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DOI
10.1109/OJITS.2025.3613259

Publication date
2025

Document Version
Final published version

Published in
IEEE Open Journal of Intelligent Transportation Systems

Citation (APA)
Khan, M. A., Burghout, W., Cats, O., Jenelius, E., & Cebecauer, M. (2025). A Simulation Framework for Evaluating Mobile Autonomous Charging pod Operations. *IEEE Open Journal of Intelligent Transportation Systems*, *6*, 1282-1297. https://doi.org/10.1109/OJITS.2025.3613259

IEEE Open Journal of
Intelligent Transportation
Systems

Received 18 October 2024; revised 4 July 2025 and 26 August 2025; accepted 20 September 2025. Date of publication 22 September 2025;
date of current version 30 September 2025.

Digital Object Identifier 10.1109/OJITS.2025.3613259

A Simulation Framework for Evaluating Mobile Autonomous Charging Pod Operations

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This was supported by the Swedish Transport Administration through the Project Smart 3 under Grant nr 2022/8287.

ABSTRACT Recent advances in automation have accelerated the development of autonomous electric vehicles (AEVs), which offer the potential for continuous operation, constrained primarily by the need for recharging. We propose a dynamic charging strategy based on Mobile Autonomous Charging Pods (MAPs), which are battery-equipped electric vehicles capable of transferring energy to AEVs while in motion. We introduce a dedicated simulation framework within the microscopic traffic simulator SUMO, incorporating MAP-specific modules for assignment, navigation, and real-time energy transfer under realistic traffic constraints. We model the behavior of both MAPs and AEVs in a stylized looped network and evaluate system-level performance under various demand and fleet configurations. Key performance indicators include energy consumption, charging efficiency, battery utilization, and reductions in AEV battery capacity requirements. Simulation results demonstrate that MAPs can effectively support continuous AEV operation, achieving up to 14% battery downsizing with minimal infrastructure investment, while also reducing travel time by 7%, relative to fixed charging solutions. This study lays the foundation for simulation-based evaluation of MAP-based dynamic charging as a scalable, flexible, and efficient alternative to fixed charging solutions.

INDEX TERMS Autonomous electric vehicles, dynamic charging, mobile autonomous charging pods, vehicle-to-vehicle charging, SUMO.

I. INTRODUCTION

WITH the exponential rise of Electric Vehicles (EVs) and the corresponding efforts of governments to encourage their adoption, electrification of transport has been the subject of extensive research in the past decade. Conventional charging solutions such as stationary or static charging face many challenges with high infrastructure costs, low flexibility and low utilization rates. In tandem with the rise of EVs, new modes of transportation such as autonomous electric vehicles (AEVs) are emerging, with companies such as Waymo already deploying robotaxis for public use [1]. These AEVs pose additional challenges to the EV charging infrastructure as they have different needs and requirements.

The introduction of AEVs is expected to reshape the transportation sector, enabling cheaper and safer modes of transport. As these vehicles also have the capability to communicate with other vehicles and infrastructure, they have the potential to generate improvements in safety, cost and time savings for users and other entities [2]. Moreover, these improvements may generate potential benefits in other sectors like technology, freight and logistics, insurance as well as infrastructure and land use [3]. The overall potential impact of these AEVs is expected to amount to around 1.3 trillion dollars annually in the U.S. alone [4]. In particular, AEVs can improve the efficiency and lower costs for public and freight transport due to the absence of human drivers, which account for about 40% to 70% of total operation costs for these transport modes [5], [6]. The increased penetration of AEVs in traffic may also increase road capacity as these vehicles can travel more closely to each other, and use less energy due to efficient and coordinated use of brakes and acceleration (eco-driving) [7].

The review of this article was arranged by Associate Editor Weichao Zhuang.

Compared to conventional EVs, AEVs have the potential to reduce travel times as these vehicles can theoretically drive continuously, the only constraint being recharging [8]. The reduction in travel times offered by autonomous vehicles can have significant impacts on various industries, for instance emergency services, where reductions in response times can lead to reduced mortality rates [9]. With a market penetration of 50% of connected vehicles and 50% of autonomous vehicles, the response times of these emergency services can be reduced by up-to 68% as estimated in [10].

For the freight industry, AEVs can enhance efficiency and reduce operation times, potentially generating economic gains of up-to 500 billion dollars/year [4]. For last-mile logistics, where delivery times are important, AEVs are expected to handle the majority of demand due to shorter travel times, lower operational costs and growing customer demand in urban city areas [11]. However, with conventional charging technologies, the charging time including routing to charging stations, queuing at stations and active charging time, can significantly increase the total travel time of these AEVs. A study in Germany found that additional travel to charging stations can increase total travel time by 30%, compared to non-stop travel [12].

To reduce travel time and exploit the advantages of AEVs, dynamic charging solutions, which charge vehicles while in motion, are being researched by both industry and academia. These charging solutions can be broadly categorized into (i) charging lanes which relate to charging via an electrified road or overhead line, (ii) vehicle-to-vehicle (V2V) charging which relates to charging from other vehicles and, (iii) dynamic battery swapping methods, i.e., battery swapping while in motion by either drones or other mobile robots [13], [14]. These charging technologies have the potential to significantly reduce the overall travel time as there is no need to stop, queue or change route to charge, thus improving the economic benefits of autonomous vehicles.

There are several challenges associated with the aforementioned dynamic charging technologies. For charging lanes, the major obstacles are large investment costs and the requirement of lower speeds for an efficient charge, thus restricting their potential use to bus stops, intersections, or near traffic lights [15], [16]. For dynamic battery swapping, the main challenges are the technological complexity, the need for common standards, and logistics for handling the batteries [14], [17]. The principal challenges for V2V charging are the requirements for vehicles to travel closely in a platoon and the enhanced communication to manage the fleet and total charge. With recent advancements in connected and autonomous vehicles to travel closely in a platoon while having enhanced communication, V2V charging may be one of the most promising options for implementing dynamic charging [18], [19], [20], [21], [22].

In this work, we explore the use of mobile autonomous charging pods (MAPs), which are autonomous battery vehicles that can travel and provide dynamic charging via V2V energy transfer. These MAPs exploit the enhanced communication advantages offered by autonomous vehicles to get the required information from the vehicle, including its speed, location and energy required. The charging pods then travel to the vehicles, connect and charge the EVs while moving, and then disconnect to return to their stations.

These MAPs provide several potential advantages: With portable batteries, they can increase energy storage at low prices during low demand, and then either charge AEVs, or sell the energy back to the grid at higher prices via vehicle-to-grid (V2G) [23] connections. MAPs can also spread energy demand over time and space, by charging vehicles at different times along the route, thereby reducing energy peaks. With the possibility of charging en-route, the vehicles will need smaller batteries, considerably reducing their weight and costs [24].

The principal contributions of this paper include:

- Development of a MAP-specific simulation framework within a microscopic traffic environment. Extending the capabilities of the SUMO platform, the framework introduces custom modules for the modeling of MAPs, encompassing task assignment, navigation behavior, and real-time charging interactions with energy-deficient AEVs.
- Implementation of decision logic for dynamic MAP—EV interactions. The framework integrates (i) an assignment algorithm based on spatial proximity and state-of-charge (SOC) thresholds, (ii) navigation routines enabling MAPs to safely approach, couple with, and detach from target AEVs while respecting traffic dynamics and safety constraints, and (iii) energy transfer protocols for platoon-based charging, including support for preemptive disengagement based on MAP energy limitations.
- Simulation-based validation in a stylized looped urban network. The feasibility and effectiveness of the MAP framework are evaluated in a synthetic traffic environment. Controlled experiments measure key performance indicators such as energy consumption, charging efficiency, the number of vehicles served, and overall battery utilization under varying traffic and demand scenarios.
- Proposal of a baseline and modified greedy heuristic algorithms for MAP operations. The study introduces a heuristic approach that governs MAP deployment, routing, and energy transfer decisions. These algorithms serve as a computationally efficient baseline and enable multi-metric performance evaluation in terms of system-wide energy efficiency, demand coverage, and energy consumption.
- Assessment of system-level implications and operational challenges. The study further identifies limitations and research opportunities related to fleet sizing, routing logistics, spatial safety, and integration into real-time operational frameworks.

The remainder of this article is organized as follows: the literature review is presented in Section II followed by methodology in Section III and experimental design in Section IV. Section V presents the results and analysis and Section VI discusses the limitations. Section VII concludes and outlines future work.

II. LITERATURE REVIEW

There have been considerable developments in V2V charging in recent years, spanning technological innovations, application models, and coordination frameworks. These can be organized into the following thematic areas:

A. TECHNOLOGICAL FOUNDATIONS FOR DYNAMIC V2V CHARGING

Recent progress in enabling technologies has made V2V energy transfer increasingly feasible. Advancements in power converters, wireless transfer, and blockchain are central to creating reliable, secure V2V systems. For example, [25] highlights that while V2V can mitigate range anxiety, it may accelerate battery degradation, underscoring the importance of integrating the battery's state of health (SoH) into charging protocols.

Wireless energy transfer has also been extensively studied in the context of dynamic charging for unmanned ground vehicles. Xu et al. (2023) [26] discuss developments in magnetic coupling design, compensation topologies, and system control strategies, projecting efficiencies of over 90% for short-range (less than 50 cm) carrier-type vehicles and moderate efficiencies (around 70%) for formation-type groupings (1-7 meters). These works suggest that the technical feasibility of in-motion energy transfer is steadily improving, though efficiency, alignment, and stability remain practical concerns.

B. PLATOONING-BASED AND WIRELESS V2V CHARGING APPROACHES

A major stream of research frames V2V charging within platooning or convoy-based operations. Nezamuddin et al. (2022) [27] propose a system where a charger vehicle travels alongside a user EV until sufficient charge is delivered, modeled via MATLAB/Simulink. Their results indicate potential travel time reductions of up to 20%. Similarly, Qu et al. (2022) [28], using 24-hour taxi GPS data in Shenzhen, show that even at 50% transfer efficiency, V2V can offset two-thirds of the need for static charging stations, and at 75% efficiency, EV battery sizes could be halved [29].

Mobile Energy Disseminators (MEDs), such as buses or trucks repurposed as mobile chargers, have been proposed as scalable solutions for both urban and highway contexts. Simulation studies show that MEDs can improve driving range and travel time by up to fourfold when deployed alongside fixed infrastructure [30], [31]. To improve deployment efficiency, Yan et al. (2022) [32] apply multi-objective optimization and reinforcement learning for real-time MED routing, while [33] extends the concept to platoon-based charging, where an MED supplies the lead EV, which then redistributes charge wirelessly to following vehicles.

Building on this line of research, [16], [17] propose a peer-to-peer highway charging solution in which vehicles can share charge among each other, complemented by the use of mobile charging stations as roaming energy providers. Using a 240 km highway simulated in SUMO over 5 hours, the study examines the effects of charge transfer rate, the number of mobile chargers in the network, and EV battery capacity reductions. Results show that such hybrid systems can reduce halts and lower the overall battery capacity needed for travel, highlighting the potential of integrating peer-to-peer exchange with mobile infrastructure.

These approaches demonstrate the promise of continuous, in-motion charging, but they are still largely restricted to structured highway or bus-route settings rather than heterogeneous urban networks.

C. OPTIMIZATION AND ASSIGNMENT MODELS FOR V2V CHARGING

Parallel to technological development, many studies frame V2V charging as a vehicle routing or assignment problem (VRP/AP). Qiu and Du (2021) [34] model Charging-as-a-Service (CaaS) by routing dedicated provider vehicles to synchronize with demand vehicles en route. This formulation accounts for features unique to V2V, such as trip synchronization and partial charging by multiple providers.

Dynamic assignment formulations extend this idea. For example, [35] designs integer programming and local search heuristics on time–space networks to pair energy suppliers with requesters. Such approaches mirror Dial-a-Ride problems with moving targets, where synchronization in time and space is as important as route optimization. Other studies also considered the deployment of V2V along with static chargers. Results show that when used in combination with fixed charging infrastructure, this charging method can improve energy usage and travel time, and the higher flexibility of vehicles in the V2V positively affects the performance of the system [36].

These centralized optimization models highlight the efficiency gains of coordinated V2V scheduling but rely heavily on global information and centralized dispatch, assumptions that may be unrealistic in decentralized urban settings.

D. DECENTRALIZED AND MARKET-BASED ENERGY SHARING MECHANISMS

Another stream of research focuses on peer-to-peer and decentralized charging frameworks, where ordinary EVs with surplus charge assist others opportunistically. These approaches often emphasize decentralized matching, pricing mechanisms, and participant incentives rather than preset fleets of dedicated chargers [37]. Similarly, Zhang et al. (2023) [38] propose a cooperative EV-to-EV charging protocol with adaptive matching algorithms to balance energy distribution in a way that is fair and efficient.

These protocols often leverage game theory or market-based control, for instance, auctions or bargaining to allocate charging opportunities among EVs.

These systems often leverage market-based mechanisms, such as auctions, bargaining, or incentive pricing, to allocate charging opportunities. Bulut et al. (2019) [39] emphasize spatio-temporal matching, pairing vehicles already in close proximity and traveling in similar directions to minimize disruption. Such decentralized frameworks reduce the reliance on central control but face challenges in communication, trust, and uncertain driver behavior.

Together, these studies illustrate that localized decision-making can produce system-wide benefits but also introduce complexity in coordination and incentive design.

E. IDENTIFIED RESEARCH GAPS

Most of the aforementioned studies validate their algorithms via numerical experiments or coarse simulations. These approaches capture routing and energy constraints but do not explicitly simulate vehicle kinematics or traffic rules. As a result, they often assume that when a charging rendezvous is needed, it can happen seamlessly. In reality, coordinating two moving vehicles to safely form a charging platoon involves complex maneuvers – merging into the same lane, maintaining a stable short gap, and possibly slowing surrounding traffic.

Despite growing interest in dynamic V2V charging, the above literature reveals several research gaps that motivate the present work:

- *Lack of realistic traffic modeling of MAPs:* Most existing V2V charging models assume ideal conditions vehicles meet on command and transfer energy instantly, without accounting for traffic conflicts or time lost coupling and decoupling. They neglect constraints such as maintaining safe following distance, coordinating lane changes, and obeying signals during a charge. This gap in realism means it is unclear how V2V charging would perform in practice.
- *Limited exploration of dynamic in-motion charging:* Many prior works require the charging vehicle and target EV to be stationary (e.g., meeting in a parking lot) or at least to complete charging before moving on. While some recent studies examine charging on the move, they often rely on simplified scenarios such as highway platooning with predefined routes. The general case of ad-hoc on-demand charging in city traffic has received little attention.
- *Underexplored use of specialized charging agents vs opportunistic EVs:* Most V2V energy-sharing concepts assume either regular EVs as opportunistic chargers or large mobile charging trucks. The concept of purpose-built, compact charging agents (such as MAPs), that can be efficiently dispatched, vertically stored [40] and dynamically routed for in-motion charging, is underexplored and requires investigation.

III. METHODOLOGY

This section describes the methodology used to assess the performance of MAPs in facilitating continuous AEV operation. We adopt a microscopic approach to model the behavior of MAPs and AEVs using the open-source traffic simulator SUMO. As illustrated in Fig. 1, the framework integrates SUMO, network inputs, and the MAP modeling contributions from this study, with corresponding performance assessment metrics, offering a structured approach to analyze MAP-EV interactions, routing behavior, and system-wide impacts on operational feasibility, energy efficiency, and battery capacity reductions.

To model the autonomous behavior of AEVs and MAPs, we use the cooperative adaptive cruise control (CACC) [41] car-following model available in SUMO. The selection of CACC is motivated by its capacity to emulate inter-vehicle cooperation, reduced reaction times, and tighter headways, characteristics that are critical for accurately capturing the high-precision platooning required during dynamic in-motion charging. The cooperative dynamics embedded in the CACC model facilitate stable vehicular formations and sustained spatial alignment between MAPs and AEVs, which are essential for enabling uninterrupted and efficient energy transfer while vehicles are in motion [42], [43].

For the charge sharing between MAPs and EVs, we assume a conductive transfer through robotic conductive arms as proposed in [16] or through charge sharing in modular pods proposed in [44]. We assume that AEVs cannot share charge amongst each other, and that each MAP can only charge one AEV at a time.

A. ALGORITHMS FOR AEVS AND MAPS

Each AEV operates according to a decision-making algorithm illustrated in Fig. 2, adapted from [31], [45]. The algorithm continuously monitors the SOC of the AEV. When the SOC falls below a predefined threshold, the system identifies and assigns the nearest stationary MAP with sufficient available energy. As MAPs are strategically positioned along the network, AEVs are not required to deviate from their planned routes, thereby maintaining route continuity and minimizing operational disruption.

If no suitable MAP is available, either due to insufficient energy reserves or because all MAPs are currently engaged, the AEV continues along its path, periodically reassessing the availability of charging support. Once a MAP is successfully assigned, the AEV temporarily reduces its speed to facilitate safe rendezvous and coupling. Upon establishing a stable platoon formation, dynamic energy transfer commences, and the AEV resumes its nominal cruising speed. The algorithm continues to monitor the SOC in real-time and triggers disengagement from the MAP once the AEV attains a sufficient charge level.

This study employs a baseline charging algorithm for MAP deployment and assignment, grounded in greedy heuristics [35]. These heuristics offer computational

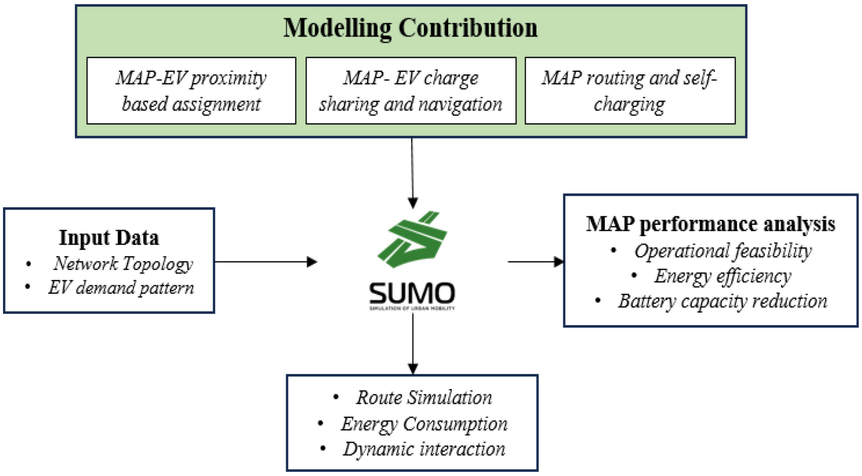


FIGURE 1. Simulation modeling framework integrating MAP–EV interactions in SUMO to evaluate deployment feasibility of MAPs.

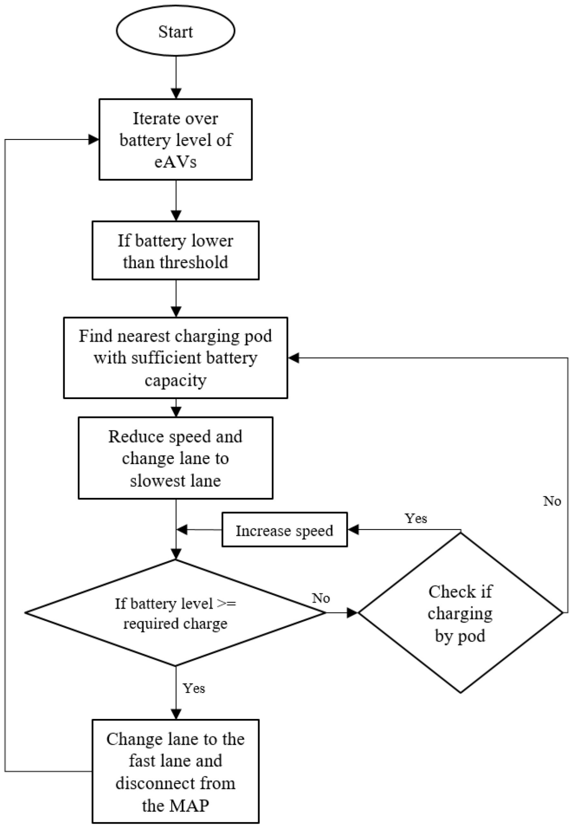


FIGURE 2. Baseline Algorithm for charging AEVs in the simulation.

efficiency and are well-suited for generating operational benchmarks in large-scale traffic simulations [46]. Nevertheless, their myopic nature—favoring locally optimal decisions without considering system-wide implications, can result in feasible but suboptimal charging schedules [35].

The operational logic governing MAPs follows a three-phase structure, illustrated in Fig. 4, and draws conceptual inspiration from the time-expanded charging framework proposed in [47]:

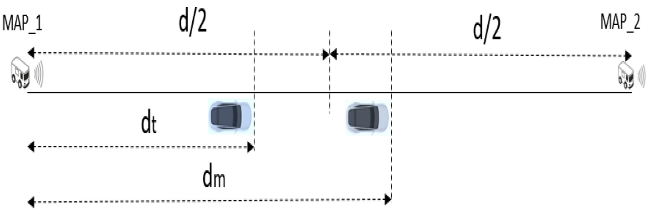


FIGURE 3. Minimum distance threshold for MAP-to-AEV assignment.

Matching phase: Each MAP is initially stationed at a designated parking location, remaining idle until it is assigned to an AEV with a low SOC. The assignment is based on spatial proximity, with each AEV dynamically seeking the nearest available MAP that has sufficient energy reserves [48], [49]. Given the mobility of the AEVs, a proximity threshold is introduced to prevent inefficient MAP assignments. Specifically, a MAP will not be matched if the time taken to reach the AEV renders the energy transfer inefficient—i.e., when the AEV would have already moved closer to another MAP location by the time contact is established as shown in Fig. 3.

This threshold distance is defined as:

$$d_t \leq \frac{d}{2} - d_m \tag{1}$$

where d_t is the threshold distance, d denotes the distance between consecutive MAP parking positions, and d_m represents the distance traveled by the AEV before the MAP can initiate charging.

Substituting $d_m = s_c \cdot t$ yields:

$$d_t \leq \frac{d}{2} - s_c \cdot t \tag{2}$$

Assuming the MAP reaches the midpoint between stations in time $t = \frac{d}{2s_m}$, we derive:

$$d_t \leq \frac{d}{2}\left(1 - \frac{s_c}{s_m}\right) \tag{3}$$

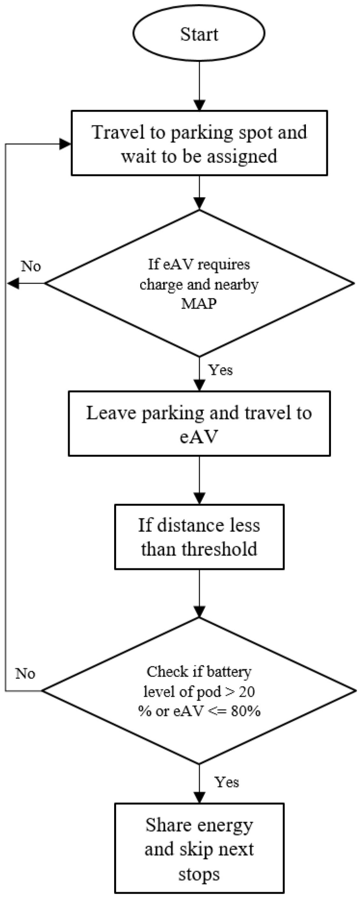


FIGURE 4. Algorithm for assigning MAPs in the simulation.

where s_c and s_m are the maximum speeds of the AEV and MAP, respectively.

Charging phase: After successful matching, the MAP navigates to the assigned AEV and initiates a moving platoon for dynamic charging. This interaction is modeled in SUMO using the CACC car-following model to simulate high-precision vehicle following behavior. While SUMO does not natively support physical vehicle coupling, dynamic charging is approximated by minimizing the inter-vehicle distance to replicate a trailer-like configuration. Charging continues until one of the following termination conditions is met: (i) the AEV reaches its target SOC, or (ii) the MAP's remaining energy drops below the threshold needed for a return trip. At intersections, MAPs temporarily disengage for maneuvering and resume charging upon completion of the turn.

Post-Charging phase: Following disengagement, the MAP autonomously navigates to the nearest designated parking zone to recharge. The simulation incorporates SUMO's charging lane model, wherein the parking locations are equipped with static charging infrastructure that allows MAPs to replenish their energy before being reassigned to a new AEV.

B. NETWORK SETUP

To evaluate the feasibility and performance of the proposed MAP-based dynamic charging system, we develop a stylized

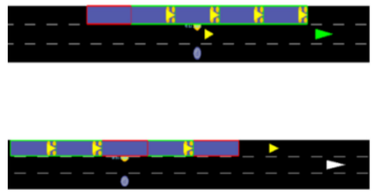


FIGURE 5. Charging process of MAPs where charging pod (in yellow) leaves parking spot and starts charging the AEV (green denotes charging) and disengages when charging is finished to move to next parking spot.

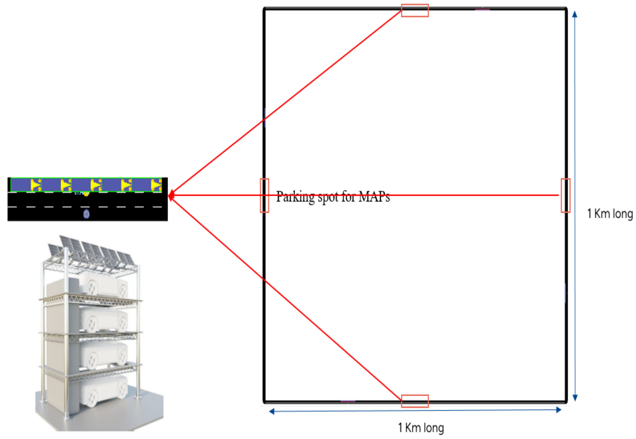


FIGURE 6. Simulation network of four edges of 1 Km long each, with pods stationed in the middle. The multiple pods per station represent the pods being stacked vertically to save space [40].

synthetic network that captures essential interactions between MAPs and AEVs while maintaining manageable computational complexity. Given the complexity of V2V dynamic charging in a microscopic traffic simulation framework, this abstraction allows controlled experimentation and parameter sensitivity analysis before transitioning to more complex, real-world scenarios.

The network is configured as a closed-loop circuit comprising four directed road segments (edges), forming a rectangular structure as shown in Fig. 6. Each edge is 1 km in length, resulting in a total loop length of 4 km. This configuration was chosen to provide a balance between computational tractability and sufficient network space for evaluating charging behaviors, platoon formation, and interactions between multiple MAPs and AEVs. The 4 km length ensures that MAPs can engage in realistic charging interactions long enough for sustained platooning and short enough to test system responsiveness across multiple charging events. While longer loops could be considered, our choice is guided by the need for controlled analysis under steady-state conditions and for preserving runtime efficiency during repeated simulations.

Each edge consists of three lanes, with the leftmost lane exclusively reserved for MAP operations. This dedicated lane fulfills two primary functions: (1) it enables MAPs to park safely without obstructing regular traffic, and (2) it allows MAPs to maneuver and synchronize with target AEVs for dynamic charging while minimizing traffic disruptions. In the midpoint of each MAP lane, a dedicated parking lot is embedded to represent a MAP charging station. These lots allow multiple MAPs to be simultaneously recharged using a simplified static infrastructure model, simulating vertical MAP storage and charging schemes as proposed in [40].

To address common initialization issues in microscopic simulators, particularly insertion backlog errors that may arise due to insufficient road capacity at simulation startup, we introduce an auxiliary edge connected to the main loop. During the warm-up phase, this edge allows AEVs to be loaded into the simulation without congestion. Additionally, the primary edge is temporarily initialized with a higher number of lanes to facilitate vehicle insertion. Once the AEVs have entered the main loop, the auxiliary edge is no longer utilized, and all operations are restricted to the intended 4 km network circuit.

In all experiments:

- The AEVs continuously circulate within the loop without exiting, allowing analysis under steady-state conditions. This abstraction ensures that transient behaviors due to entry and exit do not dominate results.
- The initial state assumes that all MAPs are fully charged and evenly distributed across the four parking locations.
- The vehicle fleet is composed of 100% autonomous electric vehicles, including both AEVs and MAPs, with full communication and coordination capabilities.

C. ANALYZING THE PERFORMANCE OF THE SYSTEM

To analyze the performance of the system, we consider the energy consumed by MAPs, the number of vehicles discharged and the efficiency of the system. For determining the efficiency of the system we use equation (4), where E_s is the energy shared with the AEVs by the MAPs and E_c is the total energy provided by the charging station to these MAPs. Thus, we consider the system efficiency rather than energy transfer efficiency between AEVs and MAPs.

$$\eta = \frac{E_s}{E_c} \tag{4}$$

D. PARAMETER SCALING

As SUMO is a discrete-time microscopic simulation model, and as an average EV can travel up to 4 hours on a single charge, we scale down battery capacities to allow for more frequent charge and discharge cycles of the AEVs within a reasonable duration of the simulation. To be as consistent as possible, we also scale down the weight and charging time of AEVs and MAPs in the simulation. For all AEVs in the simulation, we reduce the battery capacity and weight by a factor of 100 to allow for frequent charge and discharge cycles.

As the battery capacities are scaled down in the simulation and AEVs run out of charge earlier than in the real world, we also scale down the charging time (which also represents the amount of time MAPs and AEVs travel together). To scale down the charging time, we consider the ratio of time the vehicles spend charging and the respective time they can travel before requiring a charge as shown in eq. (5):

$$r_t = \frac{t_c}{t_t}, \tag{5}$$

where t_c is the charging time for the vehicles and t_t is the travel time for the vehicles before requiring another charge. To account for the fact that AEVs also expend energy while moving, the charging time in the simulations for AEVs is longer than the charging time for MAPs.

All other parameters are kept the same for both the AEV and MAP. While parameters such as air drag coefficient and front surface area may also play a role in energy consumption [50], in particular at higher speeds, these parameters are kept the same (are not scaled down), for simplicity.

E. GENERATING SOC LEVELS OF AEVS

The AEVs enter the simulation with their SOC level being drawn from a Gaussian distribution (truncated to strictly positive values). The AEVs keep moving in the loop until the simulation ends. The random seed of the simulation is kept fixed so that the only source of stochasticity in the simulation is the random SOC level of AEVs entering the simulation.

F. DETERMINING NUMBER OF SIMULATION RUNS

To calculate the required number of replication runs due to the stochasticity in the arrival SOC values of AEVs from m initial runs, we use equation (6) [51], [52]:

$$N(m) = \frac{S(m)t_{m-1,1-\alpha/2}}{X(m)\varepsilon}^2, \tag{6}$$

where $N(m)$ is the number of replications required given the m initial runs, $X(m)$ denotes the estimate of real mean μ from the m initial runs, $S(m)$ is the estimate of real standard deviation σ, α and ϵ are the level of significance and allowable percentage error of $X(m)$, and $t_{m-1,1-\alpha/2}$ represents the critical value of the two-tailed t-distribution at a level α of significance, given $m-1$ degrees of freedom [53]. A value of 0.05 for both the significance level α and the allowable percentage error ϵ is used in the subsequent experiments.

G. DETERMINING SIMULATION TIME

To determine the required simulation time, we first identify the duration needed for the SOC levels to stabilize. In our experiments, we assume all the MAPs to have full battery capacity when AEVs enter the simulation. To facilitate this, we set a warm-up period for MAPs to occupy the parking spots and reach full battery capacity at each edge. To identify whether the simulation reaches a steady state within the simulation duration, we examine the box-plots as well as the mean, median and standard deviation values of SOC of all AEVs entering the simulation. All of our experiments are conducted using this simulation setup.

TABLE 1. Parameter values used in the simulation (before scaling).

Parameter	Value
Length of the Network	4 Km
No. of Lanes per Edge	3
Maximum Speed of AEVs (s_c)	36 Km/h
Maximum Speed of MAPs (s_m)	108 Km/h
Maximum battery capacity of AEVs	64 KWh
Maximum battery capacity of MAPs	200 KWh
Maximum weight of AEVs	1830 Kg
Maximum weight of MAPs	500 Kg
Charging Time (t_c)	20 minutes

IV. EXPERIMENTAL DESIGN

We conduct a series of experiments to assess the viability of the proposed charging approach. The python source code for these experiments is available [54]. We consider the parameters proposed in [55] of KIA Soul EV 2020 for AEVs, 64 kWh battery capacity and a weight of 1830 kg (real-world values). For MAPs, we assume a battery capacity of about three times the AEV capacity, 200 kWh (real-world), and weight of about three times less, 500 kg (less weight due to the absence of passengers and smaller size). This battery capacity is smaller than in previous works, where the capacity of the mobile charger is proposed to be ten times that of the AEVs [16]. The weight and battery capacity of MAPs are based on recent advancements in battery energy density of 700 Wh/Kg [56] and the fact that batteries generally make up to 25% of the vehicle's weight. The values of the important parameters used in the experiments are mentioned in Table 1.

We only charge AEVs from 20% to 80% of battery capacity to maintain their state of health (SOH). Based on real-world data [57], we assume the values of t_c to be 20 minutes and t_t to be 210 minutes, which results in a ratio r_t of 0.095 in eq. (5).

The SOC levels of AEVs entering the simulation are drawn from a Gaussian distribution (truncated to strictly positive values), using a mean of 34 KWh and a standard deviation of 13 kWh (in real-world values), based on the real-world dataset presented in [58]. The AEVs enter with a gap of 10 seconds in their departure times. The AEVs travel in the simulation with a speed of 36 Km/h, based on recent values of speed of autonomous vehicles and mobile charging stations [59], [60]. These speeds are also most commonly used for public buses and delivery vehicles in urban settings.

As the main aim of MAPs is to charge as many AEVs as possible, the MAPs are allowed to speed up to 108 km/h to catch up with AEVs, while reducing their speeds to 36 km/h when charging the AEVs in a platoon. The AEVs travel with 36 km/h and only reduce their speeds to 24 km/h on low batteries (below 20% SoC) to allow the MAPs to catch up more easily.

A. DETERMINING THE MAXIMUM NUMBER OF AEVS THAT CAN BE SUPPORTED

This experiment aims at determining the maximum number of AEVs a fixed number of MAPs can support. Understanding this limit is crucial for identifying use cases and establishing the feasibility of the technology. To identify the maximum number of AEVs that can be supported by a fixed number of MAPs in the network, we fix the number of MAPs to 20 vehicles, where five MAPs are parked in the middle of each edge. The MAPs are initially parked at these spots and are fully charged in the warm-up time before the AEVs start entering the simulation as mentioned in the previous section. The algorithms to charge AEVs and assign MAPs are shown in Fig. 2 and Fig. 4, respectively. We test various numbers of AEVs in the network ranging from low-density scenario of 25 AEVs, to a high-stress scenario of total of 95 AEVs in the network, in steps of 10. We evaluate the SoC levels of AEVs and MAPs as well as the efficiency of MAP charging system, the energy consumed by MAPs, and the percentage of fully discharged vehicles, for the various numbers of AEVs in the network.

B. IMPACT OF AEV BATTERY CAPACITIES

One of the potential benefits of dynamic charging is the reduction in required battery capacities of vehicles. As the vehicles can charge en-route, they no longer have a need to travel with large battery capacities [61]. The batteries have a significant contribution to the total costs and overall weight of electric vehicles, which has been one of the main reasons for their slow adoption. With the use of MAPs, AEVs will be able to charge en-route, thereby considerably reducing their weight as well as costs. To analyze this potential benefit of V2V dynamic charging, we investigate the potential of reduction in battery capacities of AEVs in this network. We consider the highest number of AEVs that can be supported in the network, as determined from previous experiments and scenarios examined. We then generate the SOC demand based on a Gaussian distribution as mentioned in Section III, while varying the maximum battery capacity of AEVs. The battery capacity of MAP is kept constant at 200 KWh (real-world values). The results are reported in terms of efficiency of MAP charging, the energy consumed by MAPs, and the percentage of fully discharged AEVs.

C. COMPARISON WITH STATIC CHARGING AND BATTERY SWAPPING

To evaluate the performance of the proposed MAP-based charging infrastructure, we conduct a comparative experiment involving two conventional charging approaches: (i) static DC fast charging and (ii) battery swapping. In this scenario, MAPs are removed from the network, and AEVs must rely exclusively on fixed infrastructure to recharge their batteries. The parking areas previously designated for MAPs are repurposed to serve as static charging stations and battery swapping facilities. For static charging we assume about 5 charging station at each edge similar to MAPs, while for battery swapping we assume only one charging spot per edge due to their huge costs.

The charging rate for the DC fast charging stations is set equal to the rate used during MAP-based charging to ensure consistency in energy transfer capabilities. For battery swapping, we incorporate empirically observed replacement times of 144 seconds [62], scaled to simulation time using Equation (5). To simplify modeling complexities, we introduce a fixed charging delay of around 2 minutes (real-world-values) representing the total time from arrival to commencement of actual charging, based on average values reported in prior studies [63].

Upon detecting low SOC, each AEV checks for availability at the upcoming parking area. If a charging space is available, the vehicle stops and begins charging or battery swapping. If the station is fully occupied and the AEV retains sufficient battery, it proceeds to the next available station. Conversely, if the SOC is critically low, the vehicle queues at the occupied station. Queue dynamics are handled using SUMO's internal parking area queuing model, which allows for simulation of waiting times and charging station congestion.

To facilitate performance comparison, we evaluate key traffic metrics—mean speed, vehicle density, and average travel time, aggregated per edge over the full simulation duration. Consistent with prior experimental setups, all AEVs continuously circulate within the network without exiting the simulation. The number of AEVs is fixed at the maximum capacity identified in earlier MAP-based experiments to ensure comparability. Furthermore, all vehicles maintain uniform cruising speeds and decelerate under low SOC conditions to extend their operational range.

Finally, simulation duration is adjusted to reflect the absence of MAP initialization delay, thereby ensuring parity in temporal conditions across all experimental scenarios.

D. COMPARING ALTERNATIVE CHARGING STRATEGIES

To assess the impact of varying operational policies, we consider an alternative charging strategy in which AEVs initiate charging only when in close proximity to a MAP, rather than requiring MAPs to travel to the AEVs' locations. This proximity-based approach aims to reduce MAP travel distances, thereby conserving energy and enhancing overall system efficiency. The baseline algorithms for AEVs and MAPs, depicted in Figures 2 and 4, are accordingly modified to implement this strategy, as illustrated in Fig. 7.

In this modified configuration, the distance threshold derived in Equation (3) is further constrained such that a MAP is assigned to an AEV only when the vehicle is sufficiently close to a designated MAP parking location. This adjustment minimizes MAP travel energy, supporting more energy-efficient operations. Additionally, the AEV algorithm is updated to incorporate a proximity check before assignment: when an AEV's SOC falls below the threshold, the vehicle assesses the spatial proximity of available MAPs. If the nearest MAP is deemed too distant, the AEV postpones charging until it approaches the next pod location.

This operational mode promotes more strategic deployment of MAP resources and mitigates inefficient MAP movements across the network. As a result, the system may realize improvements in charging coverage, energy consumption, and fleet-level efficiency, key performance dimensions explored in the comparative simulations.

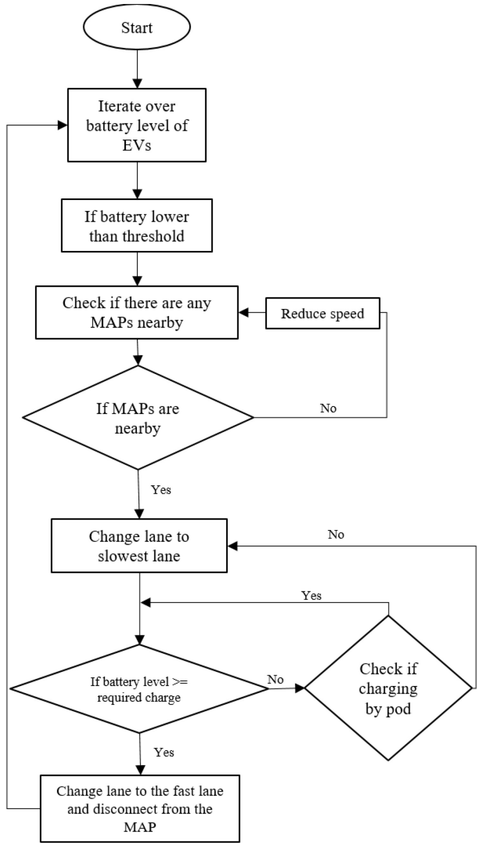


FIGURE 7. Alternate charging Algorithm for AEVs in the simulation to account for proximity to the MAPs.

V. RESULTS AND ANALYSIS

This section presents the results obtained from each experiment and discusses relevant consequences. The results in this section are aggregated from eleven simulation runs per scenario, as determined using (6). The corresponding figures are the aggregation of these eleven simulation runs, where each simulation run has a different distribution of SOC levels of arriving AEVs.

A. STEADY STATE

As described in Methodology Section III-G, the achievement of steady state is determined based on the spread of SOC levels evaluated in 5-minute intervals as shown in Fig. 8. AEVs enter the simulation from 3000 seconds and undergo about 5 to 7 charging cycles. From the box-plots in Fig. 8, we can see that the SOC steady state is reached as the spread of box-plots is similar at each time-step of 5 minutes interval. The SOC spread is somewhat uneven at the beginning of the simulation, due to vehicles entering the simulation, but reaches a stable level at around 3600 sec. Based on these results, we ran all simulation experiments for 7,500 seconds in simulation time.

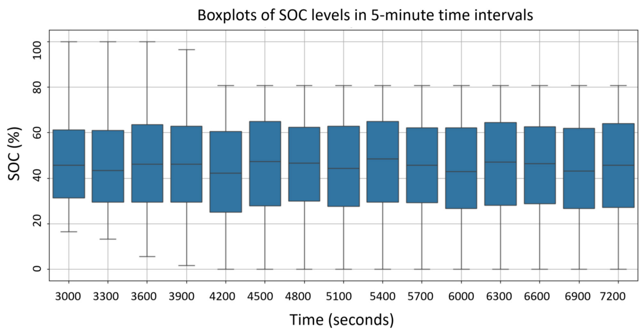


FIGURE 8. Distribution of SOC levels over time with the boxplots showing the distribution of SOC levels of AEVs.

B. MAXIMUM NUMBER OF SUPPORTED AEVS

Fig. 9 shows the histogram of SOC levels of AEVs for different numbers of AEVs in the network. The performance of each scenario is evaluated based on the frequency of AEVs reaching a 0% SOC and the proportion of vehicles with a SOC below 10%. In most scenarios, the number of AEVs dropping to these critical SOC levels is relatively low, indicating a generally stable performance. However, in the high-stress scenario depicted in Fig. 9d, there is a noticeable increase in the count of AEVs reaching both 0% and below 10% SOC levels, resulting in a significant number of vehicles running out of charge.

The histogram of SOC levels of MAPs is shown in Fig. 10, which shows that many of the MAPs remain at full battery SOC, especially for low demand scenarios. This shows great potential for using optimization algorithms to improve their usage and better spread the charging demand across all the MAPs [32], [64].

The efficiency of the system, calculated using eq. (4), peaks at around 74%. The resulting metrics of efficiency of the system, total energy consumed by MAPs and percentage of vehicles discharged are shown in Fig. 11.

From Fig. 11b, we consider 75 AEVs to be the threshold for the number of continuously running AEVs in the system that can be supported with this setup with 20 MAPs. Increasing the number of AEVs beyond this point substantially increases the number of fully discharged AEVs. At the 75 AEV level, around 2% of the AEVs run out of charge, and this scenario also has a high efficiency of about 69%.

Thus, based on the scenarios examined, we could determine that the highest number of AEVs that can be supported in this small network with just 20 MAPs is around 75.

This experiment highlights that the energy consumed by MAPs also needs to be considered when analyzing the overall efficiency of the V2V charging system. Moreover, the V2V charging system will only be feasible if the energy transfer rate between the vehicles is highly efficient, either through conductive or battery swapping technologies [16], [17], or wireless transfer [65], as the MAPs themselves consume energy to move.

C. IMPACT OF AEV BATTERY CAPACITIES

This experiment investigates if it is possible to reduce the AEV battery capacity due to the use of MAPs. Based on the previous experiment, we consider 75 AEVs and 20 MAPs in the network and vary the battery capacities. The results from the simulations are shown in Fig. 12, displaying the efficiency, percentage of vehicles discharged and energy consumed by MAPs with varying battery capacities of AEVs.

In Fig. 12c, we observe that with reduced battery capacity, the probability of an AEV running out of charge increases, especially for capacities smaller than 55 kWh. Fig. 12a shows a local peak in system efficiency, with only the original capacity of 64 kWh showing higher efficiency. This implies a 14.06% reduction in battery capacity, at a 3% reduction of efficiency. Note that in Fig. 12b the energy consumed by the MAPs is similar across all scenarios, showing a slight downward trend towards the larger AEV battery capacities. In conclusion, we note that the battery capacities of AEVs can likely be decreased with the usage of MAPs, by around 14% in the scenarios tested.

D. COMPARISON WITH STATIC CHARGING AND BATTERY SWAPPING

This experiment evaluates the relative performance of MAP-based charging against two conventional alternatives: static DC fast charging and battery swapping. We consider a scenario with 75 AEVs and 20 MAPs, representing the upper bounds of network capacity established in prior simulations. Fig. 13 presents a comparative analysis of key traffic metrics—travel time, speed, and density, across all network edges for each charging strategy.

The deployment of MAPs leads to a 17% increase in average vehicle density compared to static charging and a 2% increase relative to battery swapping. Despite the elevated density, the average vehicle speed improves by approximately 6% compared to static charging and 34% compared to battery swapping. Consequently, MAP-based charging reduces average travel time by around 7% and 26% when compared to static charging and battery swapping, respectively. These improvements are expected to scale more significantly in larger and more congested networks, where queuing delays at static infrastructure become increasingly pronounced.

E. COMPARING ALTERNATIVE CHARGING STRATEGIES

In this experiment, we consider an alternate charging strategy using the modified algorithm in Fig. 7, where the MAPs do not need to travel to AEVs, as they only start charging when in the proximity of MAPs to improve the efficiency of the system. However, from the simulation results, we find that this MAP assignment performs poorly compared to the baseline algorithm where MAP travel to AEVs.

The results are shown in Fig. 11, where although the highest efficiency is indeed considerably improved from 74% to about 80%, it has a major shortcoming in leading to an increase in the percentage of AEVs being fully discharged.

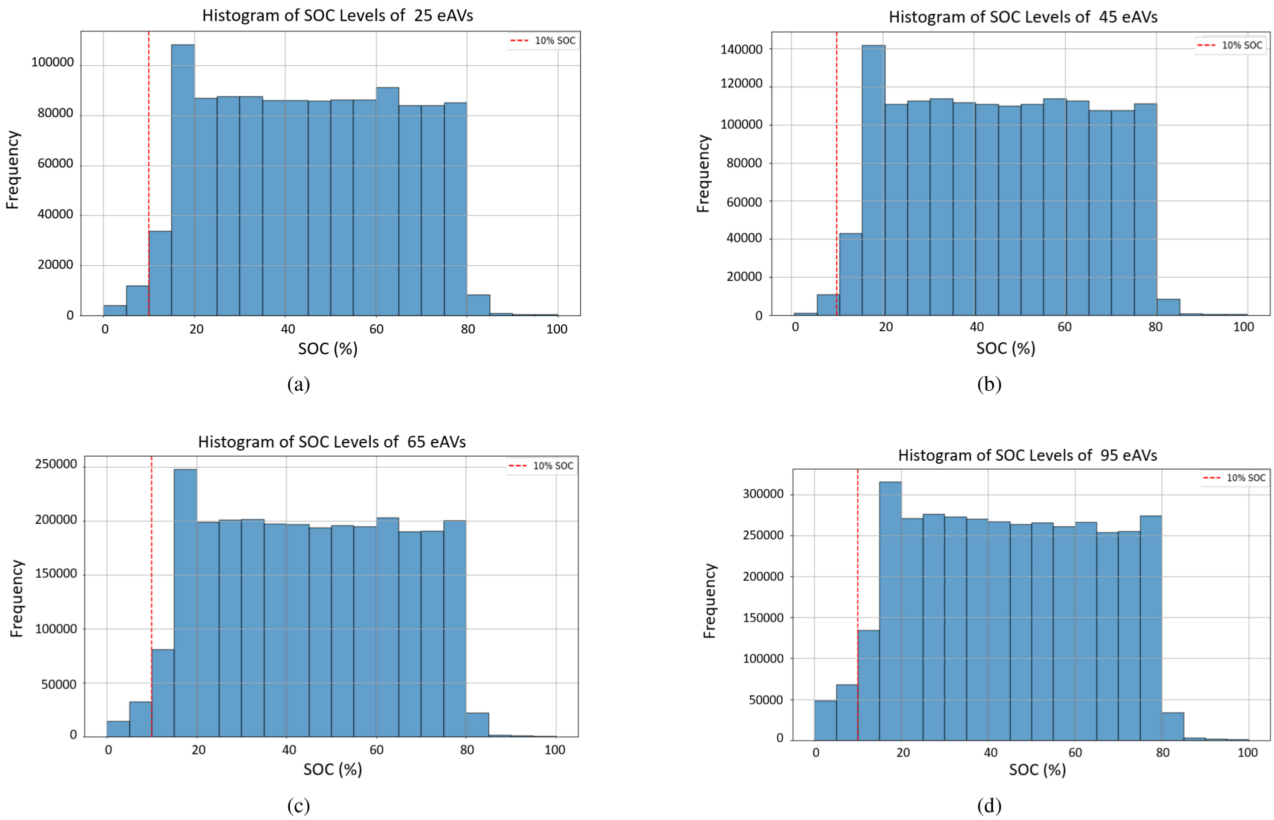


FIGURE 9. Histogram of SOC percentage of AEVs in the simulation under (a) low density of 25 AEVs (b) medium density of 45 AEVs (c) high density of 65 AEVs and (d) high-stress test with 95 AEVs in the simulation.

From the analysis of the simulation results, the main reason for this poor performance is the unavailability of MAPs in multiple parking lots simultaneously when AEVs required charge.

Thus, we find that making MAPs travel to AEVs performs much better in this network and demand scenario, than AEVs only initiating charge when near MAPs. This is due to the fact that when MAPs travel to AEV, they also spread the energy demand over space. Thus, the MAPs are continuously moving in the system and are available to charge most of the AEVs. In contrast, the alternate charging strategy only allows AEVs to charge when they are nearby the MAPs. This causes multiple MAPs to be assigned at the same time in multiple locations, leaving no MAPs for other AEVs on the same edge. This performance analysis illustrates that the behaviour of the system also depends on network configuration and the location of parking spots, the adaptation of which might yield better performance.

VI. DISCUSSION AND LIMITATIONS

This study introduces and evaluates the operational feasibility of MAPs as a flexible, infrastructure-light dynamic charging solution for AEVs. Simulation results suggest that MAPs can enhance charging flexibility, reduce required battery capacity, and lower overall infrastructure investment relative to static or battery-swapping systems. However, several limitations inherent to the study design warrant attention, as they influence the generalizability and practical applicability of the findings.

This study utilizes a stylized, closed-loop network with uniform traffic characteristics and assumes 100% penetration of AEVs. While this abstraction allows for controlled parametric evaluation and isolation of MAP–AEV interactions, it simplifies the complexities of real-world traffic systems, including variable routing, mixed traffic flows, signalized intersections, and heterogeneous energy demand. Moreover, interactions such as MAP–MAP and AEV–AEV energy exchange are not modeled, although they may offer considerable gains in collaborative charging architectures.

The deployment strategy relies on greedy heuristics, which, while computationally efficient, may not fully exploit the optimization potential of coordinated MAP behavior. Although computationally efficient and well-suited for benchmark simulations, such heuristics tend to prioritize local optima at the expense of system-wide performance.

Despite these limitations, the study presents several meaningful insights. Under the assumed simulation parameters, a fleet of 20 MAPs can support up to 75 AEVs. However, this threshold is inherently use case-dependent and sensitive to the acceptable proportion of discharged vehicles in the network. In our experimental setting, a discharge rate of approximately 2% was deemed acceptable, corresponding to

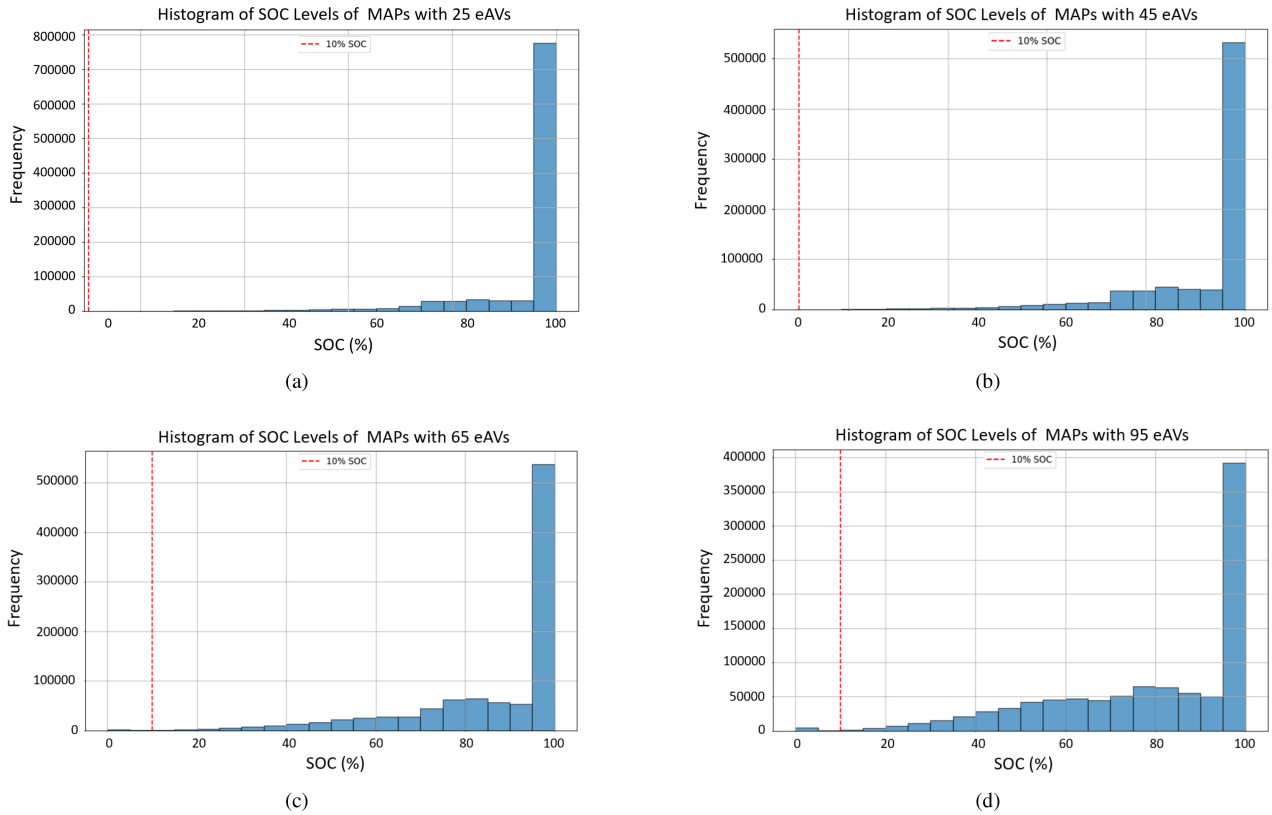


FIGURE 10. **Histogram of SOC percentage of MAPs in the simulation (a) with of 25 AEVs (b) with 45 AEVs (c) with 65 AEVs and (d) with 95 AEVs in the simulation.**

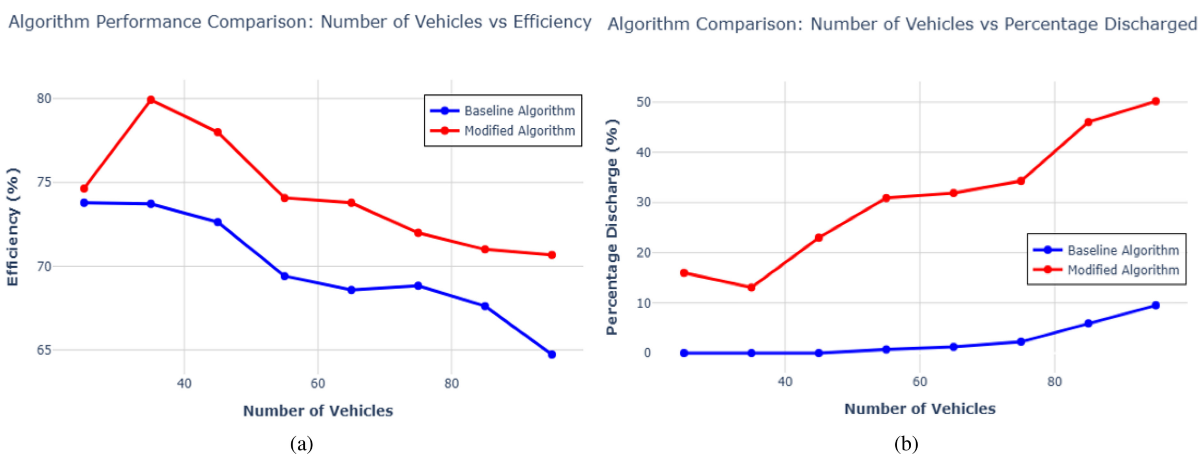
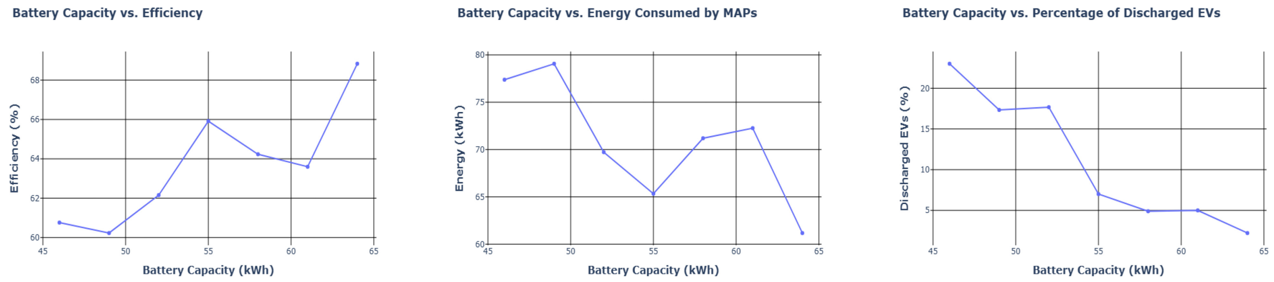


FIGURE 11. **Performance of MAP charging system with variable AEVs in terms of (a) efficiency of MAP charging system and (b) percentage of AEVs fully discharged in the network.**

a maximum supportable fleet size of 75 AEVs. Many use cases with more stringent service reliability requirements, such as emergency or logistics fleets, would require that no vehicle would ever run out of charge, thereby reducing the effective number of AEVs that can be supported by a fixed number of MAPs.

Conversely, relaxing the acceptable discharge threshold to 10%, based on the assumption that vehicles can resort to static charging or reduce cruising speeds to extend range, would allow up to 95 AEVs to be sustained, as illustrated in Fig. 11b. Furthermore, if the system objective shifts toward maintaining a higher average SOC, such as above 50% as proposed in [66], the network could potentially accommodate more than 100 AEVs. This underscores the trade-off between service reliability, battery reserve levels, and MAP fleet utilization. Such trade-offs between service reliability and efficiency would be a recommended area for future research.

Further, in low-demand scenarios, we observe substantial underutilization of MAPs. As shown in Fig. 10, many MAPs retain high SOC levels, indicating skewed operational load distribution across the fleet. This asymmetry may adversely affect the SOH of heavily used units, leading to accelerated



(a) (b) (c)

FIGURE 12. **Performance of MAP charging system with variable battery capacities (a) efficiency of MAP charging system (b) Energy consumed by MAPs and (c) percentage of AEVs fully discharged in the network.**

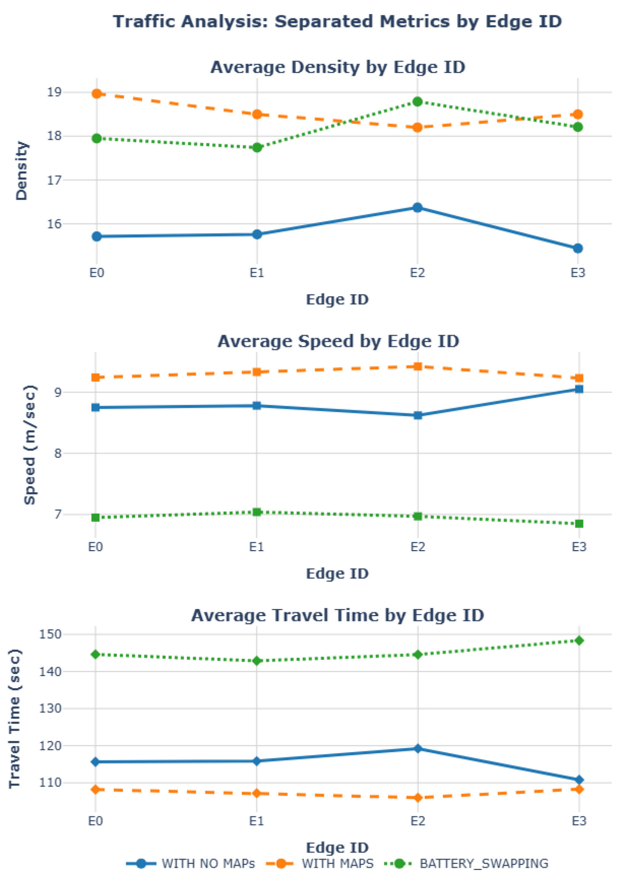


FIGURE 13. **Performance comparison of MAPs with static charging and battery swapping across density, speed, and travel time.**

degradation. The number of AEVs that can be effectively supported is therefore not only a function of MAP quantity, but also of the charging assignment strategy and operational efficiency.

One contributing factor to MAP underutilization is the current model's constraint that limits each MAP to charging a single AEV before returning to a parking area for replenishment. Future enhancements should explore multi-session charging, whereby MAPs charge several AEVs sequentially during a single dispatch cycle. This would involve dynamically identifying AEVs approaching SOC thresholds along the MAP's route. Additionally, inter-MAP charging, where MAPs recharge one another, could further improve overall energy utilization and routing efficiency, especially in sparse traffic scenarios.

A. COMPARISON WITH STATE-OF-THE-ART APPROACHES

To situate our findings within the broader literature, we compare the MAP-based approach against other state-of-the-art dynamic charging paradigms. While previous studies demonstrate that V2V charging can reduce EV battery size requirements by up to 50–70% [28], and travel time by up-to 20% [27], under idealized transfer efficiencies, our results suggest a more modest reduction of 14.06% in battery capacity and 7% reduction in travel time using MAPs. However, unlike previous V2V systems, our modeling explicitly incorporates the propulsion costs of mobile chargers, which diminish the net savings but offer a more realistic system-level assessment. Similarly, dynamic wireless charging lanes are reported to achieve battery downsizing of up to 70% [61], but at the expense of extremely high infrastructure cost and limited deployment flexibility. In contrast, MAPs require only modest fleet investment and no embedded road infrastructure, making them more scalable for heterogeneous urban networks.

Relative to reinforcement learning–based MED systems [32], which improve charger routing efficiency but rely on deployments of buses or trucks, MAPs introduce higher spatial flexibility by allowing autonomous pods to reposition dynamically across the network. This flexibility comes at the cost of slightly higher traffic density (17% increase in our experiments), yet still provides measurable system benefits, including a 7% reduction in travel time and a 6% improvement in average speed. Compared to battery swapping, which can offer quick replenishment but has shown poor energy efficiency in our tests and carries capital costs exceeding USD 1 million per station [67], MAPs deliver improved service reliability with significantly lower investment barriers.

Furthermore, the environmental implications of battery downsizing are notable. Recent studies have shown that non-exhaust particulate matter (PM) emissions, such as those from tire and road wear, can equal or exceed those of internal combustion engine vehicles (ICEVs), primarily due to the higher mass of battery-electric vehicles [68], [69]. By reducing battery size through dynamic charging with MAPs, the overall vehicle weight may decrease, potentially lowering PM emissions and contributing to improved environmental sustainability [70].

Ultimately, our contribution lies not in maximizing any single metric (e.g., downsizing potential as in DWC, or efficiency as in idealized V2V), but in demonstrating that MAPs offer a balanced trade-off across multiple performance dimensions, including moderate battery reduction, improved travel times, flexible deployment, and lower infrastructure cost, while accounting for realistic propulsion energy costs. This broader evaluation complements and extends prior works, which often isolate one aspect of the charging process without considering its systemic effects.

VII. CONCLUSION AND FUTURE WORK

This study introduces a vehicle-to-vehicle (V2V) dynamic charging paradigm for autonomous electric vehicles (AEVs) utilizing mobile autonomous charging pods (MAPs). A dedicated simulation framework, integrated within a microscopic traffic environment, was developed to model MAP operations, including real-time task assignment, energy transfer protocols, and traffic-aware navigation. The performance of MAP-based dynamic charging was evaluated and benchmarked against conventional static charging infrastructure and battery swapping systems.

Simulation results reveal that MAPs can reduce average travel time by up to 7% and increase vehicle speeds by approximately 6% compared to static DC fast chargers. While battery swapping offers faster individual charging sessions, it underperforms overall due to queuing delays and substantial infrastructure demands. Notably, MAP deployment enables an estimated 14.06% reduction in required battery capacity for AEVs, contributing to operational efficiency and potential reductions in vehicle weight and associated particulate emissions.

Urban environments are identified as particularly promising for MAP implementation. These areas often face space constraints and high land costs, limiting the feasibility of extensive static charging or swapping infrastructure. The dynamic and relocatable nature of MAPs allows them to adapt to spatiotemporal fluctuations in charging demand, mitigate congestion around fixed charging hubs, and operate effectively at lower urban speeds. Furthermore, MAPs offer potential to serve high-priority user groups, including emergency responders, logistics providers, premium ride services, and transit fleets, with targeted, on-demand charging.

Several directions for future research are identified. First, the development of congestion-aware dispatch algorithms and dynamic fleet management strategies, could enhance system performance and reduce operational disruptions. Second, real-world deployment scenarios should be explored, particularly in areas with limited grid coverage (e.g., rural and peri-urban zones) or temporary high-load demand (e.g., public events, logistics hubs).

In addition, further work is needed to establish quantitative criteria, such as grid capacity thresholds, demand surge intensities, and acceptable vehicle discharge levels, to inform MAP deployment decisions and fleet sizing strategies. A comprehensive cost-benefit analysis comparing MAP systems to conventional infrastructure should also be undertaken. Such analysis must account for capital and operational expenditures, energy efficiency, maintenance costs, and broader environmental externalities under varying traffic conditions and market penetration levels.

In conclusion, this study lays the groundwork for MAP-based dynamic charging as a scalable, flexible, and efficient alternative to fixed charging solutions. While the initial results are promising, future research integrating empirical traffic data, advanced optimization models, and detailed economic assessments will be essential to validate and guide the real-world implementation of this emerging paradigm.

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