A Reinforcement Learning Based Strategy for Optimal Placement of Electric Vehicle Charging Stations in Smart City for Urban Planning

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Abstract—**In this paper, we present a Reinforcement Learning (RL) based strategy for placing optimal charging stations (CS) of electric vehicles (EVs) in the case of Urban planning and smart city development under digital twin. The objective is to minimize the energy required by EVs to reach the CS for recharging. Our approach shows the efficacy of computationally identified CS placement over random placement. Extensive research has demonstrated that an RL-based strategy yields better results in identifying suitable CS locations than random positioning. Based on our investigation, the proposed method finds the most effective positions and some alternative locations for the placement of CS. This study presents a novel approach with 20.97% enhancement in energy efficiency compared to related research findings. Furthermore, our proposed approach demonstrates expedited attainment of an optimal policy, outperforming existing literature.**

Index Terms—**Charging station placement, reinforcement learning, epsilon–greedy policy, energy consumption, Urban Planning, Smart City**

I. INTRODUCTION

The late transportation sector experiences a paradigm shift due to the threat of environmental pollution and fossil fuel depletion. Because of the scarcity of fossil fuels, almost all countries, including India, face the challenge of sustainability and securing sufficient stocks of natural resources for long-term viability. To address the issue, EVs emerge with huge promises and potential for intelligent city development. However, the most significant barrier to the wider acceptance of EVs is the inadequate development of charging infrastructure [1]–[7]. Effective charging infrastructure planning [6] covers several operations such as placing of CS, estimating charging demand, assessing charge utilization, charging scheduling and pricing, and so on.

Moreover, the development of smart cities is revolutionizing the way urban infrastructure is planned and managed, with a focus on sustainability, energy efficiency, and the integration of advanced technologies. In the context of electric vehicles (EVs), the strategic placement of charging stations plays a crucial role in supporting the transition to greener transportation. Urban planning for smart cities must account for the growing demand for EVs, ensuring that charging infrastructure is both accessible and energy-efficient. The placement of EV charging stations is a key component of this effort, requiring intelligent systems to optimize locations that minimize energy consumption, reduce travel distances for users, and integrate seamlessly with other smart city technologies. By leveraging data-driven approaches, such as Reinforcement Learning, urban planners can dynamically adapt to changing traffic patterns and user behaviors, ensuring that charging stations are placed in the most efficient and convenient locations. This enhances the overall energy infrastructure of a smart city, contributing to reduced emissions, improved energy management, and a better quality of life for its residents [8].

Various approaches, including both meta-heuristic and machine learning (ML) strategies, have been employed to address the issue of effective charging infrastructure planning. The use of RL strategies [6], [9]–[11] is also done in recent time. In [7], Genetic Algorithms (GA) are used to study EVs' driving ranges. The work in [12] employed the shortest path method and branch-and-bound algorithms to tackle the integrated fleet sizing and charging system planning in autonomous EVs for passenger and freight transportation. In [13], the Projection and Monte Carlo methods are applied to solve an electric car routing issue with stochastic and time-dependent trips.

The work [14] integrates GA and RL for the optimal deployment of a wireless charging electric tram system. To address the problem of inadequate charging infrastructure for widespread EVs adoption, the work in [15] presents a data-oriented approach that utilizes features derived from global positioning system (GPS) data. This approach aims to investigate the associations between these features and indicators that measure the performance of charging infrastructure. Few other nature-inspired algorithms are employed in [3] [2] to determine the ideal position of CS in an EVs system. Several ML techniques have addressed several bottlenecks in CS placement for EVs. One such work [16] proposes multiple linear regression (MLR) and extreme gradient boost (XGBoost) ML techniques to expand EVs' charging infrastructure. Additionally, the work [17] employs random forest, gradient boosting, bagging, and support vector machine (SVM) with deep Q-learning (DQL), and deep Q-network (DQN) using

OpenAI Gym environment to identify the optimal locations for CS.

Researchers have also explored RL approaches to overcome charging queuing delays. For instance, a solution based on model-free deep RL (DRL) has been proposed to address uncertainties in traffic situations and dynamic arrival of EVs' charging demands [9]. Another study uses DQL to efficiently schedule EVs' charging and guide them on the optimal routes [10]. An investigation [6] presents a thorough study on ML applications for charging infrastructure planning. Hybrid GA-RL, hierarchical clustering, linear regression model, and decision tree methods are used to place the CS. The work in [11] investigates charger-based greedy strategy in conjunction with the best location on CS placement.

Finding the most effective location for CS placement is vital in developing charging infrastructure and is the research topic in the present work. Our primary aim is to determine the most suitable locations for CS placement, resulting in reduced energy requirements for EVs to reach the specified destination. Queuing delay on charging greatly impacts on the positioning of CS. Such a situation may be envisioned as a scenario where N number of EVs are attempting to reach the same CS via the shortest route, leading to extensive queues on the station and causing an increase in EVs energy consumption.

This study introduces a novel approach to the placement of electric vehicle (EV) charging stations using reinforcement learning (RL). The proposed strategy dynamically adapts to real-time road and traffic conditions, providing a more energy-efficient and optimal placement of charging stations compared to traditional static or heuristic-based methods. The use of Q-learning with an epsilon-greedy exploration policy allows the model to improve over time by learning from the dynamic environment, making it highly adaptable and effective in varying conditions. The following list demonstrates the contributions of this investigation: (i) developed a reinforcement learning-based framework for the optimal placement of EV charging stations that minimizes energy consumption, (ii) introduced a path selection strategy based on mean path weights to guide EVs toward energy-efficient routes, (iii) implemented an epsilon-greedy policy to balance exploration and exploitation during charging station placement optimization, (iv) proposed an approach for identifying computationally optimal charging station (CCS) locations and alternative random charging stations (RCS) to alleviate congestion, (v) demonstrated significant improvements (20.97%) in energy efficiency compared to existing methods such as RL-EVAS, and (vi) validated the proposed method through extensive simulations and comparisons with related work in the field.

The rest of the paper is organized as follows: Section II provides a comprehensive literature review. Section III presents the road network and problem formulation. Section IV describes the proposed solution and implementation, while Section V presents results and a discussion. Section VI outlines the conclusions and scope of future works.

II. LITERATURE REVIEW

This section provides a review of relevant work on charging station (CS) placement for electric vehicles (EVs) using various methodologies, including meta-heuristics, machine learning (ML), and reinforcement learning (RL). We further outline the scope of this study and its contributions in the context of existing research.

The work in [18] presents a bi-level paradigm and mixed-integer linear programming (MILP) reformulation for planning power distribution networks and charging station placement. The model optimizes both the construction of CS, new motorways, and power infrastructures, while also scheduling electricity and traffic flows. This method, applied to Xi'an City in China, offers a sophisticated approach but is limited by its dependence on static planning assumptions that fail to adapt dynamically to real-time traffic data and EV demand.

An identical work by [1] explores optimization techniques such as genetic algorithms (GA) and artificial neural networks (ANN), highlighting their potential for integration in smart cities. However, while these meta-heuristic approaches are useful in solving large-scale optimization problems, they do not provide real-time decision-making capabilities. A similar study in [3] compares GA, particle swarm optimization (PSO), and other bio-inspired algorithms like ant colony and firefly optimization. These methods, while effective in static optimization scenarios, lack the dynamic adaptability that RL methods offer.

In [2], the authors focus on CS placement, considering the quality of service in terms of waiting time and range anxiety. Although these aspects are important, the study does not account for dynamic variations in traffic and EV demand, which are critical in real-world urban settings.

The study in [17] employs supervised ML techniques such as random forests and gradient boosting in conjunction with deep Q-network (DQN) algorithms. This hybrid approach, while useful, requires large datasets for training and is computationally expensive. Additionally, [6] offers an in-depth analysis of machine learning (ML) approaches, where hybrid GA-RL models are used, but they still face the challenge of adapting to rapidly changing environments.

Different RL approaches have also been explored. A model-free deep RL (DRL) method was introduced in [9] to optimize route and CS selection by considering real-time traffic data. This system outperforms static models by dynamically adjusting to changing demand but does not address the full complexity of the EV charging station placement problem.

Similarly, in another study, [10] developed a novel DQL-based method for planning EV charging schedules and the best charging route. The Markov decision process (MDP), DQN, and DQL-based EVs charging scheduling algorithms are used to implement the strategy on a road network in Beijing, China. The study highlights the role of RL in handling dynamic urban road networks, ensuring that charging schedules are optimized in real time. Furthermore, the researchers in [11] investigate the best locations for CS placement in metropolitan areas using RL. These approaches validate the use of RL for identifying optimal CS locations in large urban networks by dynamically interacting with real-time data. This critical feature outperforms static or hybrid approaches.

Overall, reinforcement learning has emerged as a superior approach in this domain, compared to static meta-heuristic and machine learning methods. Our study builds on this work by focusing on a dynamic RL-based strategy for CS placement, which considers real-time road and traffic conditions, minimizes energy consumption, and balances EV distribution across multiple stations to avoid congestion. The key difference in our approach is the focus on directing EVs to alternative routes and exploring a wide range of starting points to minimize congestion effects, which many previous works did not address.

As shown in Table I, our proposed RL-based strategy offers significant improvements over traditional static methods and even other RL-based methods. By dynamically adapting to traffic conditions and providing energy-efficient solutions through Q-learning, our method represents a comprehensive solution for urban CS placement in smart cities.

1) The literature review reveals that when compared with meta-heuristic methods, RL performs better in finding the optimal route discovery.
2) RL is one learning strategy that thrives on experience from dynamic interactions with the environment.
3) It doesn't rely on the confinement of rigid pre-determined routes, making it incredibly valuable when the environment is uncertain.
4) Our proposed approach entails directing EVs to avail alternative routes to reach the CS and avoid congestion caused by traffic bottlenecks.
5) To accomplish this, we thoroughly examine various starting points and destination locations from the diverse source nodes location to assess the effects of road congestion on the travel routes.

TABLE I: Comparison of CS Placement Approaches

Method	Approach	Key Features	Our Advantage
[18]	MILP	Static optimization of CS and power networks	Lacks dynamic adaptability
[1]	GA, ANN	Meta-heuristic, solves large-scale static problems	No real-time adaptability
[3]	GA, PSO	Bio-inspired algorithms for static CS placement	Limited to pre-determined routes
[2]	Optimization (QoS)	Focuses on waiting times and range anxiety	No adaptation to dynamic traffic
[17]	ML with DQN	Hybrid ML and RL for CS placement	Computationally expensive, requires large datasets
[9]	DRL	Model-free RL for dynamic route selection	Limited scalability and complexity
[10]	DQL	Dynamic scheduling of EV charging with RL	Focuses on scheduling, not CS placement
[11]	RL	Optimal CS placement in urban areas using RL	Only focuses on static placement
Our Work	**RL with Q-learning**	**Real-time CS placement, alternative routing, minimizes congestion**	**Dynamic adaptability, energy-efficient, real-time decision making**

III. ROAD NETWORK AND PROBLEM FORMULATION

We explore a mesh-type road network (R_k) with weights in N connectivity locations where EVs begin their travels. Our method represents the node network as a weighted, unidirectional road network, $(G) = (V, E)$. Each edge represents a path segment connecting two road nodes and is depicted as a tuple list forming a graph. In this graph, every tuple (u, v, w) denotes an edge connecting locations u and v with a weight of w. A collection of locations $V = \{loc_0, loc_1, loc_2, ..., loc_N\}$ is considered. The set E comprises path segments, each linking a location u to another location v with a weight w. Random values (distances) of weights are assigned in our study to have dynamic road networks. We utilize the NetworkX Python package [19] and Matplotlib [20] to build and visualize the road networks. The route between any two locations is denoted as S_i, where

$$S_i = \{S_1, S_2, ..., S_k\} \tag{1}$$

The cost function of a sample journey for an EV over a hypothetical road network is as follows:

$$J = \sum_{i=1}^{k} S_i \tag{2}$$

A glimpse of the road layout is demonstrated in Fig. 1 for $N = 22$ nodes. The nomenclature list encompasses all the

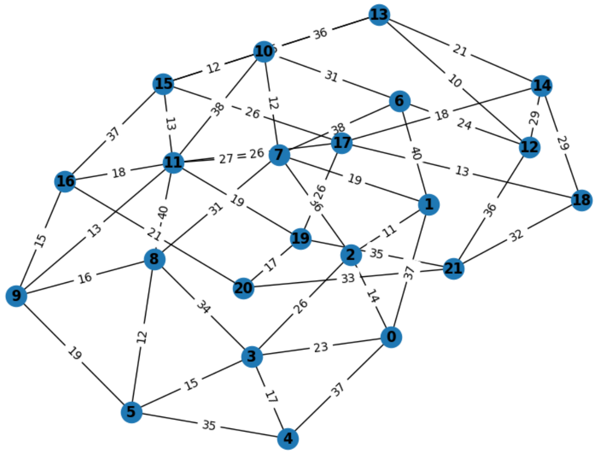

Fig. 1: A mesh type road network with segment distances determined with random values.

notations utilized in this work.

1) **Sets and Index**
   a) L_{init} : Set of locations from where EV journey begins
   b) L_{dest} : Fixed destination location where EV journey stops
   c) L : Set of all locations including L_{init} and L_{dest}
   d) S_i^M : Set of path segments and values, respectively
2) **Parameters and Variables**
   a) R_k : A mesh type road network with k number of locations
   b) loc_i : The i^{th} location is where multiple road segments are interconnected.
   c) j : An example journey of EVs'.
   d) α : Learning rate
   e) γ : Discount factor
   f) $\mathbf{A}^+$: EVs expend lower energy consumption during travel to or through charging stations (CS).
   g) $\mathbf{A}^-$: EVs expend higher energy consumption during travel to or through CS.
   h) $\mathcal{TCS}$: Category of CS.
   i) $\mathcal{ECS}$: The performance of EVs during travel through CS.
   j) $\mathcal{V}$: The percentage of visits to CS by a fleet of k vehicles traveling from source to destination locations.
   k) δ : The mean energy consumption of EVs.
   l) CCS_{loc} : Optimal positions for the placement of computationally identified CS (CCS).
   m) P_k^{seq} : k effective sequences of routes for EVs journey.
   n) E_{Total} : Total energy consumption of EVs (in joules).
   o) t : The duration needed for EVs to travel the specified distance.

A. *Problem Formulation*

An EV initiates its trip from an arbitrary starting position to a predetermined destination location. The aim is to identify the optimal location for CS placement. The sum of segment distances between the starting and the predetermined destination location determines the total weight of a road segment. Our approach runs on the extracted data from the smart city digital twin, which simulates urban infrastructure and traffic dynamics in real time, allowing for enhanced precision in strategic placement and informed urban planning. Thus, in our investigation, we exported the road trip data from the Smart City Digital Twin (such as the Nicosia [21]) to ensure that the calculations closely accurately reflect reality. Our objective is to strategically place the CS so that EVs consume minimum energy (ω_j) on their travel route to or via the CS. The problem can be equivalently formulated as:

$$Minimize \quad \sum_{j=1}^{n} \omega_j \tag{3}$$

where ω_j represents the energy consumption by EVs'. The mathematical framework [22] provides a set of equations that allows us to establish the energy consumption of EVs during their journeys.

$$F_L = F_{\text{roll}} + F_{\text{grade}} + F_{\text{air}} + F_{\text{acc}} \tag{4}$$

$$P = v \times F_L \tag{5}$$

$$E_{\text{Total}} = t \times P \tag{6}$$

Where F_L represents the forces influencing EVs, F_{roll} corresponds to the rolling resistance force between the tire and the road, F_{grade} represents the force related to the road grade, potentially having a negative value when descending, F_{air} signifies the air resistance encountered by moving EVs, F_{acc} stands for the acceleration force acting on the EVs, P denotes power in watts, and v denotes the velocity of the EVs respectively.

IV. PROPOSED SOLUTION AND IMPLEMENTATION

Q-learning, an efficient RL algorithm, functions in decision-making and problem-solving in dynamic environments. It permits a mechanism to learn optimal actions to maximize cumulative rewards over time. Several crucial stages emerge when Q-learning is concerned with EVs' CS placement. The environment, a region, divides into different states, representing potential CS zones. Features such as traffic flow, proximity to routes, population density, and EV usage conventions represent these states. The action space in Q-learning involves placing a CS in a specific location. The mechanism interacts with the environment over multiple episodes, exploring different strategies and updating the Q-table or function approximator. Off-policy learning technique [23] determines the most appropriate policy by taking into account the actual actions taken during the exploration phase. This implies that the target policy is the same as the behavior policy utilized throughout the exploration process. We adopted the epsilon-greedy policy [24] based exploration technique for our experimentation. During the training phase, our proposed algorithm examines two options for picking an action: it chooses the exploitation with

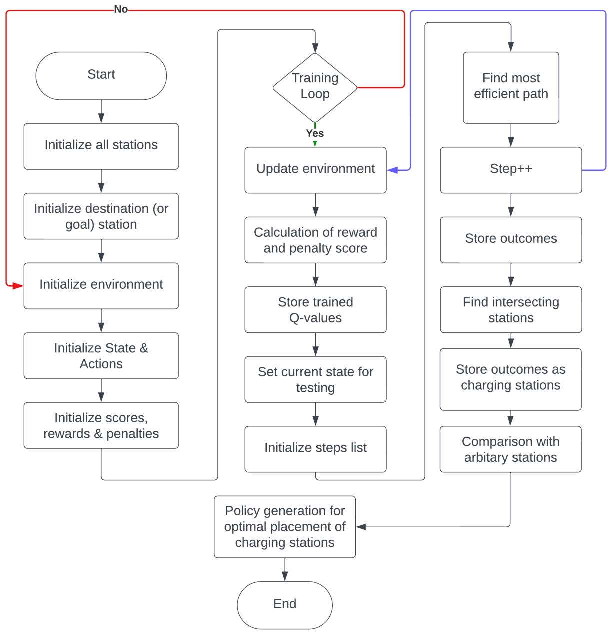

Fig. 2: Flowchart for determining the optimal CS placement.

the greatest Q-value with a probability of $(1-\epsilon)$, and it chooses the exploration with probability ϵ.

A. Solution Steps for CS Placement

To effectively place charging stations (CS) within the road network and minimize the energy consumption of electric vehicles (EVs), we propose a structured approach consisting of two key components. First, we employ a path selection strategy that guides the EVs toward paths that are optimized for energy efficiency. Second, we establish policies for recognizing optimal CS locations by using both computational and random methods. These strategies are designed to address various aspects of CS placement and are detailed as follows (see Algorithm 1):

The following steps represent the core methodology used in determining the optimal placement of charging stations (CS). The goal of these steps is to ensure that paths are selected based on their energy efficiency and that the most effective charging station locations are identified through computational and random methods.

1) Path Selection Strategy: We employ a strategy that involves a specified set of path weights (or segment distance). This technique selects a path provided that the path weight is either less than or equal to the mean path weight (or threshold ($\bar{w}$)). The threshold is the mean path weight, determined by the following equation:

$$\bar{w} = \frac{1}{n(n-1)} \sum_{i \neq j} w_{ij} \tag{7}$$

Where $\bar{w}$ is the mean path weight, n is the number of locations or nodes in the road network, and w_{ij} is the weight of the path segment between locations i and j. The summation is taken over all pairs of locations i and j where $i \neq j$. This strategy encompasses our approach of utilizing rewards and penalties to steer the selection of the optimal routes. The reward associated with $\bar{w}$, denoted as $\mathcal{R}(\bar{w})$, and the penalty associated with $\bar{w}$, denoted as $\mathcal{P}(\bar{w})$, are integral parts of our experiment.

2) Establishing policies for recognizing CS: We formulate the following strategies that combine both computationally determined and randomly selected approaches to identify optimal locations for the placement of CS in our experimental road network. The following section offers a comprehensive breakdown of determining the locations for CS placement.
   a) Strategy to identify CCS: The process of identifying CCS follows a systematic three-stage approach, which involves efficient route identification, identification of location visit occurrences, and formulation of a strategy for CS placement.
   b) Identification of alternative CS: To alleviate charging overload at CCS, we conduct experiments involving random EV journeys, selecting arbitrary locations as potential CS (RCS) placement. To find the efficacy of such CS placement, we examine the energy consumption and computational complexity associated with each EV journey.

Algorithm 1 CS Placement Strategy

```
Initialize road network $G(V, E)$ with $N$ locations and weighted paths
Initialize EV journey from source $L_{init}$ to destination $L_{dest}$
Calculate mean path weight $\bar{w}$ using equation:
    $\bar{w} = \frac{1}{n(n-1)} \sum_{i \neq j} w_{ij}$
for each EV route $S_i$ do
    if $w(S_i) \leq \bar{w}$ then
        Select $S_i$ for path
    else
        Discard $S_i$ and penalize route
    end if
end for
Identify computationally determined CS locations (CCS) based on path visitation rates
Test alternative CS locations (RCS) for potential traffic relief
Evaluate energy consumption and performance for both CCS and RCS
Output optimal CS placement
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V. Results and Discussion

This section evaluates the proposed approach in various experimental instances within the provided context, demonstrating its efficacy and feasibility. Section (V-A) provides a detailed

Location	$\mathcal{TCS}$	$\mathcal{ECS}$	$\mathcal{V}$ (%)
loc_{17}	CCS	$\mathbf{A}^{+}$	100
loc_{19}	CCS	$\mathbf{A}^{-}$	100
loc_{11}	CCS	$\mathbf{A}^{-}$	84.62
loc_{8}	CCS	$\mathbf{A}^{-}$	53.85
loc_{1}	CCS	$\mathbf{A}^{-}$	38.46
loc_{6}	CCS	$\mathbf{A}^{-}$	38.46
loc_{7}	CCS	$\mathbf{A}^{-}$	38.46
loc_{18}	RCS	$\mathbf{A}^{-}$	23.07

TABLE II: Validation Summary for CCS and RCS. $\mathbf{A}^{+}$: EVs consume less energy to reach the CS. $\mathbf{A}^{-}$: EVs consume more energy to reach the CS. $\mathcal{TCS}$: Type of CS. $\mathcal{ECS}$: The energy efficiency level of EVs while traveling through CS. $\mathcal{V}$: Rate (%) of visiting CS.

explanation of the experiment setup and the simulation outcomes. In contrast, Section (V-B) compares the results with the related works [2] [25] [26] [27].

A. Experimental Setup

We experimented on an Ubuntu 20.04.6 LTS machine powered by an AMD Ryzen 5 2600 CPU running at 3.40 GHz with six cores. The system includes an NVIDIA GeForce GTX 1660 GPU and 64 GB of DDR4 RAM. For our experimentation, we utilized PyCharm Community Edition 2023.2.1 with Python 3.8.10. The extensive simulation results detail various scenarios. Graphical representations complement textual analysis, enriching comprehension of the simulation outcomes. Detailed tables and figures clarify the findings derived from the simulation experiments. To initiate this investigation, we first explore the outcomes of an EV excursion before progressing towards multiple EVs. Our methodology encompasses driving EVs from randomly selected starting points to a predetermined destination. The primary objective of our study is to examine energy consumption in two scenarios. In both scenarios, EVs show lower energy consumption traveling from the source to the destination via loc_{17} (CCS) compared to loc_{1} (CCS). Moreover, EVs consume less energy traveling from source locations to CCS than to RCS. These findings suggest that placing the CS at loc_{17} in the analyzed road layout is feasible. Therefore, assessing energy consumption rates of CCS versus RCS is crucial to validate this conclusion.

We analyze energy consumption across routes from multiple origins to a specific destination to validate CCS and RCS consumption rates. Routes passing through loc_{12}, loc_{13}, and loc_{14} exhibit higher energy consumption for both systems.

However, routes exclusively using CCS show lower energy consumption rates, except at these locations. Our validation confirms energy consumption rates needed for vehicles from various sources to a designated destination. Initially, we verify EV compatibility with established CCS setups and assess RCS in locations where energy consumption may exceed CCS thresholds, which is crucial for preventing charging overload. We observe that EVs consume less energy when traveling from the source to the destination via loc_{17} and exhibit a 100% visitation rate at the CS. However, the CS becomes overcrowded when all EVs use it simultaneously. In such cases, we aim to identify other CS locations where EVs might consume more energy, but the visitation rate is lower than at loc_{17} (CCS). This approach helps us tackle the issue of charging overload. Building on our previous findings, we present crucial information in Table-II, guiding us in formulating strategies for selecting additional CS.

B. Comparison with the related works

The primary objective of this study is to position CS effectively within a given road network, aiming to minimize energy consumption for EVs traveling from arbitrary source locations to a fixed destination. Moreover, to assess our proposed approach's effectiveness in energy consumption, we comprehensively compare our results with those acquired from RL-EVAS [27].

We selected RL-EVAS for comparison for several reasons:

1) **Alignment with reinforcement learning (RL) approach:** RL-EVAS employs a reinforcement learning (RL) strategy, which directly aligns with the methodology used in our work. Both methods adapt dynamically to changing traffic and EV demand conditions, making RL-EVAS a relevant benchmark for assessing the performance of our RL-based strategy. Comparing with traditional methods, such as meta-heuristics like Genetic Algorithms (GA) or Particle Swarm Optimization (PSO), would not provide a meaningful evaluation, as those approaches do not adapt dynamically to the environment as RL does.
2) **Focus on energy efficiency:** The focus of both our work and RL-EVAS is on energy efficiency, which is the central performance metric in this study. Energy consumption directly impacts the feasibility and user satisfaction in EV charging infrastructure, making it a key criterion for evaluating the effectiveness of charging station (CS) placement strategies. Other studies that focus on metrics such as queuing delays, travel times, or utilization rates, while important in certain contexts, are not directly relevant to our goal of minimizing energy consumption. This makes RL-EVAS an ideal choice for comparison, as both approaches share the same primary objective.
3) **Exclusion of other methods:** We deliberately exclude other approaches that may use supervised learning, hybrid methods, or static placement strategies. These methods often depend on predefined conditions and do not explore the dynamic interaction between the charging infrastructure and the real-time environment, which is a core aspect of our proposed approach. By focusing the comparison on RL-EVAS, we ensure that the evaluation is based on similar methodologies and objectives, providing a more accurate and fair comparison of energy efficiency performance.

Continuing with the approaches comparison, our method demonstrates markedly superior outcomes compared to the

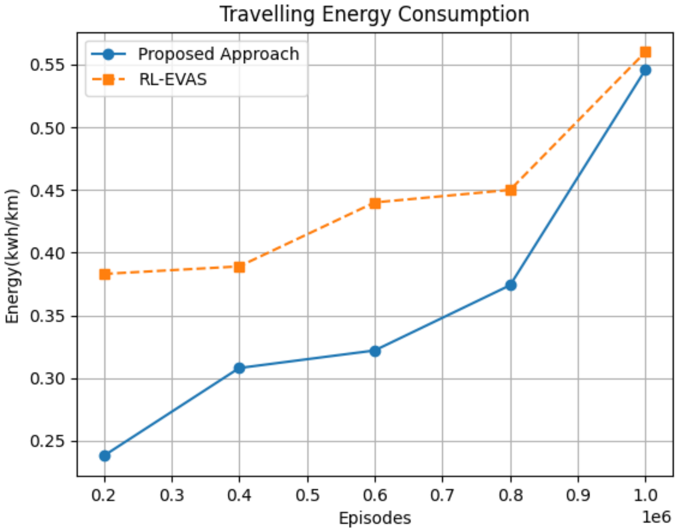

Fig. 3: Comparison between proposed approach and RL-EVAS [27]

referenced work [27]. Fig-3 visually presents the findings of this comparative analysis. The following equation presents a procedure to quantify the enhancement ($\mathbb{A}$) in minimizing energy consumption concerning the related work [27].

$$\mathbb{A}(\%) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{(\mathrm{OV}_i - \mathrm{NV}_i)}{|\mathrm{OV}_i|} \times 100\right) \tag{8}$$

In this context, 'OV' denotes the outcomes derived from the related work [27], and 'NV' represents the outcomes from our proposed approach. The variable 'n' signifies the number of pairs comprising 'OV' and 'NV.' Regarding energy consumption, our proposed approach exhibits a significant improvement of 20.97%, surpassing the results presented in the related work [27].

VI. CONCLUSION AND FUTURE WORK

This study presents an RL-based strategy to optimize CS placement to minimize energy consumption for EVs traveling from diverse source locations to a predetermined destination. Our approach outperforms RCS-based strategies through a comprehensive analysis of CCS-based strategies in CS placement. We identify loc_{17} as the most efficient location for placing CCS. Additionally, this research tackles identifying alternative CS locations to mitigate bottlenecks faced by EVs during their journeys. To address bottlenecks, we employ a strategic criterion of 50% to determine alternative locations for placing RCS. A comparative analysis with existing literature doesn't seem to show how effective our proposed method is. Considering energy consumption, our proposed approach demonstrates a notable enhancement of 20.97%, outperforming the outcomes reported in the related work [27]. Introducing a limitation of the proposed approach, we compel EVs to navigate reward paths while being constrained to select penalty paths. Consequently, path segments experience elevated congestion and energy consumption. We quantify our experiments by incorporating multiple penalty-based routes to mitigate this issue. A robust computer effectively addresses this challenge. Future improvements to the path selection strategy overcome such limitations.

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REFERENCES

[1] F. Alanazi, "Electric vehicles: Benefits, challenges, and potential solutions for widespread adaptation," *Applied Sciences*, vol. 13, p. 6016, 2023.

[2] Z. Zhao, C. Lee, J. Ren, and Y. Tsang, "Optimal ev fast charging station deployment based on a reinforcement learning framework," *IEEE Transactions On Intelligent Transportation Systems*, 2023.

[3] F. Ahmad, L. Al-Fagih, S. Qadir, and M. Khalid, "Ev charging station placement using nature-inspired optimisation algorithms," in *2023 International Conference On Power, Instrumentation, Energy And Control (PIECON)*, 2023, pp. 1–6.

[4] M. Aljaidi, N. Aslam, G. Samara, S. Almatarneh, A. Khaled, and A. Alqammaz, "Ev charging station placement and sizing techniques: Survey, challenges and directions for future work," in *2022 International Arab Conference On Information Technology (ACIT)*, 2022, pp. 1–6.

[5] D. Srinivas and M. Reddy, "Optimal placement of electric vehicle charging station by considering dynamic loads in radial distribution system," in *2022 International Conference On Automation, Computing And Renewable Systems (ICACRS)*, 2022, pp. 212–217.

[6] S. Deb, "Machine learning for solving charging infrastructure planning: a comprehensive review," in *2021 5th International Conference On Smart Grid And Smart Cities (ICSGSC)*, 2021, pp. 16–22.

[7] Q. Cui, Y. Weng, and C. Tan, "Electric vehicle charging station placement method for urban areas," *IEEE Transactions On Smart Grid*, vol. 10, pp. 6552–6565, 2019.

[8] S. Denazis, T. Politi, E. Faliagka, C. Antonopoulos, E. Christopoulou, C. Tranoris, D. Prevedourou, N. Kostis, I. Ioannou, C. Christophorou, I. Ioannou, V. Vassiliou, V. Poulkov, S. Sotirov, and A. D. Mihovska, "Metacities excellence hub: Exploiting digital twins and metaverse technologies in south-eastern europe," in *2023 IEEE International Smart Cities Conference (ISC2)*, 2023, pp. 1–5.

[9] K. Lee, M. A. Ahmed, D. Kang, and Y. Kim, "Deep reinforcement learning based optimal route and charging station selection," *Energies*, vol. 13, p. 6255, 2020.

[10] C. Zhang, Y. Liu, F. Wu, B. Tang, and W. Fan, "Effective charging planning based on deep reinforcement learning for electric vehicles," *IEEE Transactions On Intelligent Transportation Systems*, vol. 22, pp. 542–554, 2020.

[11] L. Wahl, N. Tempelmeier, A. Sao, and E. Demidova, "Reinforcement learning-based placement of charging stations in urban road networks," in *Proceedings Of The 28th ACM SIGKDD Conference On Knowledge Discovery And Data Mining*, 2022, pp. 3992–4000.

[12] H. Zhang, C. Sheppard, T. Lipman, and S. Moura, "Joint fleet sizing and charging system planning for autonomous electric vehicles," *IEEE Transactions On Intelligent Transportation Systems*, vol. 21, pp. 4725–4738, 2019.

[13] A. Florio, N. Absi, and D. Feillet, "Routing electric vehicles on congested street networks," *Transportation Science*, vol. 55, pp. 238–256, 2021.

[14] Y. Ko, “An efficient integration of the genetic algorithm and the reinforcement learning for optimal deployment of the wireless charging electric tram system,” *Computers & Industrial Engineering*, vol. 128, pp. 851–860, 2019.

[15] M. Straka, P. De Falco, G. Ferruzzi, D. Proto, G. Van Der Poel, S. Khormali, and L. Buzna, “Predicting popularity of electric vehicle charging infrastructure in urban context,” *IEEE Access*, vol. 8, pp. 11 315–11 327, 2020.

[16] D. Pevec, J. Babic, M. Kayser, A. Carvalho, Y. Ghiassi-Farrokhfal, and V. Podobnik, “A data-driven statistical approach for extending electric vehicle charging infrastructure,” *International Journal Of Energy Research*, vol. 42, pp. 3102–3120, 2018.

[17] S. Padmanabhan, A. Petratos, A. Ting, K. Zhou, D. Hageman, J. Pisel, and M. Pyrcz, “Optimal placement of public electric vehicle charging stations using deep reinforcement learning,” *ArXiv Preprint ArXiv:2108.07772*, 2021.

[18] K. Li, C. Shao, Z. Hu, and M. Shahidehpour, “An milp method for optimal planning of electric vehicle charging stations in coordinated urban power and transportation networks,” *IEEE Transactions On Power Systems*, 2022.

[19] A. A. Hagberg, D. A. Schult, P. J. Swart, G. Varoquaux, T. Vaught, and J. Millman, “Exploring network structure dynamics and function using networkx,” in *Proceedings of the 7th Python in Science Conference (SciPy2008)*, G. Varoquaux, T. Vaught, and J. Millman, Eds., Pasadena, CA USA, 2008, pp. 11–15.

[20] J. Hunter, “Matplotlib: A 2d graphics environment,” *Computing In Science & Engineering*, vol. 9, pp. 90–95, 2007.

[21] CYENS Centre of Excellence, “inicosia digital twin,” 2024, accessed: 2024-09-09. [Online]. Available: https://bit.ly/3LeHT9K

[22] R. Abousleiman and O. Rawashdeh, “Energy consumption model of an electric vehicle,” in *2015 IEEE Transportation Electrification Conference And Expo (ITEC)*, 2015, pp. 1–5.

[23] M. Dorokhova, C. Ballif, and N. Wyrsch, “Routing of electric vehicles with intermediary charging stations: A reinforcement learning approach,” *Frontiers In Big Data*, vol. 4, p. 586481, 2021.

[24] J. Zhao, F. Li, S. Mukherjee, and C. Sticht, “Deep reinforcement learning-based model-free on-line dynamic multi-microgrid formation to enhance resilience,” *IEEE Transactions On Smart Grid*, vol. 13, pp. 2557–2567, 2022.

[25] L. D’Alfonso, F. Giannini, G. Franzè, G. Fedele, F. Pupo, and G. Fortino, “Autonomous vehicle platoons in urban road networks: A joint distributed reinforcement learning and model predictive control approach,” *IEEE/CAA Journal Of Automatica Sinica*, vol. 11, pp. 1–16, 2024.

[26] M. Shin, D. Choi, and J. Kim, “Cooperative management for pv/ess-enabled electric vehicle charging stations: A multiagent deep reinforcement learning approach,” *IEEE Transactions On Industrial Informatics*, vol. 16, pp. 3493–3503, 2019.

[27] M. Aljaidi, N. Aslam, X. Chen, O. Kaiwartya, Y. Al-Gumaei, and M. Khalid, “A reinforcement learning-based assignment scheme for evs to charging stations,” in *2022 IEEE 95th Vehicular Technology Conference (VTC2022-Spring)*, 2022, pp. 1–7.