Mixed-Autonomy Traffic and Wireless Charging Problem for Autonomous Electric Vehicles Using Reinforcement Learning

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Abstract. As the adoption of electric vehicles (EVs) continues to increase, integrating vehicle-to-grid (V2G) technology while maintaining mobility and optimizing traffic flow becomes crucial. In this paper, we formulate a mixed-autonomy traffic and wireless charging problem where both autonomous and human-driven EVs coexist on the road. We aim to mitigate traffic congestion and improve V2G functionality, and therefore we propose a framework that adopts reinforcement learning, specifically the Soft Actor-Critic algorithm, to jointly enhance traffic throughput, balance the state-of-charge (SOC) among EVs, and maximize wireless charging energy in the mixed-autonomy ring-shaped road with wireless charging facilities. Experimental results demonstrate the effectiveness of our approach in stabilizing traffic, achieving SOC balance, and increasing the energy charged to EVs. This study showcases the potential for solving mixed-autonomy traffic and wireless charging problems in future wireless charging transportation systems.

Keywords: Mixed-autonomy traffic and wireless charging problem · Autonomous electric vehicles · Reinforcement learning · Reward.

1 Introduction

The maturity of electric vehicle (EV) technology is one of the driving forces behind its commercialization. According to the International Energy Agency's Global EV Outlook 2024 [13], EV sales are projected to reach approximately 17 million in 2024, representing more than one in five cars sold globally. Given this vast amount of EV on the roads, the question of how to effectively and efficiently deliver energy to and from the grid using vehicle-to-grid (V2G) technologies [15] without sacrificing their mobility remains an active area of research [3], [4]. Specifically, one may consider optimizing the placement of the charging stations [17] and determining the optimal charging locations for each after-service EV [8]. However, EVs inevitably have to stop at the charging station to have the connector being plugged in, which limits the mobility of vehicles.

Alternatively, wireless charging technology for electric vehicles can support automated charging through three modes: 1) static charging; 2) quasi-dynamic charging; and 3) dynamic charging [1]. These modes offer several benefits, respectively, including the elimination of shock hazards associated with wires, the extension of vehicle range during short stops (e.g., at traffic lights), and the potential to increase driving range and reduce the battery size of the EV while en route. To facilitate this progress, the first wireless electric road in the US was installed in Detroit [19] and the UK conducted the first wireless electric charging trial in Nottingham [25] both in 2023. We can expect that EVs will connect to the grid through wireless charging roads seamlessly while en route in the near future, supporting various V2G and other applications such as carrying renewable energy from remote generating sites to urban demand regions through EVs [16]. Hence, we must consider traffic and wireless charging problems jointly to further boost the system's efficiency.

A common traffic problem affecting transportation efficiency is congestion, which emerges on the road when the traffic flow is high. In particular, it has been proven that congestion (also known as a shock wave) still emerges on the road even without bottlenecks [24]. One possible way to eliminate the shock wave is by controlling the speed of a vehicle in the platoon, thereby stabilizing the traffic and thus improving traffic throughput and energy consumption per unit of distance traveled [23]. This is an example of mixed-autonomy traffic which studies how autonomous vehicles should behave when human-driven vehicles coexist on the roads. Therefore, researchers have transformed it into a control problem and applied control methods such as reinforcement learning (RL) to handle it [27]. However, such an RL method highly relies on a predefined reference vehicle speed as the sole reward function, which may not automatically apply to other scenarios. Moverover, the charging problem in this microscopic speed-controlling scenario remains unexplored. Hence, we need to jointly investigate the mixed-autonomy traffic and wireless charging problem.

In this paper, we first formulate the mixed-autonomy traffic and wireless charging problem in which autonomous (AEVs) and human-driven EVs (HDEVs) coexist on a ring-shaped road, with a portion of the road segment embedded with wireless charging facilities. Our aim is to jointly enhance traffic throughput, balance the state-of-charge (SOC) among the EVs, and maximize the energy charged to EVs. Next, we propose using the Soft Actor-Critic algorithm with a composite reward function that can jointly enhance traffic throughput and balance the SOC among the EVs, thereby relaxing the requirement of prior knowledge of the reference vehicle speed and enhancing the V2G flexibility. We conduct experiments to evaluate the proposed method along with other reward functions, revealing the two-fold effectiveness of addressing traffic and wireless charging problems with a single method. This study serves as a preliminary exploration into the potential benefits of solving the mixed-autonomy traffic and wireless charging problem in future wireless charging transportation systems.

The main contributions of this paper are summarized as follows:

1. We formulate the mixed-autonomy traffic and wireless charging problem in which AEVs and HDEVs coexist within the system to optimize both traffic and V2G utilities.
2. We propose a solution framework that includes the design of problem settings, state space, action space, and reward function.
3. We conduct experiments to evaluate the effectiveness of the proposed method in solving the mixed-autonomy traffic and wireless charging problem.

This paper is organized as follows. The mixed-autonomy traffic and wireless charging problem is defined in Section 2, followed by the proposed method in Section 3. We present the experimental results in Section 4. The conclusion and discussion of future work are provided in Section 5.

2 Mixed-Autonomy Traffic and Wireless Charging Problem

In this section, we present the dynamics of the mixed-autonomy system and then define the corresponding traffic and wireless charging problem.

2.1 System Dynamics

Consider a vehicle fleet set $\mathcal{K}$ with $|\mathcal{K}|$ EVs, where each EV follows its preceding EV to form a vehicle platoon. Each EV $k \in \mathcal{K}$ is represented by a 6-tuple $\langle v_k, \eta_k, a_k, b_k, s_k, e_k \rangle$, denoting the vehicle speed, speed perturbation, acceleration, deceleration, bumper-to-bumper space headway, and SOC, respectively. In the vehicle set $\mathcal{K}$, N EV(s) are autonomous and the rest of the $|\mathcal{K}| - N$ EV(s) are driven by humans. The difference is that the accelerations of the AEVs are controllable by an agent trained by our proposed method while those of the HDEVs are controlled by a microscopic car-following model called the Intelligent Driver Model [26], which models the behavior of an intelligent driver such as decelerating to prevent a crash and accelerate to shorten the headway gap. This model describes the appropriate acceleration with the following equations:

$$a_k = \frac{dv_k}{dt} = a \left[1 - \left(\frac{v_k}{v_0} \right)^{\delta} - \left(\frac{s^*(v_k, \Delta v_k)^2}{s_k} \right) \right] \tag{1}$$

$$s^*(v_k, \Delta v_k) = s_0 + v_k \tau_0 + \frac{v_k \Delta v_k}{2 a_k b_k} \tag{2}$$

where v_0, s_0, τ_0, δ and Δv_k are given parameters representing the free-flow speed, desired space headway, desired time headway, constant exponent, and speed difference, respectively.

To study the traffic problem, we reconstruct the traffic road similar to [24], which is a single-lane circular road like a ring. We follow the road length and number of vehicles used in [24]. In addition, we add a wireless charging facility with a length l_w to enable wireless charge. l_w must be larger than $Ml_k + (M-1)s_0$ so that M EVs can be charged on the wireless charging segment simultaneously. The mixed-autonomy traffic and wireless charging system is shown in Figure 1.

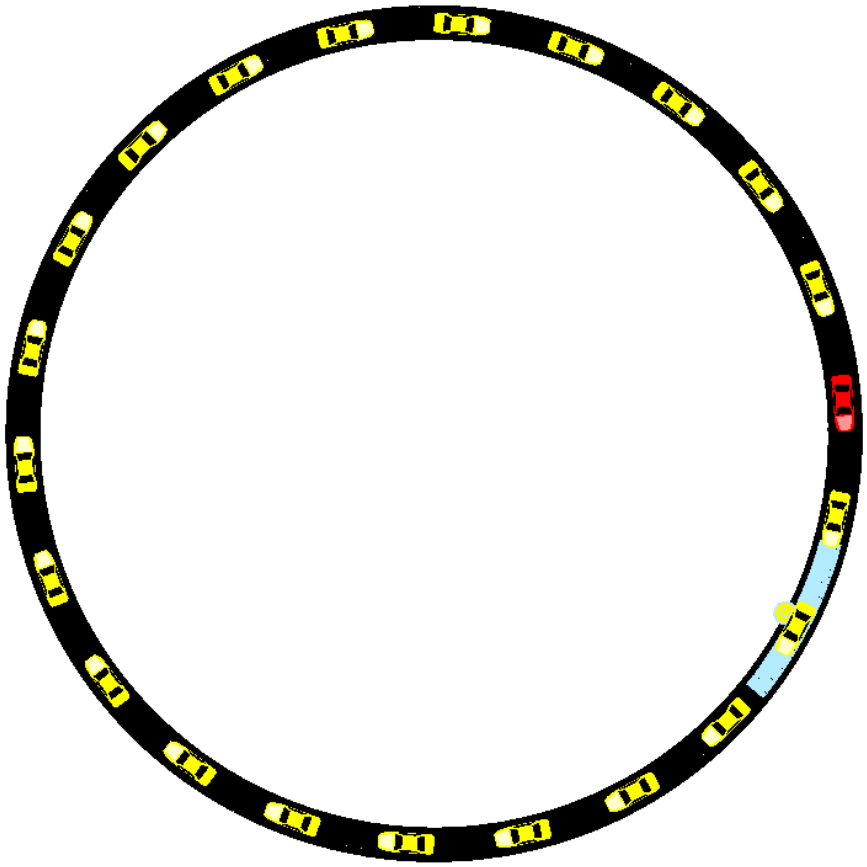

Fig. 1. An example of the mixed-autonomy traffic and wireless charging system. AEV and HDEV are indicated as red and yellow color, respectively. The blue segment is the wireless charging facility.

2.2 Problem Setting

We study the mixed-autonomy traffic and wireless charging problem, i.e., how to control a set of AEVs on the roads together with other HDEVs such that objectives conforming to both traffic and V2G systems are optimized. We define the objectives as to maximize the traffic throughput, minimize the SOC difference among the EVs, and maximize the energy charged, thereby demonstrating the capability to eliminate traffic shock waves, increase the charging time, and balance the SOC for potential V2G applications, respectively.

As a preliminary study, we simplify the problem by considering only vehicle charging instead of both charging and discharging. Consequently, the action space of the agent is reduced to one dimension (vehicle acceleration). The charg-

ing factor is reflected by the time the vehicle staying over the wireless charging facilities, which is in turn revealed by the vehicular speed. In other words, the faster the vehicle, the less the charging time it has on the wireless charging segment for per move. Since action space is one dimensional, we can further simplify the problem to a centralized control and single-agent problem, and a distributed or multi-agent system is outside of the scope of this paper.

3 Methodology

In this section, we discuss the motivation for using RL to solve the mixed-autonomy traffic and wireless charging problem, and the Markov decision process (MDP) used to model it as a control problem.

3.1 Motivation

RL is capable of solving many complex problems, such as mastering the game of Go [22]. Despite its shortcomings [10], there are many successful applications to various engineering problems, such as the field of intelligent transportation system [12] and V2G [20]. For example, RL can be used to control traffic signals based solely on images of the intersection [9], recommend preferred transport modes in a mobility-as-a-service [5], [6], and attack multi-modal transportation systems [7].

3.2 Markov Decision Process

We transform the mixed-autonomy traffic and wireless charging problem into a discrete-time MDP framework represented by $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R})$, where $\mathcal{S} \subset \mathbb{R}^m$ is the m-dimensional state space, $\mathcal{A} \subset \mathbb{R}^n$ is the n-dimensional action space, $\mathcal{P} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}+$ is the transition probability function, and $\mathcal{R} : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ is the reward function. The relationship between the attributes is that the agent determines an appropriate action $a_t \subset \mathcal{A}$ at time step t based on the given state $s_t \subset \mathcal{S}$. The transition to the next state s_{t+1} is governed by the transition probability $\mathcal{P}(s_{t+1}|s_t, a_t)$. The overall goal of the agent is to maximize the cumulative reward $\sum_{t=0}^{T} \gamma^t \mathcal{R}(s_t, a_t)$ over the time period T where $\gamma = [0, 1]$ is a given discount factor close to 1, accounting for the fact that immediate reward should be more favorable than delayed reward.

3.3 State Space

We assume the environment is fully observable to the agent, and thus the state can capture complete information about the EVs. However, we limit the state representation to vehicle speed v_k, position on the road $x_k = [0, l_r)$, SOC of EVs e_k, and charged energy c^i of the wireless charging facility i for implementation purposes. Since the road is ring-shaped, we assign a point as the starting point with a value of 0 or l_r. Those elements are concatenated together to form the overall state representation $s = [v_1, x_1, e_1, \ldots, v_{|\mathcal{K}|}, x_{|\mathcal{K}|}, e_{|\mathcal{K}|}, c^i]$.

3.4 Action Space

As discussed in Section 2, we are interested in controlling the set of AEVs. In the single-lane road setting, vehicle acceleration is the only degree of freedom for control. Hence, the action space is defined as the space between maximum deceleration and maximum acceleration, i.e., $a_k \in [-b_{max}, a_{max}]$. Although the agent can determine the acceleration value, the speed is bounded by an extra constraint layer for safety reasons. For example, the autonomous vehicle cannot accelerate if the preceding EV is too close. The speed can be changed only when within the safety bound $v_k \in [\underline{v}_{safe}, \overline{v}_{safe}]$, which is restricted by IDM. In other words, the actual vehicle speed $v_k := \max(\min(v_k + a_k, \overline{v}_{safe}), \underline{v}_{safe})$ is partially influenced by the environment, which is not controlled by the agent.

3.5 Reward Function

The objective of the problem is to maximize traffic and V2G utilities. Intuitively, we should define the reward function as a sum of two terms related to traffic and V2G, respectively. For the traffic reward term, we follow the definition in [27], which is:

$$R_{traffic} = \max\{0, ||v_{des} \cdot \mathbf{1}^{|\mathcal{K}|}||_2 - ||v - v_{des} \cdot \mathbf{1}^{|\mathcal{K}|}||_2\}, \tag{3}$$

where v_{des} is the desired speed. For V2G, one of the features is to balance the power demand through EV mobility [28], which provides flexible demand response management. However, the reference study examines a macroscopic scenario where EVs are routed on a V2G mobile energy network with multiple battery pools in different districts, which is not applicable to our microscopic case that examines vehicle acceleration and speed. Nevertheless, we can consider each EV on the road as an individual battery pool microscopically. Hence, the V2G utility can be transformed into balancing the SOC among the EVs and maximizing the energy charged to EVs, which is defined as:

$$R_{balance} = -\sigma(e) \tag{4}$$

and

$$R_{charge} = \sum_{t=0}^{T} \sum_{i} c_t^i \tag{5}$$

where $\sigma(e)$ is the standard deviation of the SOC of all EVs and c_t^i is the charged energy from wireless charging facility i at time t.

As a whole, the overall reward function is the weighted sum of the three terms, which are:

$$\mathcal{R} = \lambda_{traffic} R_{traffic} + \lambda_{balance} R_{balance} + \lambda_{charge} R_{charge} \tag{6}$$

where the λs are the corresponding weighting factors to scale each term for fair summation.

4 Experiments

4.1 Experiment Settings

We conduct experiments to evaluate the effectiveness and efficiency of solving the mixed-autonomy traffic and wireless charging problem using the proposed method. To simulate the traffic and wireless charging scenario, we utilize the Simulation of Urban MObility (SUMO) [18] to model the system and set the parameters, interfaced by GYM [2], an open-source Python library that supports communication between the learning algorithm and the environments. SUMO is an open-source microscopic traffic simulator designed to replicate real-world traffic scenarios and simulate large-scale road networks with accurate dynamic models of individual vehicles on the road.

We place $|\mathcal{K}| = 22$ vehicles on a $l_r = 230$ m single-lane ring road, similar to the experiments in [24]. As a preliminary study, only one vehicle is autonomous, i.e. $N = 1$. The length of each vehicle l_k and desired space headway s_0 are 5 m and 2.5 m, respectively. The maximum acceleration and deceleration are both 1 ms^{-2}. We add a 0.1 deviation to the IDM to represent the imperfection of human drivers. For the electric specification, we follow the parameters of the Kia Soul EV 2020 [14] such as a 64 kWh maximum battery capacity and a 150 kW electric motor. The initial SOC is half of the maximum battery capacity. The length of the wireless charging segment is $l_w = 15$ m, which can support the wireless charging of $M = 2$ EVs simultaneously if the space headway between them is small.

For the RL algorithm, we use the Soft Actor-Critic (SAC) [11] implemented in Stable-Baselines3 [21]. The hyper-parameters are set by the default values in the Stable-Baselines3. Each training episode contains 2000 time steps, representing 200 s with the 0.1 step length setting in SUMO (i.e., one step represents 0.1 s in time). 100 training episodes were conducted for each experiment.

All models and parameters use the default settings in the above tools unless specified otherwise.

4.2 Experimental Results

We conduct the experiments to investigate three aspects: traffic flow, SOC balance, and wireless charging. Let A, B, and C be the methods trained with $R_{traffic}$, $R_{balance}$, and R_{charge}, respectively. Six ablated methods (A, B, C, $A\&B$, $A\&C$, $B\&C$) are compared with the proposed one ($A\&B\&C$).

Traffic Flow Figure 2 shows the traffic flow of the vehicle fleet. In general, the total traffic flow of methods with A (A, $A\&B$, $A\&C$, $A\&B\&C$) has a higher traffic flow than those with C (C, $A\&C$, $B\&C$, $A\&B\&C$). This is because the reward term $R_{traffic}$ facilitates the vehicle speed to a desired and stable value, eliminating congestion and enhancing the traffic flow. However, R_{charge} only encourages the charging of EVs, not the speed. Based on the low traffic flow of method C, we can interpret that EVs are stopped on the road, hindering the

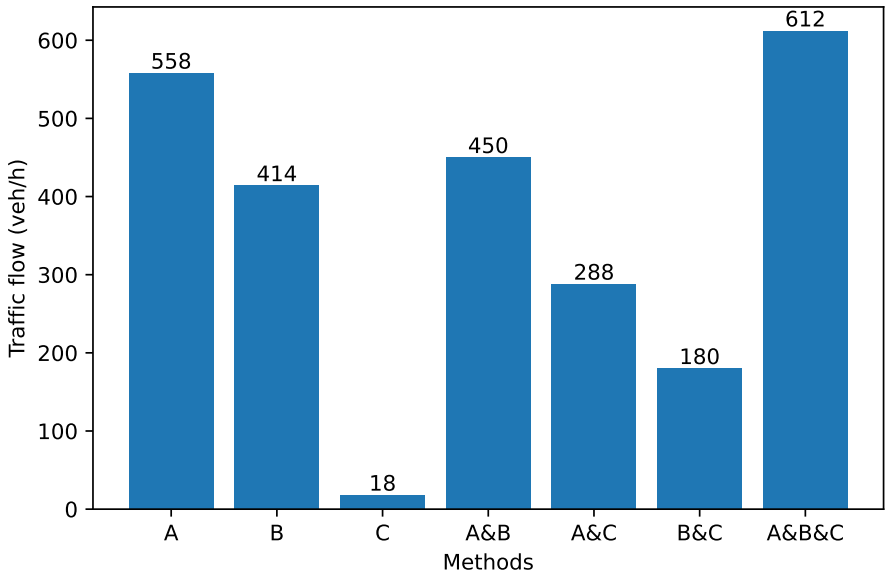

Fig. 2. Traffic flow against different methods upon testing.

flow of vehicles. Among all the compared methods, $A\&B\&C$ trains the AEV agent that produces the highest traffic flow by adjusting its speed. This means that other terms related to V2G can facilitate the policy search related to traffic specifications, without solely relying on predefined speed references.

SOC Balance Figure 3 shows the standard deviation of EVs' SOC. Note that the SOC is affected by the energy consumption due to movement and wireless charging energy. Controlling the acceleration of a vehicle to balance the changing SOC of all EVs is not an trivial task. Since we aim to balance the SOC for V2G, a lower standard deviation means a better method. The methods converge to three groups: Method C is the lowest group; Methods $A\&B\&C$, A, $A\&B$, and B are the second group; Methods $B\&C$ and $A\&C$ are the group with the highest standard deviation. It is surprising that method C is the lowest since method C attempted to maximize the charging energy but not the SOC standard deviation. The reason is that the agent trained by C failed to move when combining the traffic flow results. Hence, if we ignore it, due to the extremely low traffic flow, the proposed $A\&B\&C$ method will be the best one. This shows that our proposed method can effectively balance the SOC by controlling the acceleration of an AEV.

Charged Energy Figure 4 shows the cumulative charged energy to all EVs over the time steps. We can observe three groups from the figure. The best method

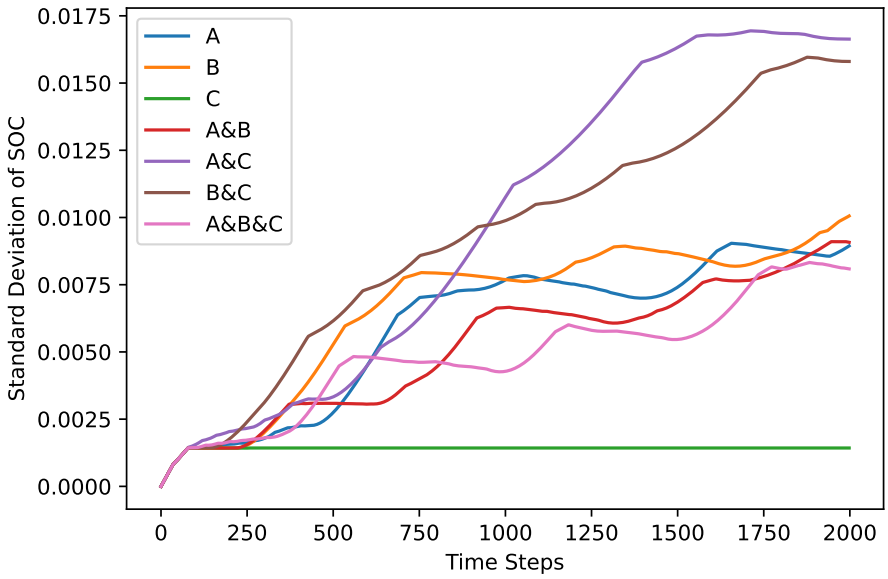

Fig. 3. Standard Deviation of SOC along vehicle traveling time steps upon testing.

for energy charging is $A\&C$ and $B\&C$. The second group is the methods A, B, $A\&B\&C$, and $A\&B$. The method with the lowest charged energy is C since the EVs do not stop on the wireless charging segment. Although it is obvious that stopping at the wireless charging segment can charge one or two EVs constantly, the agent still fails to discover this policy with only R_{charge}, implying R_{charge} should be combined with other terms such as $R_{traffic}$ and $R_{balance}$ that we proposed. Once it is combined with other terms, such as methods $A\&C$ and $B\&C$, the charged energy increases dramatically.

Combining the results from Figures 2 to 4, we can conclude that our proposed method $A\&B\&C$ can successfully stabilize traffic, balance the SOC, and increase the energy charged to EVs.

5 Conclusion

This paper presents a new formulation of the mixed-autonomy traffic and wireless charging problem where AEVs and HDEVs coexist. By integrating wireless charging technology with traffic control mechanisms, the proposed method demonstrates its potential to enhance traffic throughput, balance the SOC among EVs, and increase the energy transfer from charging infrastructure, without relying heavily on predefined speed references. Our experiments, conducted on a simulated environment, show that the SAC method with a composite reward function effectively stabilizes traffic flow, maintains a balanced SOC across EVs,

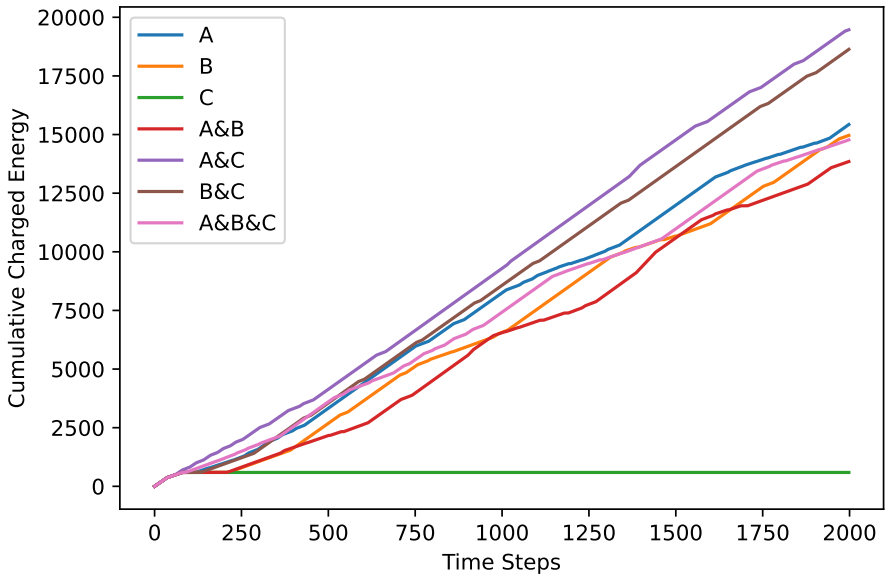

Fig. 4. Cumulative charged energy to EVs along the time steps.

and optimizes energy charging during transit. The proposed method outperforms other approaches that focus on individual objectives, demonstrating the importance of this approach in solving mixed-autonomy traffic and wireless charging challenges.

This study serves as a preliminary exploration into the integration of traffic and wireless charging optimization, paving the way for more advanced and practical implementations in future wireless charging transportation systems. Future work may focus on extending the problem to multi-agent systems, incorporating more complex road networks, and exploring the impacts of different traffic conditions and wireless charging technologies on the system's overall performance.

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