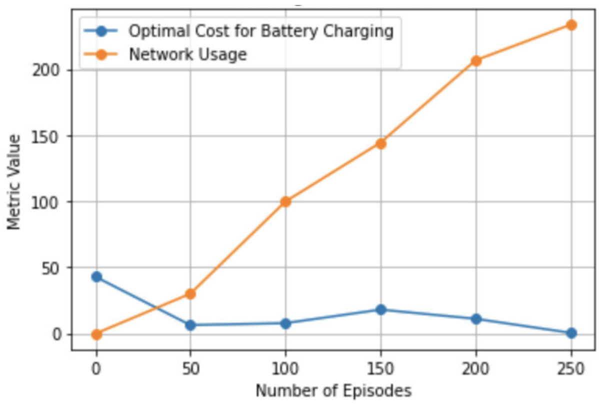

FIGURE 10. DQN optimal cost for EV end-user charging.

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.

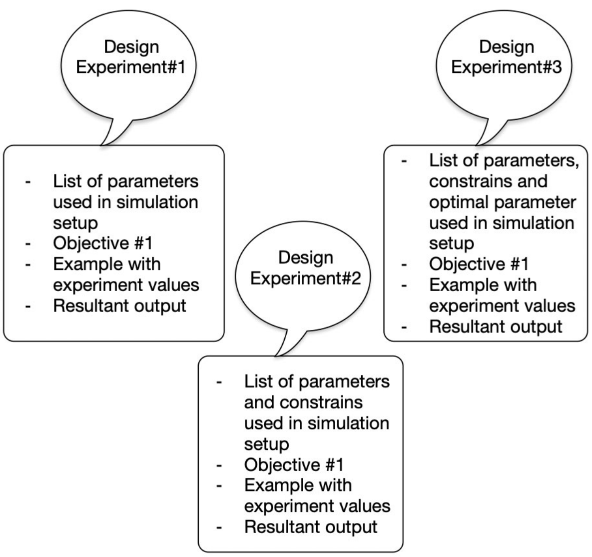

FIGURE 11. Experiment design in simulation scenario.

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 users stories is to formulate strategies for optimizing the utilization of electric car resources and resource distribution effectively.

A. USER STORY: EV-ENDUSER 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.

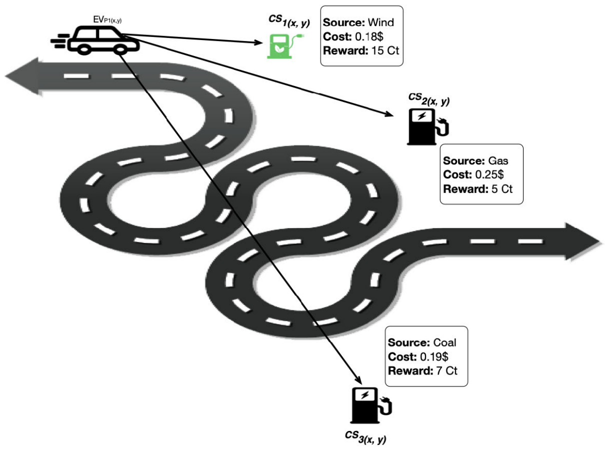

FIGURE 12. Simulation of EV without constraints and optional parameters.

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.

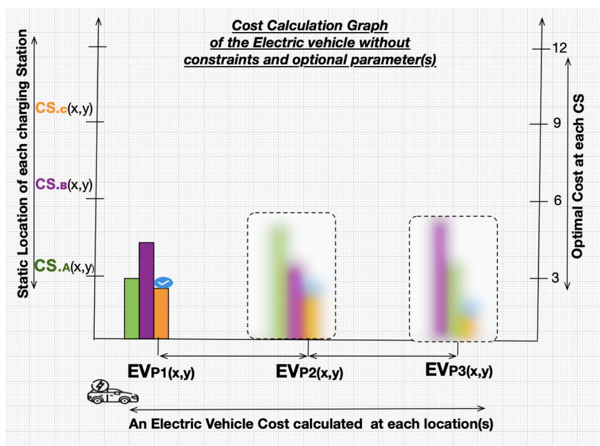

FIGURE 13. Optimal cost calculation for experiment Design 1.

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 end-user, 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.

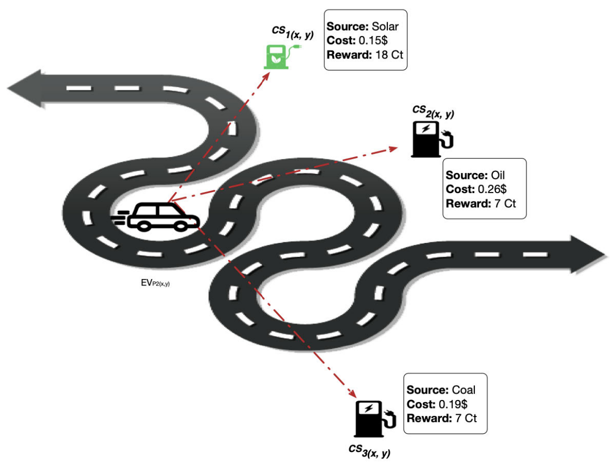

FIGURE 14. Simulation of EV with constraints and without optional parameters.

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 end-user.

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 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.

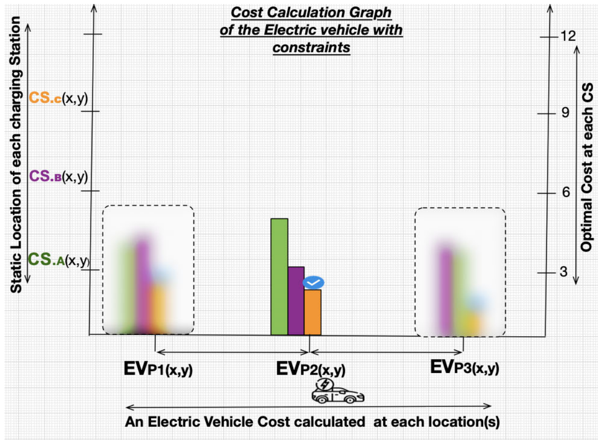

FIGURE 15. Optimal cost calculation for experiment Design 2.

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,

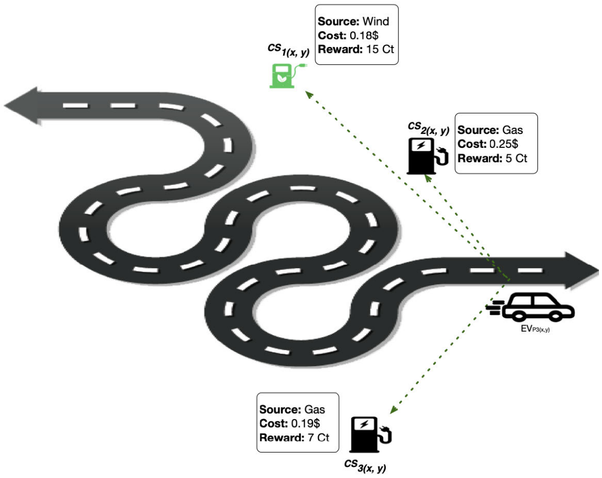

FIGURE 16. Simulation of EV with constraints and optional parameters.

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

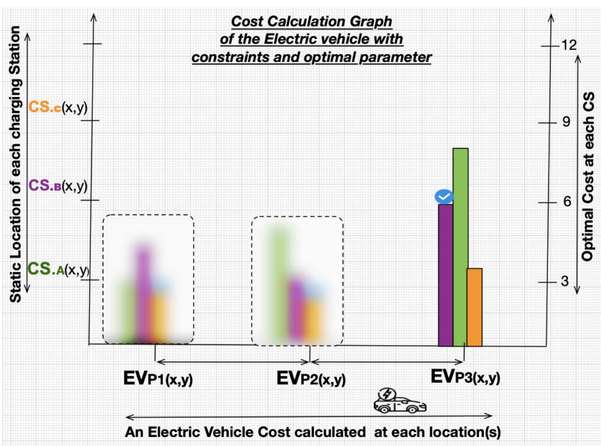

FIGURE 17. Optimal cost calculation for experiment Design 3.

From an environmental perspective, station A stands out as the most eco-friendly option due to its use of renewable energy sources. Incorporating sources like solar PV and wind can significantly decrease CO2 emissions, reducing the environmental footprint of EV charging. In conclusion, considering charging costs, reliance on renewable energy, travel time to the charging station, and the impact of external factors, station A emerges as the optimal solution for both the electric vehicle end-user and the environment.

B. USER STORY: OPTIMIZING EV FLEET CHARGING FOR TIMELY DELIVERIES

Suppose Alice, an industrious fleet operator, is responsible for the efficient management of an electric vehicle (EV) fleet dedicated to a bustling delivery service. Her primary challenge lies in orchestrating the charging process for these EVs in a manner that minimizes operational costs and, most crucially, ensures punctual deliveries. To fulfill these objectives, Alice seeks a solution that not only streamlines the charging process for her fleet but also contributes to the seamless execution of deliveries, guaranteeing customer satisfaction and cost-efficiency in her operations.

1) In the **Baseline Simulation**,Alice employs a fixed charging schedule for all her EVs, irrespective of the time of day or prevailing weather conditions. Charging intervals are uniform, with no consideration for variations in electricity prices or grid demand. For example, In this scenario, all EVs follow the same charging pattern, regardless of external factors. They charge at a rate of 50 kWh per hour for a fixed duration of 8 hours. The charging cost per kWh remains consistent at $0.10. This approach simplifies charging management but overlooks opportunities to optimize cost and efficiency based on real-time factors.However, Alice recognizes the limitations of this fixed strategy and aims to enhance her charging operations by adopting a more dynamic and context-aware approach, as outlined in the Proposed Simulation.
2) In the **Simple Time-Based Model Simulation**, Alice considers charging during off-peak hours to capitalize on lower electricity prices. Charging costs are calculated based on off-peak rates of $0.08 per kWh. For instance, charging a vehicle with a 60 kWh battery during off-peak hours would cost $4.80. This strategy aims to reduce charging expenses when electricity demand is lower.
3) In the **Grid Demand-Aware Model Simulation**, To contribute to grid stability, Alice schedules EV charging during times of lower grid demand. This model aligns with both cost efficiency and grid reliability. By strategically selecting times of lower demand, Alice not only optimizes costs but also supports the stability of the electricity grid.
4) In the **Renewable Energy-Aware Model Simulation**, Alice prioritizes charging when renewable energy sources, such as solar power, are at their peak generation. Charging is aligned with times when solar energy is available at 30%, ensuring a greener and more sustainable approach. This strategy reduces reliance on non-renewable energy sources.
5) In the **Proposed Simulation:Context-Aware DRL Charging**, represents the implementation of a context-aware EV smart charging system, underpinned by deep reinforcement learning (DRL). This advanced strategy takes into account dynamic contextual factors, including time of day, weather forecasts, and fluctuating electricity prices. Charging speeds are adapted based on station load, and predictions regarding available solar energy are factored in. For example: In this scenario, the Proposed Simulation considers real-time contextual data. During peak hours when electricity prices are at $0.15 per kWh, charging occurs at a rate of 40 kWh per hour, aiming for

maximum cost efficiency. During off-peak hours with rates at \$0.08 per kWh, charging speeds increase to 60 kWh per hour. Moreover, the simulation accounts for solar energy predictions. If solar energy is predicted to be available at 30% during the day, it adjusts charging schedules to prioritize renewable energy sources when feasible.These dynamic adaptations lead to differentiated charging costs, where during peak hours, the cost per kWh is \$0.15, and during off-peak hours, it is \$0.08, contributing to optimized charging expenses and greater overall efficiency.

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

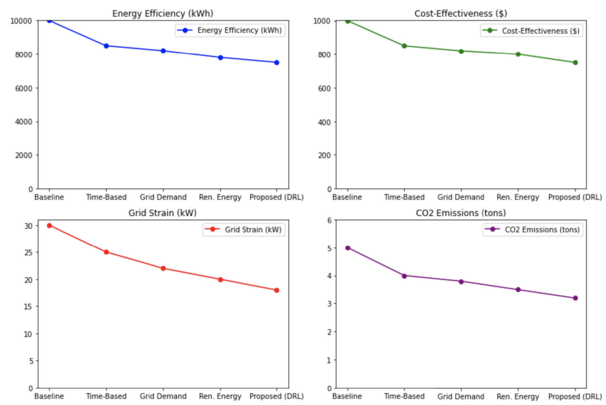

FIGURE 18. Graph(s) simulation methodology comparison.

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, cost-effectiveness, 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.

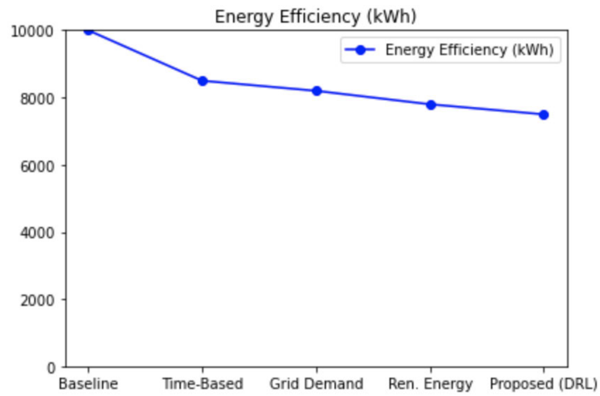

FIGURE 19. Energy efficiency (kWh) metric simulation.

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.

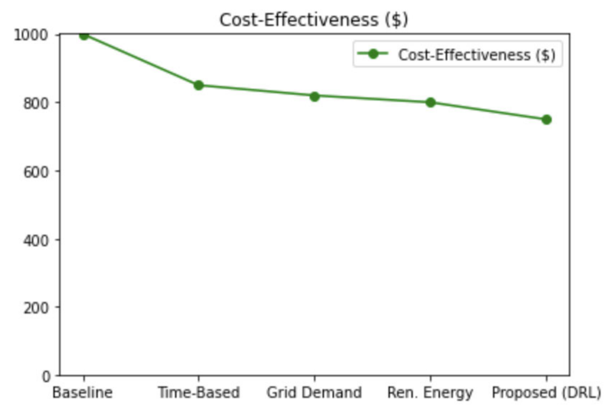

FIGURE 20. Cost-Effectiveness (\$) metric simulation.

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).

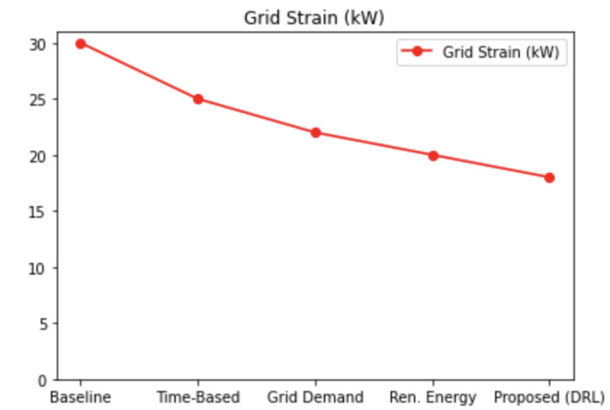

FIGURE 21. Grid strain (kW) metric simulation.

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).

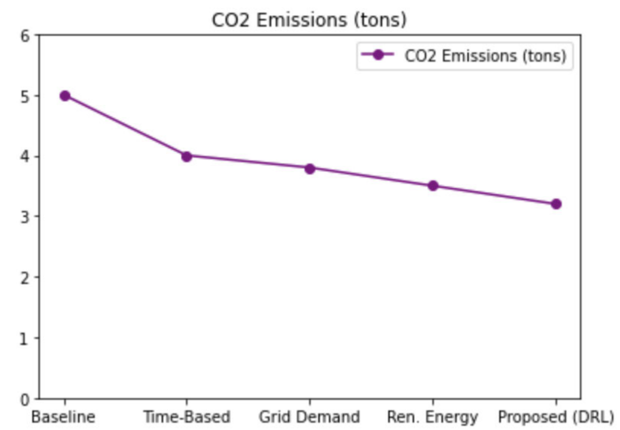

FIGURE 22. CO2 emissions (tons) metric simulation.

After a comprehensive analysis of various charging approaches across key metrics, it becomes clear that each approach offers a unique balance of advantages and trade-offs. 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.

A. COMPARISON: EV END-USER PERSPECTIVE

We can assess performance from the perspectives of both electric vehicle (EV) end-users and grid operators based on the outlined scenarios. According to the performance analysis, the cost of charging an electric vehicle is partially influenced by various factors, notably the charging station's location, energy source, and the distance between the vehicle and the charging point. In the initial scenario, we evaluated the charging cost for a battery-operated car at three different charging stations, each with a unique power source and cost per kilowatt-hour. The analysis indicated that the station with the lowest cost per kilowatt-hour proved to be the most cost-effective choice for EV end-users. However, in the subsequent scenarios, we introduced constraints such as the typical battery range and the distance between the car and the charging station. With these limitations, the analysis revealed that, on occasion, the most cost-effective charging station might not necessarily have the lowest cost per kilowatt-hour. For example, if there is a considerable distance between the vehicle and the station, the EV might be unable to reach the most economical station, potentially leading the end-user to opt for a more expensive station.

According to the performance analysis conducted by the grid operator, the total electric power needed for each charging station is determined by the quantity and variety of electric vehicles (EVs) utilizing the station. The findings highlight significant variations in energy demand based on location and time of day. For instance, a charging station situated in a densely populated area will experience considerably higher power demand compared to one in a less populated area. Additionally, if charging occurs during peak hours when electricity demand is notably high, the grid operator may need to generate more energy to meet both supply and end-user demands. In light of these considerations, the grid operator must take into account various factors when planning and managing the energy supply to charging stations. This includes the station's location, the types of EVs utilizing the station, and the time of day. Such considerations enable the grid operator to ensure a stable and efficient energy supply to the charging stations while simultaneously minimizing the environmental impact.

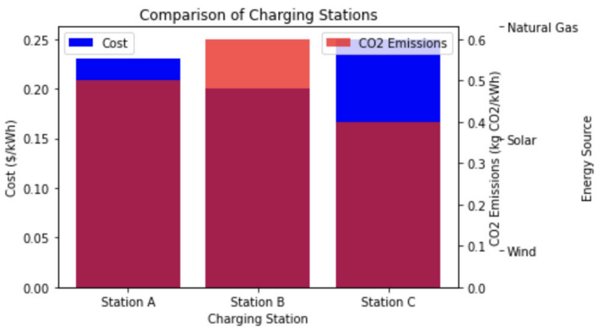

FIGURE 23. The energy source, cost, and environmental impact comparison for the three charging stations.

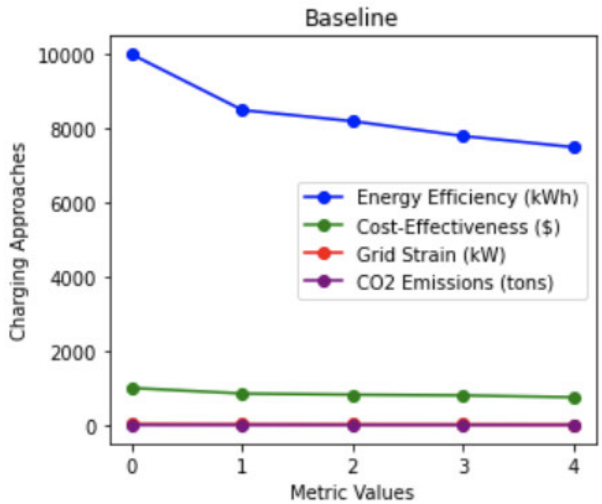

FIGURE 24. The energy source, cost, and environmental impact comparison for Fleet operator.

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 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.
2) **Cost-Effectiveness**
In the baseline simulation see figure 24, The fixed charging schedule incurs a cost of $1,000. It represents the highest cost among all approaches due to its lack of adaptability to pricing variations. In the Simple Time-Based Model simulation, Charging during off-peak hours reduces costs to $850, indicating cost savings compared to the baseline. In the Grid Demand-Aware Model simulation, This model further reduces costs to $820, showing a balanced approach that optimizes costs. In the Renewable Energy-Aware Model simulation, Prioritizing renewable energy leads to lower costs of $800, indicating both cost savings and sustainability. In the Proposed Simulation (DRL) simulation, The DRL-based approach is the most cost-effective, with costs of $750, reflecting its dynamic optimization and cost-saving capabilities. Moreover, Proposed simulation offers the lowest charging cost and is approximately 18.67% more cost-effective compared to the baseline.

3) **Grid Strain**
In figure 24, the baseline simulation contributes to a peak grid demand of 30 kW. It places a significant strain on the grid due to its inflexible charging schedule. The Simple Time-Based Model simulation, Charging during off-peak hours reduces grid strain to 25 kW, contributing to grid stability. The Grid Demand-Aware Model further reduces grid strain to 22 kW, indicating its ability to support grid stability. The Renewable Energy-Aware Model is Prioritizing renewable energy leads to a grid strain of 20 kW, further minimizing stress on the grid. Finally, the Proposed DRL-based approach excels in minimizing grid strain, with a peak demand of 18 kW, showcasing its grid-aware charging capabilities. other than this, the proposed simulation reduces peak grid demand by 10% compared to the baseline.

4) **CO2 Emissions**: Proposed simulation results in the lowest CO2 emissions, showcasing a 12% reduction compared to the baseline see figure 24. In the baseline simulation, The fixed charging schedule results in estimated CO2 emissions of 5 tons, representing higher emissions due to inefficient charging. In the Simple Time-Based Model simulation, Charging during off-peak hours reduces emissions to 4 tons, indicating a reduction in environmental impact. In the Grid Demand-Aware Model simulation,This model further reduces emissions to 3.8 tons, highlighting its sustainability benefits. In the Renewable Energy-Aware Model simulation, Prioritizing renewable energy leads to lower emissions of 3.5 tons, making it an eco-friendly choice. In the Proposed DRL-based simulation approach, emits the least CO2, with emissions of 3.2 tons, reflecting its sustainability and environmentally conscious charging.

C. DATA ACCURACY AND PROPOSED METHODOLOGY

Data accuracy is paramount for the proposed context-aware EV smart charging system utilizing Deep Reinforcement Learning (DRL). Inaccurate input data may distort the learning process, leading to suboptimal decisions and reduced adaptability to new contexts. Optimization performance relies on accurate historical patterns, user behaviors, and grid conditions for efficient resource allocation. Context-awareness, essential for dynamic adaptation, is compromised by inaccurate data, potentially resulting in misinformed decisions. The robustness and reliability of the system hinge on data accuracy, with uncertainties introduced by inaccuracies. During training and validation, accurate data is crucial to prevent biased models. User experience and trust are directly influenced by data accuracy, impacting system adoption. Ensuring the accuracy of data for DRL algorithms is critical for the success of the proposed EV charging system.

In light of the comprehensive analysis and evaluation of various charging approaches, it is 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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