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Hierarchical User-Driven Trajectory Planning and Charging Scheduling of Autonomous Electric Vehicles

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Abstract

Autonomous electric vehicles (A-EVs), regarded as one of the innovations to accelerate transportation electrification, have sparked a flurry of interest in trajectory planning and charging scheduling. In this regard, this work employs mobile edge computing (MEC) to design a decentralized hierarchical algorithm for finding an optimal path to the nearby A-EV parking lots (PL), selecting the best PL, and executing an optimal charging scheduling. The proposed model makes use of unmanned aerial vehicles (UAVs) to assist edge servers in trajectory planning by surveying road traffic flow in real-time. Further, the target PLs are selected using a user-driven multi-objective problem to minimize the cost and waiting time of A-EVs. To tackle the complexity of the optimization problem, a greedy-based algorithm has been developed. Finally, charging/discharging power is scheduled using a local optimizer based on the PLs' real-time loads which minimizes the deviation of the charging/discharging power from the average load. The obtained results show that the proposed model can handle charging/discharging requests of on-move A-EVs and bring fiscal and non-fiscal benefits for A-EVs and the power grid, respectively. Moreover, it observed that user satisfaction in terms of traveling time and traveling distance are increased by using the edge-UAV model.

Index Terms

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Mobile edge computing (MEC), autonomous electric vehicle (A-EV), trajectory planning, vehicle-to-grid (V2G), greedy algorithm

NOMENCLATURE

Abbreviations

A-EV	Autonomous electric vehicle
PL	Parking lot

Sets

\mathcal{G}	Set of aggregators indexed by g
\mathcal{I}	Set of A-EVs indexed by i
\mathcal{K}	Set of PLs indexed by k
\mathcal{M}	Set of transportation systems' nodes indexed by n, m
\mathcal{T}	Set of scheduling time horizon indexed by t

Parameters

β^i	Self-discharging coefficient of A-EV i 's battery
$\beta_1^i/\beta_2^i/\beta_3^i/\beta_4^i$	Fitting parameters related to charging/discharging power of A-EV i
η^i	Charging efficiency of A-EV i 's battery
ω^i/γ^i	Fitting parameters related to calendar degradation cost of A-EV i
\bar{C}^k	PL k capacity
$\bar{P}_{chr}^i/\bar{P}_{dch}^i$	Maximum charging/discharging power of A-EV i (kW)
$\bar{v}_{n,m}$	Maximum allowed speed between nodes n and m (km/h)
ϕ	Weighting factor in the multi-objective function
$\tau_{n,m}^0$	Traveling time between nodes n and m without considering traffic flow (h)
θ^i	Battery temperature of A-EV i
ζ_{DC}/ζ_{FC}	Degradation/fluctuation costs coefficients
a_0^k/a_1^k	Intercept (\$/kWh)/slope (\$/kWh/kW) coefficients
$d^{i,k}$	Distance between A-EV i and PL k (km)
F^i	Motor force of A-EV i (kWh/km)
$f_{n,m}$	Traffic flow at time slot t between nodes n and m (km/h)
$f_{n,m}^{cap}$	Traffic capacity at the link between nodes n and m at time slot t
$L^{k,t}$	Base load of PL k at time slot t (kW)

$l_{n,m}$	Distance between nodes n and m (km)
m^k / δ^k	Step length (kW)/incremental (\$/kWh) price
V_i	Charging/discharging duration of a-EV i (h)
$v_{ave}^{i,t}$	Average speed of A-EV i at time slot t (km/h)
v_{ave}^{tr}	Traffic average speed (km/h)

Dependent variables

$\tau_{n,m}^{i,t}$	Traveling time of A-EV i at time slot t between nodes n and m (h)
$A^{i,k} / D^{i,k}$	Arrival/Departure time of A-EV i from PL k
$DC^{i,k,t}$	Degradation cost of A-EV i at PL k and time slot t (\$)
$DC_{cal}^{i,k,t} / DC_{cyc}^{i,k,t}$	Calendar/cycle degradation costs of A-EV i at PL k and time slot t (\$)
$FC^{i,k,t}$	Fluctuation cost of A-EV i at PL k and time slot t (\$)
$MC^{i,k,t}$	Maintenance cost of A-EV i at PL k and time slot t (\$)
$OC^{i,k,t}$	Operation cost of A-EV i at parking lot k and time slot t (\$)
$p_z^{k,t}$	Real-time power price at PL k and time slot t (\$/kW)
$SoC^{i,t}$	State of charge of A-EV i at time slot t (kWh)
$T^{i,k,t}$	Waiting time of PL k at time slot t (h)
$z^{k,t}$	Real-time load at PL k and time slot t (kW)

Main decision variables

$e^{i,k,t}$	Free variable to determine charging/discharging power of A-EV i at PL k and time slot t
$x^{i,k,t}$	Binary variable such that $x^{i,k,t} = 1$ means A-EV i at time slot t is connected to PL k

I. INTRODUCTION

A. Motivation and background

THE transportation section is one of the largest contributors to greenhouse gas emissions which leads to climate change and global warming. In accord with Paris Agreement, researchers are tending to innovate zero-carbon technologies, in which the electrified transportation system has emerged as a promising solution. The advent of electric vehicles (EVs) is an opportunity to turn from internal combustion engine (ICE) transportation to electrified transportation, therefore, as a consequence of the widespread adoption of EV fleets, significant contributions could be made toward the reduction of greenhouse gasses leading to and potentially contributing to mitigating the effects of global warming [1]. As the 21st century continues to unfold, many new technologies have arisen in the EV industry and introducing autonomous vehicles is one of those technologies. An autonomous vehicle is a driverless vehicle that can be controlled via intelligent

systems and sensors to path following. To stick with environmental concerns, electric autonomous vehicles (A-EVs) have been developed and thanks to automotive companies, such as Tesla and Google, they will be prevalent in the years ahead. Due to the variety of systems and hardware, the power consumption of A-EVs is more than regular EVs; hence energy management of A-EVs is a formidable issue. Moreover, in addition to the environmental benefits of A-EVs, since A-EVs are driverless, the uncertainty of driver behaviors dramatically drops in comparison with normal EVs and they become more accurate and controllable.

The integration of A-EVs with smart cities and following that with the smart grids raise serious challenges regarding different aspects, especially from electrical and communication points of view. An A-EV, from the electrical perspective, is a mobile storage system that can be applied in grid-to-vehicle (G2V), i.e., charging, and vehicle-to-grid (V2G), i.e., discharging, modes. However, the electricity market, on the one hand, inhibits single A-EVs, especially on-move A-EVs, to participate in the market as they might compromise the economic dispatch of the power system since they have to be allocated to a parking lot (PL) to benefit from V2G/G2V facilities. By the fast-growing of the A-EVs, deciding the best PL for allocating A-EVs as well as introducing a model for charging/discharging scheduling of A-EVs is of paramount importance. On the other hand, online and real-time scheduling of a high number of A-EVs is another challenge. Centralized cloud-based frameworks due to computational burden and communication overhead fail to coordinate A-EVs on a large scale. Therefore, decentralized platforms, such as mobile edge computing (MEC) which was introduced by European Telecommunications Standard Institute, for online computation and communication have been developed [2]. Indeed, the computational burden from cloud servers has been distributed among multiple edge servers in a MEC system; hence, such a system can be extended easily to include a high number of vehicles. Another challenge concern on-move A-EVs is optimal trajectory planning according to real-time traffic flow. In this regard, unmanned aerial vehicles (UAVs) known as drones have been well utilized for different road traffic monitoring scenarios on the ground that they can move around swiftly without restricting in road traffics [3].

Motivated by the discussion above, this work tries to introduce a novel scheduling and trajectory planning of on-move A-EVs with the aim of minimizing A-EVs' cost and waiting time. Moreover, an integrated Edge-UAV communication system is proposed with the aim of online data exchange where the UAVs are used for real-time road surveillance. Since the proposed model is mixed-integer nonlinear programming (MINLP), a greedy-based heuristic algorithm is designed to solve the optimization problem. An MINLP contains both continuous and integer variables where the objective function and feasible search area are described by nonlinear functions. By using this kind of programming, on the one hand, accurate features in real-life

could be reflected in mathematical modelings. Due to this great advantage, MINLP optimization problems are widely used in different areas such as operation, economy, engineering, and process industry [4]. On the other hand, an MINLP combines complexity to the optimization problem in solving process because of handling a mixed-integer program (MIP) and a nonlinear program (NLP). In this work, the MIP subclass of the MINLP is handled by the proposed greedy algorithm. Then the remained problem, which is an NLP, is solved using a local optimizer.

B. *Paper organization*

The remainder of the paper is organized as follows. Section II includes literature review, research gaps and contributions. Section III explains model description, main objectives and assumptions. Section IV focuses on the problem formulation. Section V supplies the proposed online greedy-based solution approach and analysis of complexity and optimality. Section VI reports simulation results and numerical analysis. Ultimately, section VII concludes the paper.

II. RELATED WORKS

Following the ongoing quest for EVs in smart cities; many pieces of research have been dedicated to the scheduling of EV fleets. For instance, in [5], a two-stage scheduling model has been proposed for electric fleets, in which the first stage deals with feasible optimal load profiles of EVs, and the second stage solves an optimization problem to select the EVs to follow the load fed based on their charging priority. Another energy management model has been introduced in [6], where the objectives of the problem are to minimize the waiting time of EVs for charging/discharging services and minimize the stress level of EVs' supply component. A bilevel charging scheduling of EVs to reduce the charging station operation costs has been proposed in [7], where the upper-level deals with charging index and charging duration while the lower level optimizes the charging power at each time slot. In [8], a multi-criteria decision making for PL selection based on EVs' preferences including PL availability, SoC value and PL usage history has been presented. All the aforementioned works have considered a centralized environment for scheduling; however, centralized platforms have a computational burden and cannot be extended to large scales.

To cope with scalability and also privacy issues of EVs, decentralized energy management models have been developed in the literature. In [9], a deep reinforcement learning approach has been proposed for cooperative charging management of EVs in a decentralized platform. A security constraint charging strategy including power flow and voltage management has been proposed in [10], where a distributed online platform has been designed for EVs. Another online framework based on the greedy algorithm for charging and discharging EVs

has been introduced in [11], in which the objective of the presented optimization problem is the maximization of social welfare including profit of both EVs and parking lots. The greedy algorithm has been recognized as a fast-response method in online applications and it has been used widely in other works, e.g., [2], [12] as in online applications running time of the optimization models is highly important. Regarding trajectory planning of EVs, ref. [13] has proposed a security constraint model for path planning by coupling transportation and power grid networks. In the mentioned work, a wireless power transfer model for charging EVs has been introduced. In addition, the Floyd algorithm has been used to find the shortest path to a destination. However, this work suffers from considering the V2G ability of EVs as well as considering a decentralized approach and communication system for online data exchange.

Furthermore, the prevalent of A-EVs over the recent years has attracted researchers' attention. In this regard, several works have introduced different vehicle-following approaches. In [14], a vehicle-to-everything (V2X) enabled robust integrated longitudinal and lateral vehicle-following control model has been presented, where a packet dropout compensator has been proposed to compensate for the V2X drawbacks such as time-varying delays and dropouts. In [15], a three-layer procedure has been introduced to prevent collisions on highways while changing lanes. The first layer generates a reference trajectory, then the obtained waypoints and time stamps are checked in the second layer to decide whether a new assignment of timestamps to the waypoints is needed. Eventually, a new trajectory is performed in the third layer if the collision will not be avoided. Study [16] has proposed a path following and yaw controllers based on model predictive control (MPC) for A-EVs for double lane routes. Authors in [17] have proposed a real-time decision-making process based on real drivers' motivation on changing driving plans. Further, a risk-assessment model based on trajectory prediction of nearby drivers has been done in this work. In addition, study [18] provides a comprehensive review on X-by-wire chassis coordinated control as it is essential in autonomous vehicles. Unlike autonomous vehicle control research, few of the previous works contributed to the energy management of A-EVs. In [19], a decentralized linear algorithm for parking allocation of A-EVs considering V2G ability has been developed. A charging and parking management of A-EVs considering waiting time and traveling time has been introduced in [20]. However, traffic flow and optimal charging scheduling have been neglected. In [21], to tackle the hybrid A-EVs driving condition uncertainty and also energy management of them, fuzzy logic types 1 and 2 have been taken into consideration. An optimal sizing and charging planning of an entity that operates A-EVs has been introduced in [22], in which the presented model has been formulated as a linear problem and guarantees optimality.

With urbanization and increasing population in urban areas, roads become more congested than ever before

and traffic plays an important role in urban areas [23]. Traditionally, roadside units based on stationary low-altitude cameras were used to capture the traffic [24]. These technologies passively collect data at the point of the installed camera. Moreover, accidents could not be detected by this kind of technology because of the distance between two units. The other alternative is to use V2X technologies such as GPS sensors. However, this is not an accurate method to capture the real-time traffic as some vehicles might not carry such sensors. In today's life, UAVs are widely being used for different purposes such as civilian tasks, scientific research and transportation management [25]. For traffic monitoring purposes, a UAV is equipped with a ground-faced camera that makes it capable to capture vehicles within a wide range of areas [26]. UAVs are also flexible and can swift over the roads without stocking in traffic which increases the scalability of the monitoring system. Moreover, compared with traditional technologies which impose high investment and operational costs, UAVs are low-cost and easy to operation alternatives. Regarding data transmission, UAVs are able to transmit data efficiently and faster over short time slots using cellular networks, causing less computational and communication overheads [27]-[28]. Accordingly, UAVs outperform other technologies in traffic monitoring in many aspects. On the other hand, authors in [29] have investigated the impact of the different pricing in PLs on the load distribution of EVs and traffic flow. In this work, it has been shown that heterogeneous pricing affects EVs' decisions on PLs and traffic flow. However, a charging scheduling and optimal trajectory planning according to the traffic flow have not been performed.

As autonomous vehicles are driverless, designing a reliable vehicular communication architecture for A-EVs is another considerable research topic that has received attention. In this context, some papers have investigated communication frameworks for electric vehicles such as [2], which has proposed mobile edge computing for real-time scheduling of EVs. In [30], mobile edge computing has been employed in order to decentralize the battery switch model that the proposed model aims to allocate EVs with parking lots considering the minimum waiting time. A software-defined network (SDN) assisted mobile edge computing algorithm for charging and discharging of EVs within the minimum waiting time has been introduced in [31], where the SDN has been considered for enhancing data transition and efficiency.

A. *Research gaps and contributions*

Many prior works have presented different methods for PL selection, charging/discharging scheduling and trajectory planning of EVs and A-EVs. However, there exist serious research gaps. Firstly, some of the works have focused on centralized models for EVs such as [5], [6], [32], [33] and ignored the scalability and data security of the system. Secondly, although there are some papers that present decentralized solutions for EVs, e.g., [9]-[13], they cannot be applied for A-EVs as a trustable communication system for online

data exchange has not been proposed in these works. Moreover, in most of the works, trajectory planning has been ignored, such as [2], [6], [8], [11], [19], [30]. In some works such as [13],[22] the impact of traffic flow has not been investigated in trajectory planning, while in urban areas considering traffic flow is an important factor for routing vehicles. In addition, in [13], multiple parameters in the trajectory planning have been considered which tuning of the weights associated with each parameter is challenging. Majority of previous works concerning A-EVs, such as [3], [16], [17], [21], [22], [34], have analyzed A-EVs for sensors, signal processing and related accurate path following issues, while trajectory planning and charging scheduling of A-EVs have not been well explored. Based on the presented motivation and existing gaps, the main contributions of the current work are. Moreover, Table I concludes the existing gaps and main contributions of this work.

- Introducing a novel model for PL selection and charging/discharging scheduling on-move A-EVs. Since energy cost is very important in real-life for energy users and considering this factor in the best PL selection is vital. In addition, waiting time is highly contributing to user satisfaction. Therefore, the best parking lot is decided based on the preferences between cost and waiting time. Moreover, a local optimizer is employed to extract real-time charging/discharging scheduling for on-move A-EVs.
- Presenting a new trajectory planning based on the real-time traffic flow. Further, unlike previous works, only traveling time is used in the trajectory planning according to the real-time traffic. In light of using the MEC system, A-EVs are guided by nearby edge servers to nearby PLs, which are geographically close, and user satisfaction in terms of traveling distance is also satisfied.
- Employing an integrated Edge-UAV model for the first time with the aim of a real-time and decentralized operation. By using edge-servers, the centralized cloud-based problem is broken into multiple decentralized sub-problems in edge-servers, resulting in lesser computation/communication complexity as well as improving scalability and security due to the fact that edge-servers are isolated from the rest of the network. Moreover, the UAV technology is used for real-time traffic data gathering, in which UAVs transmit the real-time traffic data to the edge-servers from where it is communicated to the A-EVs in order to perform accurate trajectory planning.
- Finally, to reflect the accurate models on the scheduling, the optimization problem is mathematically modeled as an MINLP. Hence, to tackle the complexity and intractability of the optimization problem associated with the best PL selection, a greedy-based algorithm is developed as a solution approach. The greedy-based algorithm is a fast-response method that can provide a sub-optimal solution with an acceptable deviation from the global solution.

TABLE I: Comparison of existing works and the current work

Reference	On-move	Online scheduling	Decentralized algorithm	Trajectory planning	Traffic monitoring	Communication architecture (MEC, cloud, IoT, etc.)
Mehrabi, et. al [2]	✓	✓	✓	✗	✗	MEC
Wu, et. al [6]	✗	✓	✗	✗	✗	None
Sadreddini, et. al [8]	✗	✗	✗	✗	✗	None
Mehrabi, et. al [11]	✗	✓	✓	✗	✗	None
Zhou, et. al [13]	✗	✓	✗	✓	✗	None
Lam, et. al [19]	✗	✗	✓	✗	✗	None
Zhang, et. al [22]	✗	✗	✗	✓	✗	None
Cao, et. al [30]	✗	✗	✓	✗	✗	MEC
Current work	✓	✓	✓	✓	✓	Edge-UAV, Cloud

III. SYSTEM MODEL DESCRIPTION

The schematic view of the proposed model for charging/discharging of on-move A-EVs has been demonstrated schematically in Fig. 1. The system is composed of three different types of A-EV sets based on their operations, i.e., the set of A-EVs in charging mode \mathcal{I}^{CHG} , the set of A-EVs in discharging mode \mathcal{I}^{DSG} and the set of vehicle-to-grid A-EVs in both charging and discharging modes \mathcal{I}^{V2G} . The considered three types of A-EVs are indexed by $i \in \mathcal{I} = \mathcal{I}^{CHG} \cup \mathcal{I}^{DSG} \cup \mathcal{I}^{V2G}$. The index $s \in \mathcal{S} = \{1, 2, \dots, |\mathcal{S}|\}$ shows the number of roadsides mobile edge servers and shows the number of roadsides mobile edge servers and $k \in \mathcal{K} = \{1, 2, \dots, |\mathcal{K}|\}$ denotes the number of PLs distributed in the transportation system. These edge servers are equipped with high-power onboard processors to facilitate the processing of A-EVs requests which are widely used in vehicular communication systems. Edge servers receive data associated with PLs' real-time electricity load and prices via contact with aggregators. Each aggregator controls multiple nearby PLs which is denoted by $g \in \mathcal{G} = \{1, 2, \dots, |\mathcal{G}|\}$ and notations \mathcal{C}_g and \mathbf{G}_s represent the set of PLs that are controlled by the aggregator g and the set of aggregators communicate with the edge server $s \in \mathcal{S}$. Furthermore, there are UAVs that are surveying around to capture traffic conditions. Traffic flow in real-time is sent to the edge servers in real-time and in doing so, A-EVs can detect the nearest way to the nearby PLs. The transportation system is denoted by a set of nodes indexed by $n, m \in \mathcal{M} = \{1, 2, \dots, |\mathcal{M}|\}$ Each link between nodes n and m is denoted by weight $w_{n,m}$, in which $w_{n,m} = 0$ means $n = m$ and $w_{n,m} = \infty$ means there is not any direct link between nodes n and m . Weights of this matrix could be time, distance and etc. In doing so, the transportation system could be modeled via a weight matrix W as below:

$$W = \begin{bmatrix} w_{1,1} & w_{1,2} & \dots & w_{1,m} \\ w_{2,1} & w_{2,2} & \dots & w_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n,1} & w_{n,2} & \dots & w_{n,m} \end{bmatrix} \quad (1)$$

The scheduling time horizon is divided into multiple equal time slots indexed by $t \in \mathcal{T} = \{1, 2, \dots, |\mathcal{T}|\}$. Interactions among components are described as follows. At each time slot, as demonstrated in Fig. 1, firstly each A-EV sends its request for charging/discharging service along with its current location, state of charge, battery details and also weights of the optimization based on its own preferences to a nearby edge server. Then, according to the traffic data captured by UAVs, the edge server determines the nearest path to the nearby PLs using the Floyd algorithm [13]. Indeed, at each time slot, the weight matrix W is updated by edge servers based on real-time traffic flow. After finding optimal paths, the edge server checks which PLs are reachable to the A-EV according to its current state of charge (SoC). In the next step, the edge server runs an optimization problem using a greedy-based algorithm with internal heuristics to find out which PL is the best one according to the A-EV preferences. The proposed optimization problem is formulated as a multi-objective problem that provides flexibility in PL selection based on the cost and waiting time objectives. At the end of the optimization, the outputs, which are a PL and a path, are sent to the A-EV. At the final step, a local optimizer is run for the allocated A-EV by the selected PL to optimally determine the charging/discharging scheduling. In short, the main objectives of the proposed Edge-UAV assisted charging/discharging of A-EVs are summarized below.

- **The Best Parking Lot Selection:** The best parking lot for on-move A-EVs is decided by a nearby edge server based on a multi-objective function. The multi-objective function includes minimization of the A-EVs' charging cost and waiting time. The best PL for A-EVs is selected among the candidate PLs according to the A-EVs' preferences between objectives, i.e., waiting time and cost.
- **Optimal Trajectory Planning (Parking Lots Location):** The determination of the optimal trajectory to reach the best parking lot in real-time is an essential need for on-move A-EVs. The proposed system aims to find the nearest path based on traveling time according to the real-time traffic flow. The UAVs in the proposed system are utilized to monitor the vehicles' traffic density on different roads in real-time. To have the minimum latency, the proposed scheme is executed at the edge servers near the A-EVs.
- **A-EV Cost Minimization:** Once the A-EV reaches the best parking lots, the energy flow between the power grid and A-EV is performed by executing an efficient scheduling algorithm with the objective of

minimizing the cost.

- **Optimal Power Grid Ancillary Services:** The scheduling algorithm also takes into account the benefits to the power grid, i.e., the optimal ancillary services which are the optimal load shifting and peak load shaving patterns.

It is noteworthy that the extension of the proposed model to traditional EVs is possible but it will be subject to some modifications as follows: The implementation of the proposed model requires some basic equipment like communication devices to contact edge servers and traditional EVs do not carry such equipment. Therefore, implementation of the model on traditional EVs will be subject to installment of communication devices. Also, the traditional EVs are experiencing high uncertainty due to human behaviors. All the procedure in the proposed scheduling is done automatically without human intervention. For instance, all the real-time capacity, real-time load and price of energy which are updated according to the rendered scheduling at each time slot, will be uncertain in the case of EVs and this might cause different output results.

A. Assumptions

- 1) In this work, it is assumed that edge servers are stationary and deployed at roadsides near the cellular wireless communication systems. This assumption is practical in real-world according to [35]. Since cellular base stations are able to cover an area with a radius of 10 km based on the LoRaWAN communication technology for urban areas [35]-[36], it is practical to assume that with a sufficient number of edge servers, each A-EV will be inside the coverage of at least one edge server.
- 2) In practice, PLs are built outside of city centers because of low land cost [37]. Based on this policy, it is assumed that PLs, in addition to charging spaces, have enough space for A-EVs which are in the queue. Therefore, in this work, queuing space is not checked by edge servers. Further, it is assumed that all the considered PLs are in-service during the scheduling time horizon and disabled PLs, as well as special needs PLs, are excluded in this work.
- 3) Since the majority of the vehicles in urban areas are cars, big vehicles such as buses and trucks are not taken into consideration in this work. However, it is noted that the generality of the model will not be lost by considering big vehicles, just minor modifications will be needed. For instance, big vehicles might not be allowed to use every road in the transportation networks which affects their SoC level.
- 4) Regarding data transmission, it is assumed that data is transmitted among technologies properly without interruption. Considering fault data injection and any other uncertainty concerns data is out of scope for this work and it could be an interesting topic for future works.

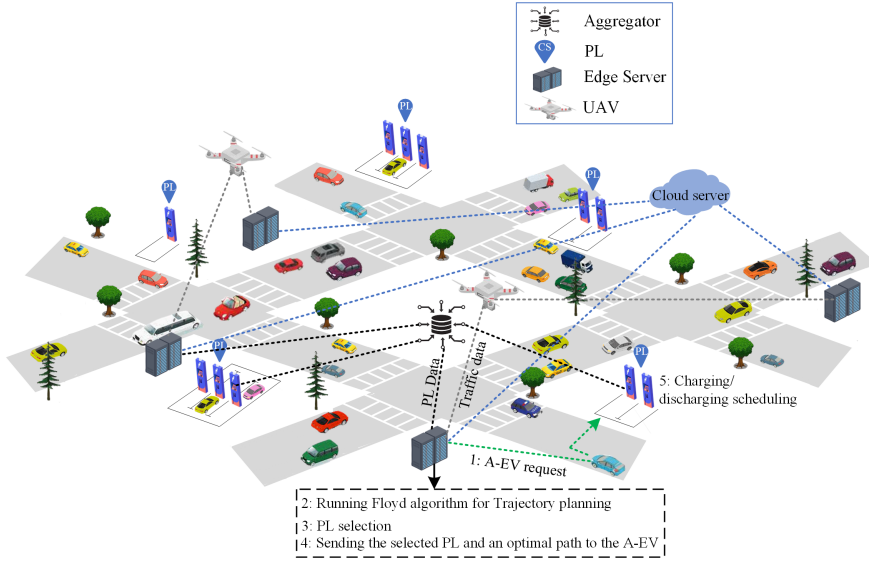


Fig. 1: The proposed system architecture

IV. PROBLEM FORMULATION

A. A-EV model

Each A-EV, from the electrical perspective, is a mobile battery energy storage system with the capacity of $B^i(kWh)$. The SoC of A-EVs' battery at each time slot $t \in \mathcal{T}$ is denoted by the following equations.

$$SoC^{i,k,t} = (1 - \beta^i)SoC^{i,k,t-1} + \eta^i \cdot e^{i,k,t} \cdot \Delta t \quad (2)$$

Where, in Eq. (2), the decision variable $e^{i,k,t}(kW)$ represents the amount of power that A-EV i receives ($e^{i,k,t} > 0$) or delivers ($e^{i,k,t} < 0$) at PL k and time slot t ; $0 \leq \beta \leq 1$ is the self-discharging coefficient and $0 \leq \eta \leq 1$ is charging efficiency. The amount of consumed energy for traveling distance $d(km)$ depends on A-EVs' motor force $F^i(kWh/km)$ and can be derived by $F^i \cdot d$.

Further, each electrical battery has operation costs $OC^{i,k,t}$ including degradation $DC^{i,k,t}$, fluctuation $FC^{i,k,t}$ and maintenance $MC^{i,k,t}$ as shown in Eq. (3). ζ_{DC}/ζ_{FC} are degradation and fluctuation costs coefficients [38]. The degradation cost has two terms to be computed which are given in Eq. (4). $DC_{Cal}^{i,k,t}$ and $DC_{Cyc}^{i,k,t}$ are related to calendar and cycle degradation costs that can be calculated via Eqs. (5) and (6), respectively. ω^i and γ^i are fitting parameters; θ_i is the battery temperature; $\alpha_1^i, \alpha_2^i, \alpha_3^i$ are fitting parameters associated with battery depth of discharging and $\beta_1^i, \beta_2^i, \beta_3^i, \beta_4^i$ are fitting parameters related to charging/discharging power. Battery fluctuation cost is due to variation of charging/discharging power during time slots which can be

obtained by Eq. (7).

$$OC^{i,k,t} = \zeta_{DC} DC^{i,k,t} + \zeta_{FC} FC^{i,k,t} + MC^{i,k,t} \quad (3)$$

$$DC^{i,k,t} = DC_{Cal}^{i,k,t} + DC_{Cyc}^{i,k,t} \quad (4)$$

$$DC_{Cal}^{i,k,t} = B^i \cdot e^{SoC^{i,k,t}/\omega^i} \cdot e^{\theta^i/\gamma^i} \cdot \sqrt{\Delta t} \quad (5)$$

$$DC_{Cyc}^{i,k,t} = [\alpha_1^i (B^i - SoC^{i,k,t})^2 + \alpha_2^i (B^i - SoC^{i,k,t}) + \alpha_3^i \cdot [\beta_1^i |e^{i,k,t}|^3 + \beta_2^i |e^{i,k,t}|^2 + \beta_3^i |e^{i,k,t}| + \beta_4^i]] \quad (6)$$

$$FC^{i,k,t} = (e^{i,k,t} - e^{i,k,t-1})^2 \quad (7)$$

B. Traveling time

In this work, weights of the matrix W in Eq. (1) are defined as traveling time since the goal is to find the nearest way to reach the parking lot in the minimum time. To do so, let $\tau_{n,m}^0$ denote the traveling time between nodes n and m without considering traffic flow and it can be calculated through Eq. (8), in which $l_{n,m}(km)$ is the associated path length and $\bar{v}_{n,m}(km/h)$ is the maximum allowed speed. However, in the real world, $\tau_{n,m}^0$ is uncertain due to traffic congestion. To cope with this issue, the Bureau of Public Roads (BPR) function, i.e., Eq. (9), is used to compute the traveling time with considering traffic flow [39], where $f_{n,m}^t$ is the traffic flow at time slot t and $f_{n,m}^{cap}$ is the capacity of the link. Accordingly, $\tau_{n,m}^t$ could be considered as weights in matrix W . Further, since the traveling time of each vehicle on roads depends on the average speed of the traffic $v_{ave}^{tr,t}(km/h)$ and the vehicle's speed $v_{ave}^{i,t}(km/h)$, the final traveling time of each vehicle is given by (10). **Indeed, traffic signals sent by UAVs impact parameters $f_{n,m}^t$ and $v_{ave}^{tr,t}$ at each time slot to capture the real-time traffic flow and average traffic speed, respectively. According to the BPR function, by increasing the number of vehicles in roads, the traffic flow ($f_{n,m}^t$) increases and subsequently the traveling time goes up.**

$$\tau_{n,m}^0 = \frac{l_{n,m}}{\bar{v}_{n,m}} \quad (8)$$

$$\tau_{n,m}^t = \tau_{n,m}^0 [1 + 0.15 (\frac{f_{n,m}^t}{f_{n,m}^{cap}})^4] \quad (9)$$

$$\tau_{n,m}^{i,t} = \tau_{n,m}^t \times \frac{v_{ave}^{tr,t}}{v_{ave}^{i,t}} \quad (10)$$

C. Waiting time at PLs

Since the waiting time is highly contributed to user satisfaction, it is taken into consideration in this work. Waiting time is the time that an A-EV must be wait to receive charging/discharging service. The waiting time of each PL at time t is denoted by $T^{i,k,t}(h)$ and is equal to the minimum of the duration time of the connected A-EVs which is given by Eq. (11).

$$T^{i,k,t} = \min \{x^{i,k,t}(D^{i,k} - t)\} \quad (11)$$

D. Energy utility pricing

Among a lot of pricing models in the literature, the real-time pricing (RTP) policy has been well-accepted since as it can generate quite fair prices based on the current load to motivate A-EVs to get a roll in grid response programs [40]. To do so, Eq. (12) is used when the load on the power grid is positive, which is a linear function of load. a_0^k (\$kWh) and a_1^k (\$kWh/kW) are intercept and slope coefficients, respectively. For the negative loads, Eq. (13) is used, which denotes the energy-buyback step pricing model. This pricing policy motivates A-EVs to sell their surplus energy to the power grid in negative load periods and achieve a high amount of profit. m^k (kW) and δ^k (\$/kWh) are step length and incremental price in this relation, respectively. Also, $z^{k,t}$ in both equations represents the load on parking lots that is given by Eq. (14), where $L^{k,t}$ (kW) is the base load and $x^{i,k,t}$ is a binary decision variable that indicates A-EVs assignment to parking lots, i.e., $x^{i,k,t} = 1$ means A-EV i has selected PL k .

$$p_z^{k,t} = a_0^k + a_1^k z^{k,t} \quad (12)$$

$$p_z^{k,t} = (|z^{k,t}|/m^k)\delta^k \quad (13)$$

$$z^{k,t} = L^{k,t} + \sum_{i \in \mathcal{I}} x^{i,k,t} \cdot e^{i,k,t} \quad (14)$$

E. Multi-objective function

The multi-objective function of the proposed model is the minimization of the weighted sum of the normalized cost and waiting time as formulated through Eq. (15). Since $Cost$ (\$) and $T^{k,t}(h)$ have different units, their normalized term, i.e., \widetilde{Cost} and $\widetilde{T}^{k,t}$, are used in the objective function. Accordingly, decision making, in addition to the cost, depends on waiting time which contributes to user satisfaction. $0 \leq \phi \leq 1$ is the weight parameter. By increasing the value of ϕ , the cost term becomes prior to the waiting time where $\phi = 1$ indicates the waiting time is ignored and the decision making completely depends on cost. In contrast, for lower ϕ , the waiting time is prior to the cost and for $\phi = 0$ the impact of cost is neglected. The $Cost$ term is defined as Eq. (16). The revenue of each A-EV is computed by integrating over price given by Eq.

(17). Constraints of the problem are defined through (14) and (18)-(27). Eq. (18) states the non-preemptive assignment of A-EVs to PLs and ensures that A-EVs are allocated to the same PL during their service. Eqs. (19)-(20) state that every A-EV must be allocated to a PL and cannot be allocated to more than one PL. Eq. (21) limits the number of allocated A-EVs to the PLs according to their capacity. At the end of the service, each A-EV's demand must be met and must not exceed its battery capacity, which is considered using Eqs. (22)-(23). The rate of the charging/discharging of A-EVs must be limited according to physical issues and in this work, these constraints are taken into consideration by (24)-(26). Finally, Eq. (27) calculates each A-EVs' SoC at the time of arriving to the PLs.

$$of : \min \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} [\phi \widetilde{Cost} + (1 - \phi) x^{i,k,t} \cdot \widetilde{T}^{i,k,t}] \quad (15)$$

$$Cost^{i,k,t} = x^{i,k,t} [OC^{i,k,t} - Revenue^{i,k,t}] \quad (16)$$

$$Revenue^{i,k,t} = - \int_{z^{k,t}}^{z^{k,t} + e^{i,k,t}} p_z^{k,t} dz \quad (17)$$

subject to

Eq. (14)

$$\sum_{t=A^{i,k}}^{D^{i,k}} x^{i,k,t} = \{0, V_i\}; \quad \forall i \in \mathcal{I}, \forall k \in \mathcal{K} \quad (18)$$

$$\sum_{k \in \mathcal{K}} \sum_{t=A^{i,k}}^{D^{i,k}} x^{i,k,t} \geq 1; \quad \forall i \in \mathcal{I} \quad (19)$$

$$x^{i,k,t} \cdot x^{i,k',t'} = 0; \quad \forall k \neq k' \in \mathcal{K}, A^{i,k} \leq t \leq D^{i,k}, A^{i,k'} \leq t' \leq D^{i,k'} \quad (20)$$

$$\sum_{i \in \mathcal{I}} x^{i,k,t} \leq \overline{C}^k; \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (21)$$

$$\sum_{k \in \mathcal{K}} x^{i,k,t=A^{i,k}} \cdot [SoC_{ini}^{i,k} + \sum_{t=A^{i,k}}^{D^{i,k}} x^{i,k,t} \cdot e^{i,k,t}] = SoC_{fin}^i \quad (22)$$

$$0 \leq SoC_{ini}^{i,k} + \sum_{t=A^{i,k}}^{D^{i,k}} x^{i,k,t} \cdot e^{i,k,t} \leq B^i / \Delta t; \quad \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, A^{i,k} \leq t \leq D^{i,k} \quad (23)$$

$$0 \leq e^{i,k,t} \leq \overline{P}_{chr}^i; \quad \forall i \in \mathcal{I}^{CHG}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (24)$$

$$-\overline{P}_{dch}^i \leq e^{i,k,t} \leq 0; \quad \forall i \in \mathcal{I}^{DCG}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (25)$$

$$-\overline{P}_{dch}^i \leq e^{i,k,t} \leq \overline{P}_{chr}^i; \quad \forall i \in \mathcal{I}^{V2G}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (26)$$

$$SoC_{ini}^{i,k} = SoC^i - F^i \cdot d^{i,k}; \quad \forall i \in \mathcal{I}, \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \quad (27)$$

V. ONLINE GREEDY-BASED SOLUTION APPROACH

A. Algorithm design

The proposed MINLP is intractable due to the binary variable associated with A-EVs allocation to PLs. On the one hand, standard solvers could not be used because the problem is non-convex. On the other hand, the hybrid approach of branch and bound along with linear relaxation programming still infeasible to apply since the high number of A-EVs and time slots incurred computationally burden. Moreover, unavailability of future data in real-time implementation makes the branch and bound infeasible as well. Hence, in order to overcome these issues, a greedy-based algorithm is designed as Algorithm 1.

At each time slot t , at first, A-EVs send their request for edge servers. Some initial data including location, SoC level and technical data of battery is transmitted to a nearby edge server. All the calculations regarding trajectory planning and scheduling are based on the initial location that has been sent to the edge servers and since the greedy algorithm is a fast-response algorithm, being on-road while the edge servers process the request for A-EVs does not affect the traveling time and trajectory planning. Edge servers execute the Floyd algorithm by receiving data from the UAVs to find the nearest paths to PLs from every node in the transportation system based on the hourly traffic congestion inroads (line 4). Then, for each A-EV i that submits a request, all the related data including location, battery details, initial and final SoC, arrival and departure time and motor force are transmitted to the nearby edge server (lines 5-7). At the next step, the edge server contact with the aggregators to receive PLs data including load, capacity, traffic and prices (lines 8-12). After that, the edge server checks which PLs could be reached by the A-EV according to the A-EV's initial SoC (line 14). Then, the edge server computes the waiting time of the A-EV at each reachable PL based on the received data from the corresponded aggregator (line 15). The following step is executing heuristics according to the A-EV type which is described in the following.

As shown in the algorithm, there are three heuristics according to the A-EV type that are executed during the procedure, i.e., $cost_charging^{i,k}$, $cost_discharging^{i,k}$, $cost_V2G^{i,k}$. These heuristics are solved to determine the incurred cost at candidate PLs if the A-EV has been assigned to them. In $cost_charging^{i,k}$, the charging demand of A-EV is divided equally between available time slots as Eq. (28). Then, the amount of charging power at each time slot is updated based on the power price at that time slot and the average power price during the interval through consecutive iterations, in which the number of iterations is equal to the time slots in the interval, i.e., $A^{i,k} \leq t \leq D^{i,k}$. At the next phase, at each time slot $A^{i,k} \leq t' \leq D^{i,k}$ Eq. (29) is used to update the charging power, where $Ph_t^{i,k,t'}$ is the charging power at time slot t' and iteration t and

p_z^{ave} is the average of the price at charging interval. In Eq. (29), relation I is a coefficient in which it increases if the price at the time slot t' is less than the average, and decreases whenever the price at the current time slot is higher than the average. Therefore, in addition to the load, the price is also updated at each iteration for use in the next iteration. At the end of the last iteration, the algorithm sets $e_{initial}^{i,k,t} = \Phi_{D^i}^{i,k,t}$; $\forall A^i \leq t \leq D^i$. A similar procedure is executed for $cost_discharging^{i,k}$ with the only difference in updating of power, in which in the discharging case if the price at a time slot is lower than the average, the discharging power decreases, and the reverse action occurs if the price is higher than the average. For the $cost_V2G^{i,k}$, if the A-EV has been applied to charging mode, then the $cost_charging^{i,k}$ procedure is taken into consideration and if it has been applied in the discharging mode, the $cost_discharging^{i,k}$ will be operated.

$$\frac{SoC_{fin}^i - SoC^{i,t=A^i,k}}{D^{i,k} - A^{i,k}} \quad (28)$$

$$\Phi_t^{i,k,t'} = \begin{cases} \left[\frac{p_z^{ave} - (p_z^{k,t'})}{p_z^{ave}} \right] \Phi_{t-1}^{i,k,t'}; & A^{i,k} \leq t' \leq t \\ \frac{SoC_{fin}^i - SoC^{i,t=A^i,k} - \sum_{t''=A^{i,k}}^t \Phi_t^{i,k,t''}}{D^{i,k} - t}; & t \leq t' \leq D^{i,k} \end{cases} \quad (29)$$

After completing the algorithm, a target PL is selected for each A-EV. It means that the binary variable $x^{i,k,t}$ associated with PL assignment is already relaxed and the remained problem is an NLP with a decision variable $e^{i,k,t}$. To determine this variable, i.e., the actual amount of charging/discharging power at each time slot, a local optimizer considering power grid ancillary services has been taken into consideration as below:

$$\min \left[\sqrt{\frac{1}{D^{i,k} - A^{i,k}} \sum_{t'=A^{i,k'}}^{D^{i,k'}} (z^{kt'} + e_{actual}^{i,k,t'} - \bar{z}^{k'})^2} \right] \quad (30)$$

subject to Eqs. (23)-(29)

Indeed, the objective function of (30) is the root mean square deviation and tries to minimize the deviation of the final load from the average load which is totally in accord with power grid ancillary services.

B. Complexity and optimality

At each time slot, first of all, the Floyd algorithm is run, which has the complexity of $O(|\mathcal{M}|^3)$. Considering that every A-EV sends a request for receiving service, it takes complexity with third order, i.e., $O(|\mathcal{T}|^3)$. Since there are $|S|$ edge servers, the selection of PLs using a linear function adds complexity $O(|\mathcal{I}|/|S|)$. Also, solving the local optimization problem in (30) yields a complexity of $O(|\mathcal{T}|\sqrt{|\mathcal{T}|})$. All in all, the

Algorithm 1 The proposed greedy-based algorithm for the Edge-UAV problem

Data: Set of A-EVs, edge servers, UAVs, PLs, aggregators, A-EVs' data (location, battery details, $SoC^{i,t}, SoC_{fin}^i, F$, PLs' data from aggregators ($z^{k,t}, L^{k,t}, \bar{C}^k, a_0^k, a_1^k, m_k, \delta_k$), traffic data from UAVs

Result: $x_{i,k,t}, e_{i,k,t}$ and a path to the target PL

```

for each time slot  $t \in \mathcal{T}$  do
  run the Floyd algorithm and extract successor matrix;
  for each A-EV  $i \in \mathcal{I}$  do
    if A-EV  $i$  submits a request for charging/discharging then
      send A-EV's request and data to the nearby edge servers  $s \in \mathcal{S}$ ;
      for each aggregator  $g \in \mathcal{G}$  do
        for each PL  $k \in C_g$  do
          | send PLs data to the edge servers
        end
      end
      for every nearby PL  $s \in \mathcal{S}$  do
        if  $SoC^{i,t} - F^i \cdot d^{i,k} \geq 0$  then
          | calculate  $T^{i,k,t}$ ;
          | if  $i \in \mathcal{I}^{CHG}$  then
          | | run  $cost\_charging^{i,k}$ ;
          | else
          | | if  $i \in \mathcal{I}^{DSG}$  then
          | | | run  $cost\_discharging^{i,k}$ ;
          | | else
          | | | run  $cost\_V2G^{i,k}$ ;
          | | end
          | end
          | calculate  $e\_initial^{i,k,t}$ ;
        end
      end
       $x^{i,k,t} \leftarrow \arg \min [\phi \widetilde{Cost} + (1 - \phi) x^{i,k,t} \cdot \widetilde{T}^{i,k,t}]$ ;
      run local optimizer (30) s.t. (23)-(29);
       $e\_actual^{i,k,t} \leftarrow \arg \min \left[ \sqrt{\frac{1}{D^i - A^i} \sum_{t'=A^i, k'}^{D^i, k'} (z^{kt'} + e\_actual^{i,k't'} - \bar{z}^{k'})^2} \right]$ ;
      update  $z^{k,t}, p_z^{k,t}$ 
    end
  end
end

```

whole complexity of the problem is $O(|\mathcal{T}| \cdot |\mathcal{M}|^3 + |\mathcal{T}| \frac{|\mathcal{I}|}{|\mathcal{S}|} (|\mathcal{T}|^3 + \frac{|\mathcal{K}|}{|\mathcal{S}|} + |\mathcal{T}| \sqrt{|\mathcal{T}|})$. Compared to the central cloud-based system, which is $O(|\mathcal{T}| \cdot |\mathcal{M}|^3 + |\mathcal{T}| \cdot |\mathcal{I}| (|\mathcal{T}|^3 + |\mathcal{K}| + |\mathcal{T}| \sqrt{|\mathcal{T}|})$ the complexity has considerably reduced and the scalability of the system increases.

As stated in section V-A, a greedy-based algorithm solves the PL selection problem. Since the greedy-based algorithm has been designed using heuristics, a globally optimal solution cannot be achieved, therefore, the proposed algorithm provides a sub-optimal solution. Let ρ_1, ρ_2, ρ_3 denote approximation factors for, respectively, optimal trajectory planning, PL selection based on the greedy-based algorithm and charging/discharging power scheduling at each time slot. Regarding the first part, the Floyd algorithm has been used and the

optimality has been guaranteed. For the second part, the problem could be devoted to identical machines as a minimum makespan scheduling problem that the upper bound for such problem is equal to 2 [41]. In addition, as for the charging/discharging scheduling part a standard solver is employed, $\rho_1 = \rho_3 = 1$. Therefore, the existing optimality gap is not greater than $\rho \leq \rho_1 \cdot \rho_2 \cdot \rho_3 = 2$ and the results are reasonable.

VI. RESULTS AND DISCUSSION

A. Simulation setup

The presented Edge-UAV-assisted online trajectory planning and charging scheduling of A-EVs is rendered on the Sioux Falls transportation network (TN). The test system, which has been shown in Fig. 2, comprised 24 nodes and 76 links between nodes. The full data of the TN parameters and daily origin-destination trip demand is available in [42]. Further, the hourly traffic pattern, as depicted in Fig. 3-a, has been extracted from [43]. In this work, the distances between nodes have been quadrupled and the daily demand has been scaled up 8 times. It is assumed that five edge servers are installed beside the cellular base stations which cover an area with a radius of 10 km based on the LoRaWAN communication technology for urban areas. In addition, five aggregators and 12 parking lots have been considered and the average initial load of PLs is illustrated in Fig. 3-b. The proposed problem is run for 1000 on-move A-EVs, which are randomly distributed in the TN. Six different types of A-EVs are considered in the simulation with the battery details same as Table III. The data in this table is belong to popular existing EVs' batteries and has been obtained from [44]. The temperature of batteries is a random selection from the uniform interval $U[-20^\circ\text{C}, 60^\circ\text{C}]$. The fitting parameters of the degradation and calendar costs are $\omega^i = -3.8898$, $\gamma^i = -6.9242$, $\alpha_1^i = 4.24 \times 10^{-8}$, $\alpha_2^i = -4.24 \times 10^{-7}$, $\alpha_3^i = 8.2 \times 10^{-6}$, $\beta_1^i = -1.2$, $\beta_2^i = 3.84$, $\beta_3^i = -2.3$, $\beta_4^i = 0.66$, which they have been derived from [45] based on experimental results. It is noted that fitting parameters have been considered the same for all A-EVs. Coefficients of degradation and fluctuation costs are considered $\zeta_{DC} = 1 \times 10^{-3}$ and $\zeta^{FC} = \times 2 \times 10^{-3}$ according to the ref. [38]. Moreover, maintenance costs could be obtained from the interval $U[\$0.3, \$0.5]$ [2]. Regarding energy utility pricing parameters, the linear pricing parameters is selected from the uniform interval $a_0^k \in U[10^{-3} - 5 \times 10^{-4}, 10^{-3} + 5 \times 10^{-4}]$ and $a_1^k \in U[2 \times 10^{-3} - 5 \times 10^{-4}, 2 \times 10^{-3} + 5 \times 10^{-4}]$ whereas the step length and incremental coefficients in the energy-buyback step pricing model are selected from form the uniform intervals $m^k \in U[5\text{kW}, 10\text{kW}]$ and $\delta^k \in U[\$/\text{kWh}0.1, \$/\text{kWh}0.3]$, respectively [12]. Table II shows charging levels according to SAE J1772 standard [44]. Among different charging levels, charging level I is inefficient for smart charging which the charging power is adjusted at each time slot. Moreover, using this charging level A-EVs cannot be fully charged in public parking lots and it is suitable for residential cases. Charging level III is not available at standard parking lots due to the high current rate

TABLE II: Charging levels based on SAE J1772 standard

Charging level	Voltage (V)	Power (kW)
Level I (AC)	120	1.44-1.92
Level II (AC)	240	Up to 19.2
Level III (DC)	200-450	Up to 36

TABLE III: Battery details of considered A-EVs

A-EV type	Battery type	Battery capacity B^i (kW)	Electric motor force F^i (kWh/mile)
I	Lithium-ion	75.0	0.33
II	Lithium-ion	75.0	0.34
III	Lithium-ion	30.0	0.28
IV	Lithium-ion	90.0	0.36
V	Lithium-ion	35.0	0.26
VI	Lithium-polymer	30.5	0.27

as the power distribution system cannot supply this current rate. However, charging level II is most suitable for PLs and can be implemented at the power distribution level easily. Therefore, in this work, it is assumed that all the considered PLs supply charging level II with the maximum charging power of 19.2 kW [44]. All simulations have been conducted in a PC with Intel® Core™ i7-4710HQ CPU @ 2.5 GHz and 8GB RAM using MATLAB R2019b, which the CVX package has been used for solving the local optimizer. The following metrics are used for comparison:

- **Average cost:** One of the important factors in PL selection is charging/discharging cost. Therefore, the average cost of charging/discharging service of vehicles is reported as an evaluation metric. This metric is the ratio of the summation of all A-EVs total cost to the number of A-EVs.
- **Average waiting time:** This metric reports the average waiting time of A-EVs at PLs as the waiting time of PLs directly affects the best PL selection. This metric is the ratio of the summation of all A-EVs waiting time to the number of A-EVs.
- **Average Traveling time:** In trajectory planning, average traveling time is one of the user satisfaction and it is reported as a comparison criterion. This metric is the ratio of the summation of the traveling time of all A-EVs to the number of A-EVs.
- **Average Traveling distance:** This metric is also reported since contributes to user satisfaction in trajectory planning. This metric is the ratio of the summation of the traveling distance of all A-EVs to the number of A-EVs.

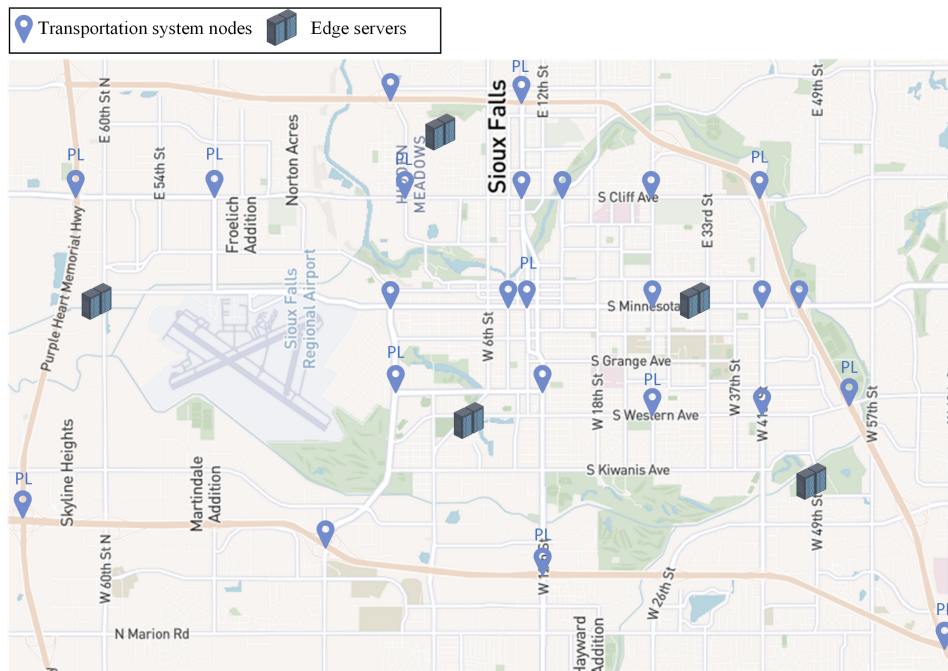


Fig. 2: The test system based on the Sioux Falls transportation network

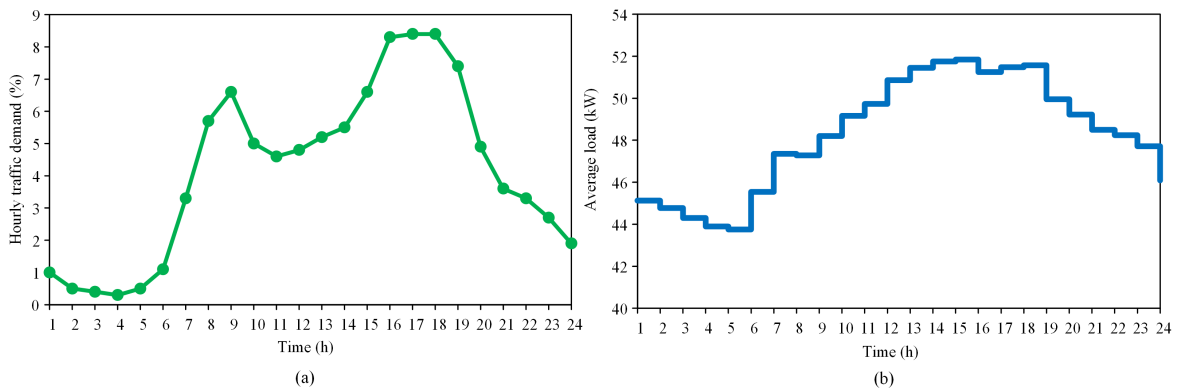


Fig. 3: (a) Hourly traffic pattern (b) Hourly average load

B. Simulation result

1) Impact of the weighting factor

In this part, the impact of the weighting factor (ϕ) on the decision-making of PL selection for A-EVs is evaluated. To do so, the problem has been run for different values of ϕ starting from 0 to 1 with 0.1 intervals. The obtained results have been depicted in Fig. 4. In general, by increasing the value of the weighting factor, the average cost decreases, and the average waiting time of PLs increases. As can be seen, the maximum amount of the average cost, which is \$1.636, and the minimum amount of the average waiting time, which is 10.00 min are occurred for $\phi = 0$, which the PL selection is completely based on the waiting time of

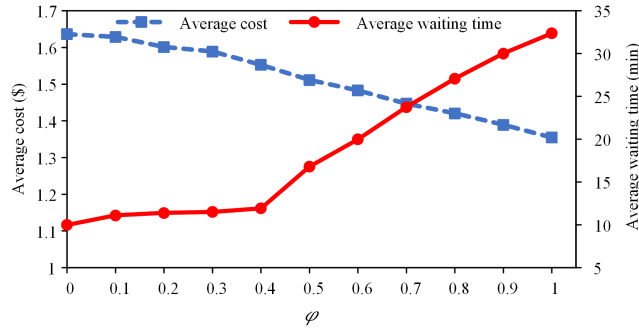


Fig. 4: Average cost and waiting time for different values of the weighting parameter

PLs and the cost term has been ignored. By increasing the amount of ϕ , the average cost declines and the weighting time climbs as the decision making is going to be based on the cost for $\phi = 1$. At this point, the average cost is fallen to \$1.354 with \$0.282 drop, where the waiting time witnesses its maximum at 32.37 min with a 22.37 min growth. Although this is a multi-objective problem and a compromise could be derived for objectives, the decision-maker, i.e., edge-servers, lets users submit their preferences over time and cost in an online platform since in the real-world different users might have different preferences.

2) Trajectory planning

As mentioned before, the trajectory planning is carried out based on traveling time considering traffic flow. However, as various strategies have been proposed in different works for trajectory planning, such as in [13], [22] that traveling time has been taken into consideration without considering traffic flow, in this section, different strategies including trajectory planning based on traveling time with considering traffic flow, trajectory planning based on traveling time without traffic flow and trajectory planning based on roads' length are compared. First of all, as can be seen from Fig. 5 waiting time for all strategies remained the same since the trajectory planning only deals with path selection for target PLs and does not affect the waiting time of PLs. However, the average cost slightly falls for the second and third strategies. This is because, in the trajectory planning based on traveling time with traffic flow, the edge servers guide A-EVs to the PLs through less congested paths. Hence, this issue leads to a drop in the SoC level of A-EVs while arriving at the PLs.

In order to provide a comprehensive result Table IV is provided for $\phi = 1$. As enumerated, average cost, average traveling time and average distance have reached, respectively, \$1.354, 17.25 min and 14.49 km. Although all these parameters have decreased in the case without considering traffic, these results are unrealistic because in real-world traffic has a great impact on traveling time. Further, in the third strategy, the average cost has decreased because of less traveling distance; however, the average traveling time rose. Compared with the first strategy, the average cost reduction is negligible, where the increment of average

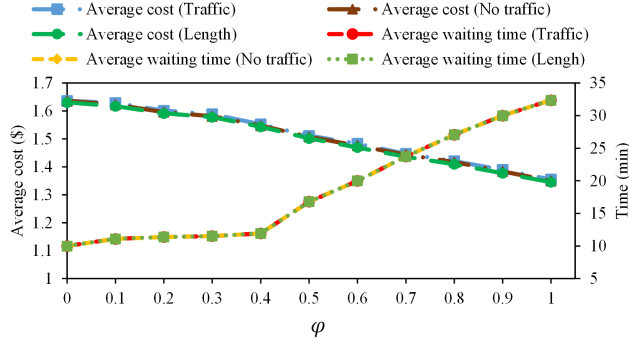


Fig. 5: Impact of the different strategies for trajectory planning

TABLE IV: Comparison of different strategies in trajectory planning for $\phi = 1$

Strategies	Average cost (\$)	Average traveling time (min)	Average traveling distance (km)
Traveling time considering traffic	1.345	17.25	14.49
Traveling time without traffic	1.349	15.3	14.15
Length	1.45	17.84	14.07

traveling time is nearly 1 min per A-EV. Indeed, by employing a decentralized platform using edge servers, A-EVs are guided to nearby PLs which are close to physical distance. Hence, the important factor for trajectory planning is traveling time by considering the traffic flow, which has reached 17.25 min per A-EV, which could improve user satisfaction. Moreover, in doing so, there is no need for considering multiple weightings by adding weighting factors in trajectory planning like ref. [13] since tuning these factors is another complex issue.

3) Impact of the V2G

In this subsection, the impact of the V2G is evaluated in two respects. Firstly, in Fig. 6, variation of load in two of the most congested PLs has been demonstrated for $\phi = 1$. Overall, by increasing the percentage of the V2G participants, the load of the PLs during off-peak hours goes up and during on-peak hours goes down. For instance, in Fig. 6-(a), during hours $t = 2 - 5, 10, 17 - 18, 23 - 24$ load of the PL has been climbed and during hours $t = 6 - 9, 11 - 16, 19 - 20$ it has been declined. The main reason is V2G capable A-EVs act like energy storage systems that are available for a specific time period. Hence, they can be applied in charging mode during off-peak hours and then discharged during on-peak hours. A similar pattern is obvious for Fig. 6-(b) that during $t = 2 - 5, 17 - 24$ load has been increased and during a period between $t = 7 - 16$ has been decreased.

Accordingly, the V2G ability assists the power grid in peak load reduction which provides ancillary service for the grid. On the other hand, providing ancillary services for the grid benefits V2G in economic terms.

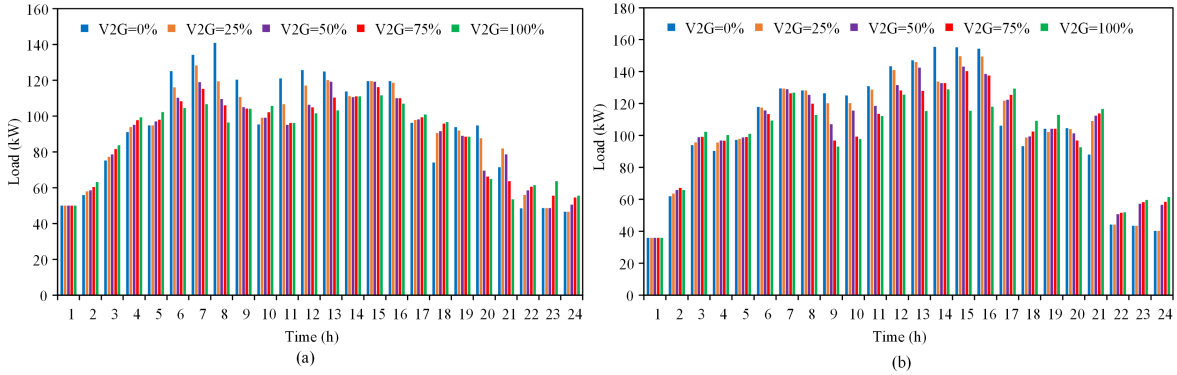


Fig. 6: Impact of the V2G ability on loads of (a) PL#6 (b) PL#9 for $\phi = 1$

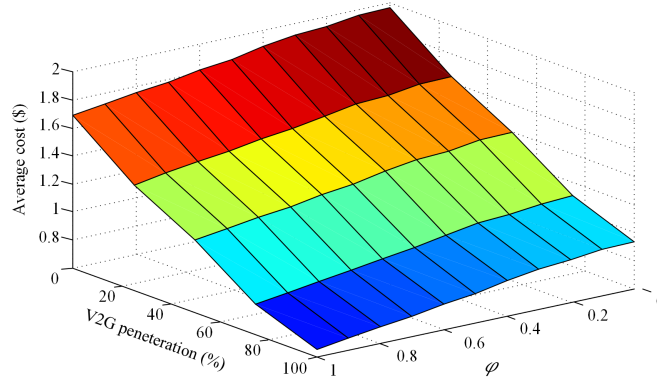


Fig. 7: Impact of the V2G ability on the average cost

A-EVs by charging during off-peak periods, in which the electricity price is low, and discharging during on-peak hours, when the electricity price is high, gain benefits to reduce their costs. Fig. 7 illustrates the average cost concerning the percentage of V2G participants and the weighting factor. As can be seen, by increasing the V2G participants, the average cost has a downward pattern, in which the minimum achievable average cost is \$0.656 (about 61.15% reduction) for $\phi = 1$ and 100% V2G participants. Therefore, the V2G can provide a win-win outcome for the both power grid and A-EVs in an online scheduling platform in light of the proposed algorithm.

4) Impact of the local optimizer

After allocating an A-EV to a PL the charging/discharging scheduling of the A-EV is scheduled using a local optimizer. To show the positive impact of the local optimizer, Fig. 8-(a) has been provided. In this figure, the average final load in the presence of the local optimizer and without the local optimizer has been depicted. Accordingly, the flatness of the load, meaning how much deviation the load has from its average, by implementing the local optimizer is improved about 12.42% compared with the non-local optimizer case

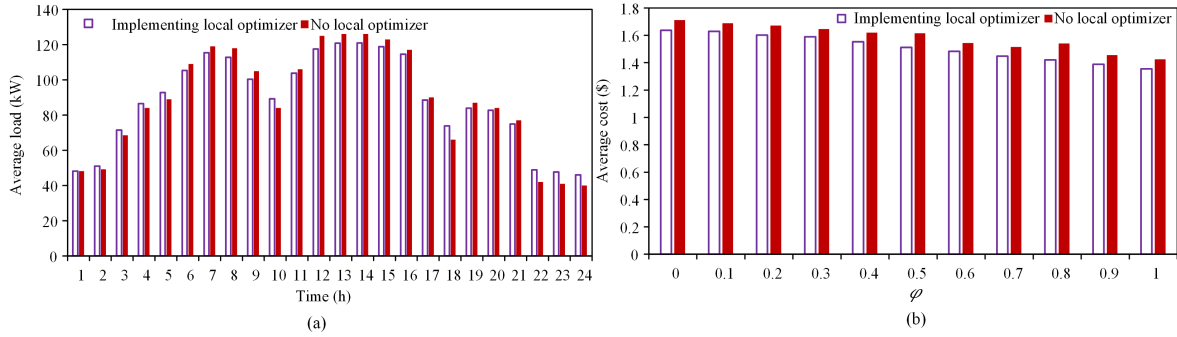


Fig. 8: Impact of the local optimizer on the (a) average final load for $\phi = 0.5$ and (b) average cost

on the ground that the local optimizer, for example in the charging scheduling, reduces the charging power during the on-peak hours and increases the charging power during the off-peak hours. Furthermore, the average cost for the different amounts of weighting factors by implementing the local optimizer and without the local optimizer has been compared in Fig. 8-(b). As shown in the illustration, employing the proposed local optimizer brings economic benefits for A-EVs because of the mentioned reason for the load as the price is a function of the load. Therefore, it can be concluded that the local optimizer has the potential to provide both fiscal and non-fiscal benefits.

5) Comparison with other works

In this subsection, the current work is compared with other works in terms of the defined metrics. To do so, two different strategies are defined: 1- Random selection: in this strategy, which has been employed in [46], A-EVs are guided to nearby PLs randomly after submitting their requests. 2- Near PL allocation: in this strategy, which has been used in [47], A-EVs are guided to the nearest PLs in terms of traveling time. The comparison is conducted for different numbers of A-EVs. It is noted that in the comparison, in the proposed Edge-UAV model, the weighting factor is set to $\phi = 0.5$.

The obtained results for comparison have been depicted in Fig. 9. In terms of the average cost, as can be seen in Fig. 9-(a), by using the proposed Edge-UAV algorithm for PL selection, the average cost is lower than the other two strategies. It can be clearly observed that the Edge-UAV achieves a noticeable reduction in average cost by \$0.289 (19.17%) compared to Random selection and by \$0.425 (28.17%) compared to the Near selection methods. By increasing the number of A-EVs, the reduction has reached \$1.170 (30.65%) between the proposed and Random methods as well as \$0.997 (26.11%) between the proposed and Near methods.

In terms of average waiting time, which is shown in Fig. 9-(b), the proposed method outperforms other methods. For 1000 A-EVs, the average waiting time for the proposed method is 16.806 min; however, this

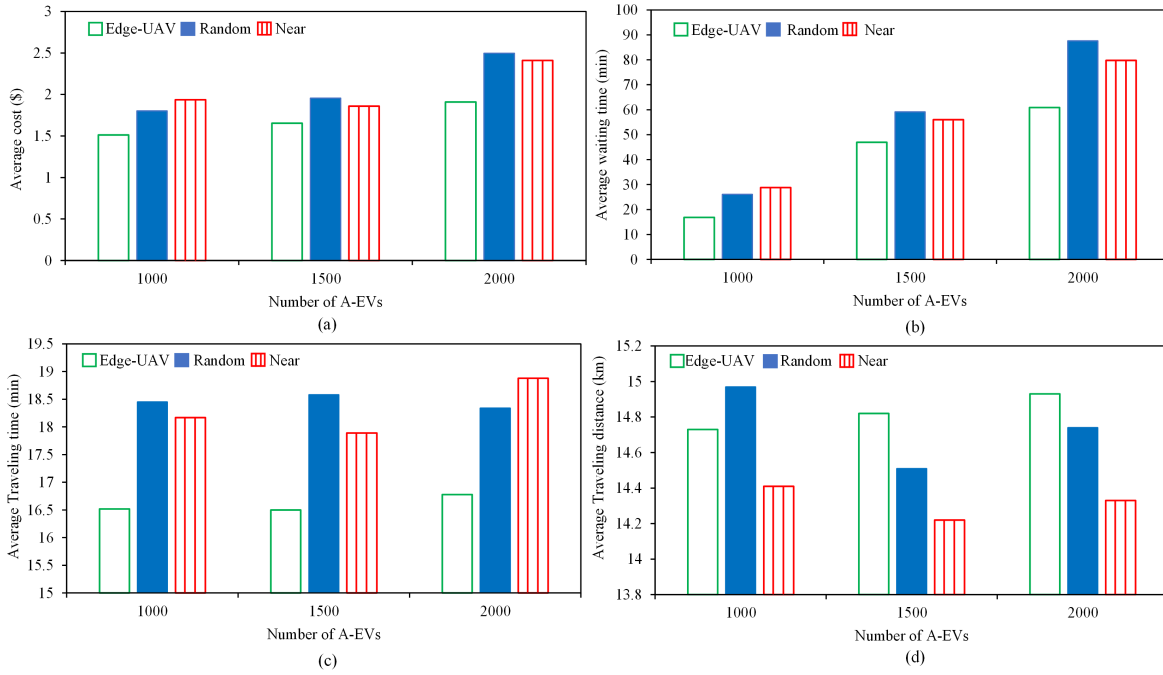


Fig. 9: Comparison of the edge-UAV with other works in terms of (a) average cost (b) average waiting time (c) average traveling time (d) average traveling distance

amount for the Random and Near methods is 26.04 min and 28.752 min, respectively. By rising the number of A-EVs, the average waiting time in PLs is rose as the PLs host more A-EVs. In the case of Edge-UAV, the growth is 44.094 min; however, for Random and Near methods, this amount is 61.56 min and 51.04, respectively. Considering the limited capacity of PLs in the real world, PLs could be very congested in Ransom and Near methods for the higher number of A-EVs which this issue decreases user satisfaction since they should wait for long hours to receive charging services; however, this could be handled in the proposed Edge-UAV method.

Moreover, looking at Fig. 9-(c), it can be perceived that the minimum average traveling time is achieved in the proposed Edge-UAV method because employing UAVs for traffic monitoring in trajectory planning has been ignored in other methods. Yet, in order to minimize the traveling time, A-EVs might be guided through longer paths as shown in Figure 9-(d). Although average traveling distance is increased in the Edge-UAV method and A-EVs witness a drop in their SoC levels, it does not have a great impact on their cost compared to other methods as shown in Fig. 9-(a). The reason is the cost term has been included in the PL selection and the best PL is selected for A-EVs considering their costs. However, in the other two methods cost and traffic have not been considered neither in PL selection nor trajectory planning.

6) Edge-UAV performance comparison with the cloud-based system

In order to compare the proposed decentralized Edge-UAV model with the centralized cloud-based system, the waiting factor is set to $\phi = 0.5$. The performance of both systems is evaluated in four terms including average cost, average waiting time, average traveling time and average traveling distance.

As shown in Fig. 10-(a), the performance of the cloud-based system is better than the edge-UAV system in terms of average cost. For 1000 A-EVs, the cloud-based system could reach \$0.096 (6.8%) less cost than the edge-UAV system. This amount for 2000 A-EVs increased to \$0.204 (5.6%). The reason is in the cloud-based system, all the PLs data is available to the central operator. Therefore, the target PLs are selected among all PLs which leads to a reduction in the average cost. For the same reason, the average waiting time is decreased in the cloud-based system as demonstrated in Fig. 10-(b). For 1000 A-EVs, the average waiting time in the cloud-based system is 14.7 min while in the Edge-UAV system is 16.806 min since the decentralized system is selecting target PLs among a limited number of PLs. However, in terms of average traveling time and average traveling distance, the performance of the cloud-based system is worse than the Edge-UAV system. The traveling time, as shown in Fig. 10-(c), is increased dramatically in the cloud-based system. For 1000 and 2000 A-EVs, the average traveling time for the cloud-based system is 18.4 min and 19.6 min, respectively. However, these values for the edge-UAV system are 16.52 min and 16.78 min, respectively. Further, the average traveling distance is grown in the cloud-based system compared to the edge-UAV system as depicted in Fig. 10-(d). The average traveling distance witnessed a rise of about 1.67 km and 4.52 km for 1000 and 2000 A-EVs, respectively. The reason for increasing the average traveling time and average traveling distance in the cloud-based system is that the cloud-based system for reducing the objective function, i.e., cost and waiting time, might select some PLs as target PLs for A-EVs which are far away. In other words, the traveling time and traveling distance are sacrificed to reach less cost and waiting time. Another notable point is that by looking closely at Fig. 10-(c) and (d), by increasing the number of A-EVs, the average traveling time and average traveling distance are still very close to each other since nearby PLs are selected for A-EVs. However, in the cloud-based system, they have ascending pattern which reduces user satisfaction.

In order to improve the performance of the edge-UAV system for reaching better results in terms of cost and waiting time, increasing the number of aggregators is a feasible solution. Fig. 11 shows the obtained results for 1000 A-EVs, weighting factor $\phi = 0.5$ and the different number of aggregators. As it is observed, by increasing the number of aggregators, the average cost and average waiting time are declined, in which for 10 aggregators, the average cost is \$1.426, and the average waiting time is 15.59 min. As can be seen, the gap is fallen in comparison with the cloud-based system. This is because by increasing the number of

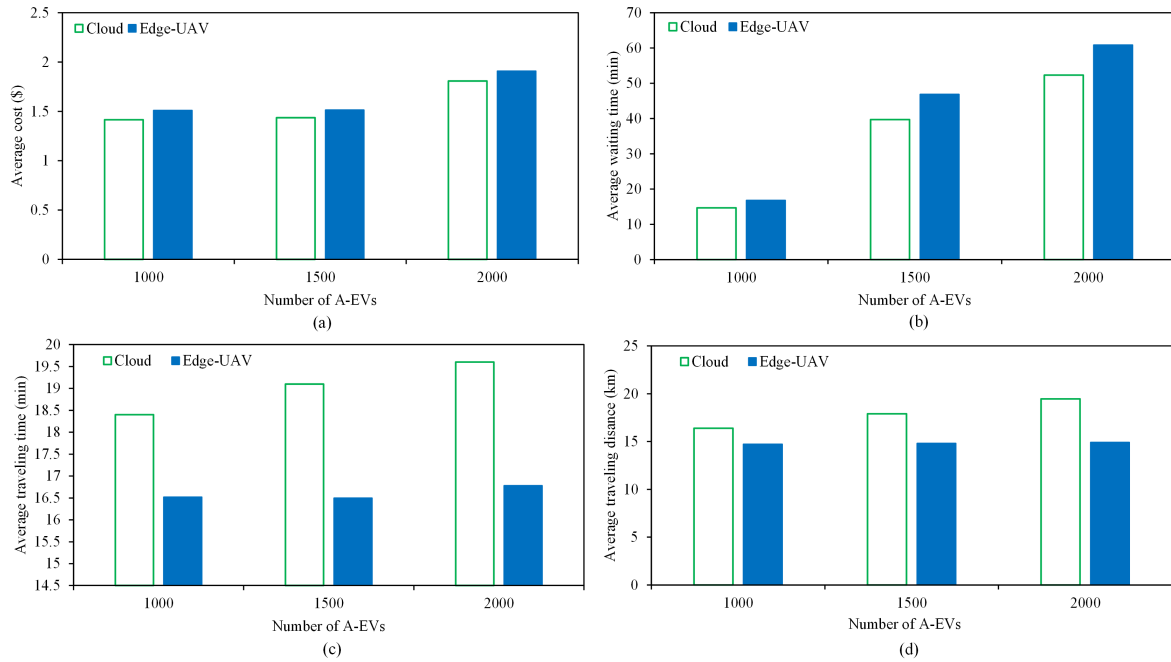


Fig. 10: Edge-UAV performance comparison with the cloud-based system in terms of (a) average cost (b) average waiting time (c) average traveling time (d) average traveling distance

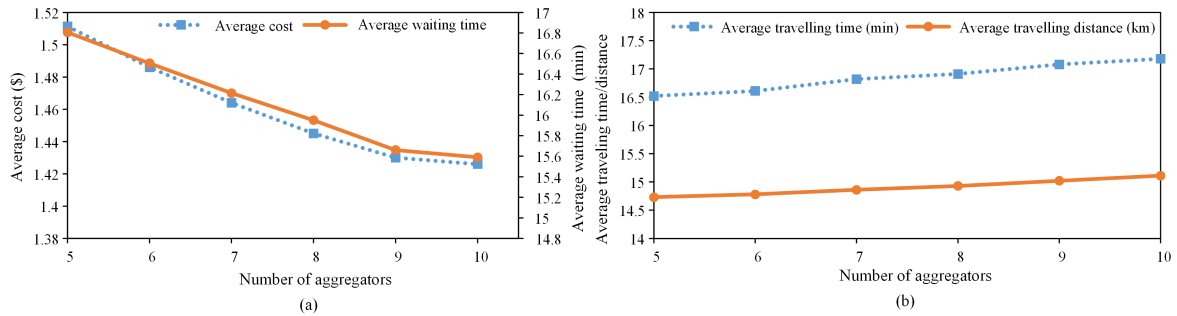


Fig. 11: Impact of the number of aggregators on (a) average cost and waiting time (b) average traveling time and average traveling distance

aggregators data of more PLs are available for edge servers. On the other hand, average traveling time and average traveling distance are gone up as more PLs are available for edge servers and edge servers might guide A-EVs to farther PLs in order to reach better objectives. In the end, Table V shows execution time for different number of A-EVs. As is obvious, the execution time of the proposed model per A-EV is less than one second which shows the applicability of the proposed model in real applications. It is noteworthy that one of the reasons for low execution time is the designed greedy-based algorithm to tackle the intractability of the MINLP.

TABLE V: Execution statistics

Number of A-EVs	Execution time (sec)	Average execution time (sec)
1000	269	0.269
1500	408	0.272
2000	543	0.272

VII. CONCLUSION

Advent of autonomous electric vehicles (A-EVs) has opened new research areas regarding trajectory planning and charging scheduling of these vehicles. The presented work aimed to introduce a hierarchical user-driven trajectory planning and charging scheduling of on-move A-EVs. The proposed trajectory planning was based on traveling time considering real-time traffic flow captured by unmanned aerial vehicles (UAVs). To improve the scalability, security and user satisfaction, the mobile edge computing (MEC) system was employed to break the central cloud-based system into multiple decentralized subsystems. Comparison with other methods revealed the superiority of the proposed model by reducing average cost by 19.17% with respect to the Random selection and 28.17% respect to the Near selection methods. Moreover, in light of using the vehicle-to-grid (V2G) ability of A-EVs, the average cost could be reduced up to 61.15% in the case of 100% V2G penetration. In addition, the proposed scheduling contributed ancillary service of the grid by improving the flatness of the load by 12.42%. In addition, the average waiting time was also reduced by about 9.2 min and 11.9 min with respect to the Random and Near methods, respectively. Finally, the performance evaluation of the proposed Edge-UAV system with the cloud-based system showed that although the performance of the cloud-based system is better than the proposed edge-UAV system by about 6.8% in average cost, using the edge-UAV system improves user satisfaction in terms of traveling distance and traveling time by 1.67 km and 1.88 min, respectively.

Future research could be focused on concerning cyber-security and uncertainty associated with data transmission of an Edge-UAV system. Moreover, considering different types of PLs such as disabled and special needs PLs as well as considering different types of A-EVs such as buses and trucks could be another interesting area to extend this work.

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