On the Coordination of Charging Demand of Electric Vehicles in a Network of Dynamic Wireless Charging Systems

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ABSTRACT The utilization of dynamic wireless charging (DWC) systems to charge on-the-move EVs is currently gaining an increasing popularity, as it addresses range and charging downtime issues of EV users. To ensure optimal utilization of this charging infrastructure, coordination of EV charging demand is essential to achieve grid load balancing and prevent grid overload. In contrast to offline, day-ahead charging scheduling, this work proposes an online, mobility-aware, spatial EV allocation algorithm within a DWC coordination strategy. This strategy allocates EVs requesting charge to the most optimal DWC lanes within an EV charging network (ECN) in an Internet of EVs (IoEVs). A detailed charging request scenario is presented to highlight the required communication for authentication between the EVs and the charging infrastructure, to achieve the desired coordination. Description of the proposed EV allocation algorithm is then presented and the performance of the algorithm is evaluated using a hypothetical case study of predicted EV traffic trips in the cities of Dubai and Sharjah, UAE. Upon parameter optimization, results of the conducted analysis reveal that the proposed EV allocation algorithm achieves an almost flattened load profile across the DWC lanes that reduces the PAER by more than 44% in comparison with a shortest distance allocation algorithm, for a maximum $2\times$ increase in trip length, and sufficient received energy to compensate for the energy consumed during the trip. This acknowledges grid supply limitations, EV traveling velocities and the maximum service capacity per DWC lane.

INDEX TERMS Electric vehicle charging network, dynamic wireless charging system, charging coordination, spatial allocation, peak-to-average-energy ratio.

NOMENCLATURE
Abbreviations
CEM	Centralized energy management.
DSM	Demand side management.
DSRC	Dedicated short range communication.
DWC	Dynamic wireless charging.
ECN	Electric vehicle charging network.
EV	Electric vehicle.
G2V	Grid-to-vehicle.
PAER	Peak-to-average energy ratio.

PDN	Power distribution network.
RSU	Road side unit.
SoC	State of Charge.
TCO	Total cost of operation.
V2G	Vehicle-to-grid.

Sets and Matrices
D	Distance matrix between locations of EVs and charging lanes.
M	Number of EVs requesting charge.
N	Number of DWC lanes.
T	Number of time slots within the scheduling window.
χ_j	Set of EVs assigned to lane j.

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Indices

i	Index of EVs, $i \in M$.
j	Index of DWC lanes, $j \in N$.
t	Index of time slots, $t \in T$.

Variables

δ	Algorithm execution time.
ΔT	Duration of each scheduling time slot.
η_j	Power transfer efficiency at lane j.
B_j	Available supply of the power bus at the location of lane j.
c	Average EV energy consumption rate.
C	EV battery capacity.
b_i	Current state-of-charge (SoC) of EV battery.
e_i	Energy allocated by the algorithm to EV i.
E_{avg}	Average energy supplied by all DWC lanes within the ECN.
E_j	Total energy supplied by DWC lane j.
G_j	Available energy supply for DWC lane j.
$\mathbf{l_j}$	Location of charging lane j.
L_j	Length of the charging lane j.
m_i	Remaining mileage of EV i.
P_j	Rated power supply at DWC lane j.
R	Maximum EV driving range.
o_i	Coordinates of the origin of EV i.
d_i	Coordinates of the destination of EV i.
q_i	Direct trip length between origin and destination of EV i.
r_{ij}	Trip length between origin and destination of EV i through DWC lane j.
$T_{c,ij}$	Average charging time of EV i on lane j.
X_{nE}	Non-EV load schedule.
u_i	Current traveling velocity of EV i.
v_j	Recommended traveling velocity on lane j.
x_{ij}	Binary decision variable of EV allocation.

I. INTRODUCTION

With the increasing concerns on fossil fuel consumption and global warming, extensive research and development activities are taking place to encourage large-scale adoption of electric vehicles (EVs), aiming to reduce pollution and conserve energy, while ensuring driver satisfaction [1]. Inevitably, this growing interest in transportation electrification is coupled with studies into EV charging infrastructure planning, charging/discharging coordination, EV energy demand management, and the integration of renewable energy sources (RES) to support in addressing the energy requirements of EV charging networks (ECN) [2]–[4]. These studies aim to motivate increased adoption of EVs through behaviorally-informed strategies [5], that: (a) address the range anxiety concerns of current and potential EV users by optimally deploying the charging infrastructure to offer ubiquitous charging opportunities, (b) reduce the total cost of operation (TCO) of EVs through effective energy management models, to compensate for the higher EV purchase prices compared to their internal combustion engine (ICE) counterparts, and (c) provide

sufficient incentives and energy pricing subsidies to help build a community of satisfied EV owners.

Different EV charging solutions are developed to address the energy availability concerns of potential EV buyers and meet the charging requirements of current EV owners. The most widely deployed EV charging system is plug-in charging, in which EVs are physically connected through charging inlets to the power buses of the utility power distribution networks (PDN). However, with the inconvenience associated with physical connectivity and the hardware incompatibility issues of plug-in charging [6], [7], as well as the risks of electrocution from bare charging wires, wireless EV charging systems are gaining an increasing popularity. This is because wireless charging offers increased flexibility and convenience with minimal electrical contact between the EV and the charging infrastructure. In these systems, charging power is transferred wirelessly, typically through resonant inductive coupling, from a primary charging pad placed on the ground and connected to the grid, to a secondary receiver pad fitted at the bottom of the EVs.

The introduction of wireless EV charging systems is expected to increase EV adoption by at least 15%, according to [8], as they improve drivers' convenience and quality of experience (QoE). However, stationary EV charging introduces driving delays because the EVs are not drivable while they are being charged. It also contributes to range anxiety, as EV drivers fear running out of charge before reaching their destinations and/or the nearest charging point [9]. Accordingly, dynamic wireless EV charging (DWC) systems are developed, in which the charging pads are laid on the roads commuted by the EVs, to enable EVs to recharge their batteries during their motion [10], [11]. In this way, charging and driving are decoupled and the charging downtime is eliminated, which helps reduce the range anxiety of EV drivers. The deployment of DWC systems also reveals opportunities for EV battery downsizing which contributes to reduced EV prices, and reduces the frequency of complete battery depletion, which improves the lifetime of the EV batteries [12]. Hence, by optimally planning a network of EV charging solutions, both stationary and dynamic, wired and wireless, ubiquitous charging opportunities can be offered to EV drivers to address their range concerns, while encouraging larger EV purchases due to expected long-term savings.

With the implementation of different user-oriented strategies to encourage large-scale EV adoption, the coordination of EV charging requests becomes essential to ensure effective and adequate EV demand management while acknowledging the energy supply capabilities of the electricity grid [13], [14]. This is because, without coordination and/or charging scheduling, the EV charging load is anticipated to introduce new peaks to the grid load profile, which increases the energy supply required to meet this demand. It may also further amplify existing peaks as home EV charging patterns may coincide with hours of high residential load demand. According to [15], [16], a typical EV is reported to utilize approximately 7 kW of grid power with level-2
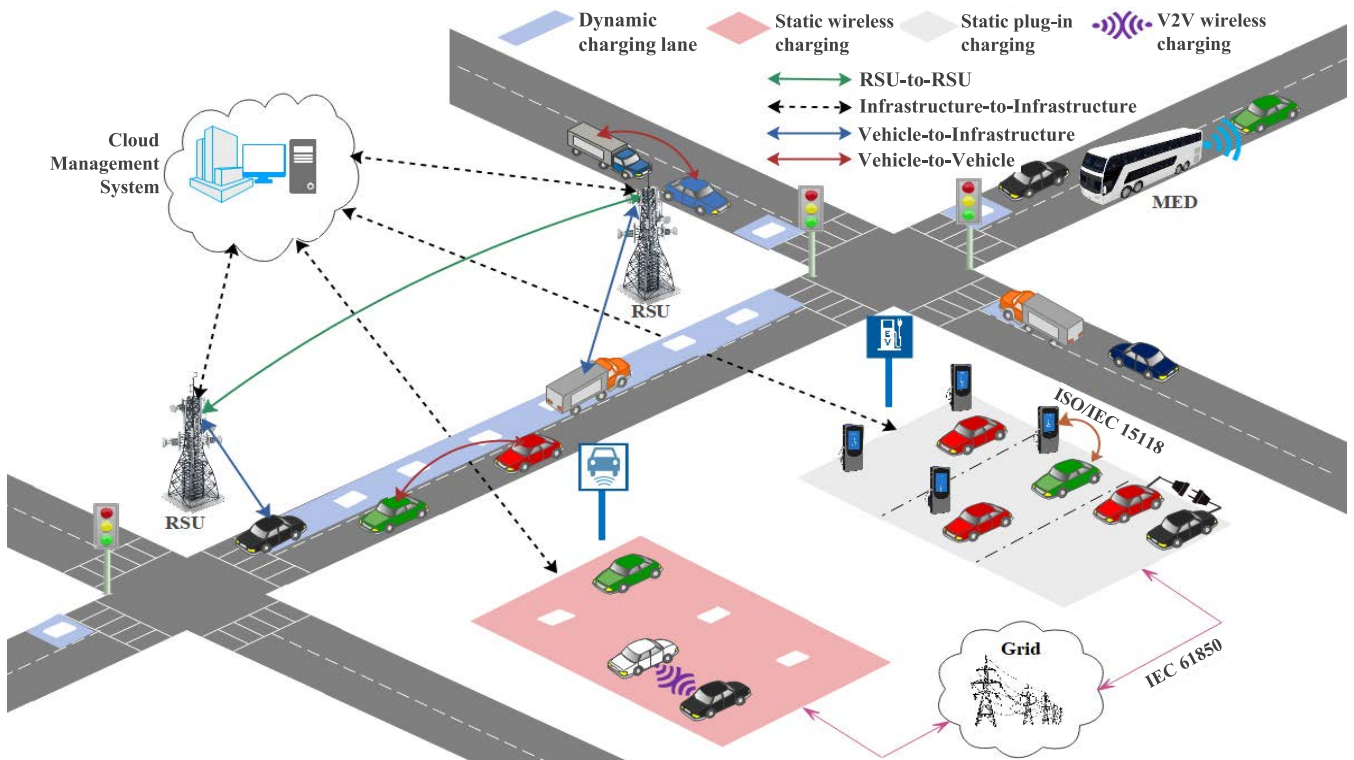
FIGURE 1. Overview of EV charging solutions in an IoEV within a smart city infrastructure.

charging, which is several times higher than the peak demand of typical residential households. Studies also reveal that uncoordinated EV charging can cause unacceptable voltage variations with as low as 10% EV penetration [17]. Furthermore, as the penetration of EVs increases, simply shifting the EV load to off-peak hours may introduce new load peaks during these times, causing what is known as herding or Avalanche effect [18]. The mobility of EVs also causes unexpected load variations, due to the spatial distribution of the charging loads across the different EV charging locations, all of which impact the stability of the grid supply.

In order to manage this increasing and mobile energy demand and ensure effective charging coordination, EVs need to be interconnected with one another and with the ECNs, forming an Internet of Electric Vehicles (IoEV), analogous to the general concept of smart, connected vehicles in an Internet of Vehicles (IoV) [19]–[21]. This is shown in Figure 1.

Similar to IoVs, EVs in IoEVs are considered as smart objects that can gather and process data, and securely exchange information with one another and with the surrounding infrastructure using low latency and high reliability vehicle-to-everything (V2X) communication. The exchanged information may include details of the EV location, destination, traveling speed, potential routes, and energy requirements. This helps EVs coordinate their charging requirements and traveling routes, and achieve charge ubiquity, while

minimizing grid load imbalance [22]–[24]. Nevertheless, sufficient incentives also need to be offered to EV drivers to motivate them to coordinate their charging time and power, and hence reschedule their charging activities, for the mutual benefit of themselves and the grid [25].

Furthermore, to enhance the computational capabilities of EVs and improve the efficiency of vehicular coordination, software-defined (SD) IoEV networks are considered, to enable faster information processing through a more flexible network architecture in which the control and data planes are decoupled [26], [27]. Cloud-based SDN further improves the performance of IoEVs by utilizing edge computing nodes to aggregate vehicular data and communicate it to centralized cloud-based SDN controllers, which perform the required computations for smart routing and energy coordination tasks [28]. SD-IoEVs can also utilize information-centric networking (ICN), in which information is distributed among the EVs via multicast and network caching techniques to improve the quality, security and speed of disseminating charging decisions and other details to the EV users [16], [29]. Hence, while SD-IoEVs enable centralized coordination on cloud-based SDN controllers, they also allow for decentralized coordination by utilizing ICN and edge computing nodes, which can be also referred to as EV aggregators, for performing scheduling and coordination decisions, to provide groups of co-located EVs with reliable and real time energy allocation plans. This decentralization helps in reducing delays in data transmission, as well as reducing the

computational complexity by managing smaller batches of vehicular requests at a time.

The scale at which EV charging coordination takes place may differ depending on the EV penetration levels and the volumes of EV charging requests received within a certain time slot. Acknowledging high EV mobility and to leverage on the eliminated charging downtime when using DWC systems, this work proposes an online, edge aggregator-based EV charging coordination strategy that allocates EVs to the most optimal DWC lane to balance the EV charging load across the different lanes. The optimal EV-to-lane allocation is the one which addresses the EV energy demand without significantly adding to the total traveling distance of the EV, while achieving an overall load balance across the different lanes connected to the grid. In essence, the strategy proposed in this work aims to achieve mutual benefits for both the EV users and the grid, to reduce the impact of EV load on the electricity grid while improving the customer's quality of experience (QoE).

A. RELATED WORKS

Different objectives are addressed in the literature for EV charging coordination problems, some of which are user-oriented while others are grid-oriented. User-oriented coordination problems aim to address the charging demands of EV users by allocating them to the most optimal charging locations while minimizing the overall trip time, as in [30]–[32], minimizing charging delays, as in [33]–[35], or maximizing the received energy, as in [36]. These user-oriented models acknowledge the road traffic conditions and the congestion levels at the different charging points [30], [32], and propose intelligent EV routing strategies that acknowledge the different drivers' behaviors [33], [35], [36].

In order to incorporate uncertainties in user demand and driving patterns, most user-oriented EV demand management problems are deployed using online, i.e. real time coordination approaches. Online coordination is enabled using decentralization, in which coordination strategies are executed on a set of EV aggregators, also known as edge devices, as in [32], [37], [38], or on individual EVs in collaborative game-based models, as in [35], [39], [40]. In aggregator-based coordination, each edge aggregator handles a group of EVs within a reasonable communication distance to coordinate the energy requested per EV in each time slot. Decentralized coordination overcomes scalability issues, by motivating EV owners to execute optimal charging decisions through communication with nearby EVs and charging units. Furthermore, decentralized coordination also reveals opportunities of utilizing state-of-the-art blockchain-based energy trading, in order to facilitate the authentication, billing and transaction verification between EVs in a smart ECN [41], [42].

In contrast, grid-related objective are mainly focused on maintaining grid stability and preventing grid load imbalance, and hence typically involve centralized coordination. In centralized coordination, a management entity performs the required optimization and computations to obtain looka-head schedules for allocating EVs to the most optimal charging location at the most optimal time [43], [44]. Centralized coordination typically takes place offline, based on demand predictions and/or historical data, to efficiently allocate grid resources among EV- and non-EV loads [45]–[47]. The authors in [44] aim to schedule EV loads across different time slots such that the aggregate load profile of a given area is matched to a target load profile with balanced loads, through valley-filling. A similar strategy is also proposed by the authors in [48] to achieve peak shaving and smoothen the load profile. In addition, spatial distribution of predicted EV demand among available charging locations is proposed in [14], to balance the charging load across different electric power buses.

The key issue with offline coordination is the inherent uncertainty when dealing with on-the-move charging requests from mobile EVs, for which the allocation decision needs to be rapidly and optimally performed without impacting the grid performance. Furthermore, the computational complexity of centralized coordination increases as the number of EVs within the IoEV increases, which introduces scalability issues and reduces the efficiency of the demand management strategy. Communication delays and information security risks are also inevitable in centralized coordination, as each EV needs to communicate its details and required demand with the centralized decision maker.

Two-staged, centralized then decentralized coordination strategies are proposed in [28], [40], [49] to leverage on the advantages of both approaches and reduce their drawbacks. Nevertheless, most literature on the coordination of EV charging demand assume only public and private plug-in charging stations are included in ECNs, with minimal reference to DWC systems. This, as highlighted earlier, can be resorted to the currently low investments in the deployment of DWC infrastructure due to fear of failing to achieve the desired returns. Furthermore, few works have simultaneously addressed grid-related and user-related objectives [50], [51]. Nevertheless, several deployment optimization strategies are currently being developed to optimize the deployment of DWC lanes within the city infrastructure, acknowledging the return-on-investments (RoI) of the infrastructure owner, the required coverage of customers' demand and the locations of power buses within PDNs [52]–[54]. This motivates the need to optimize EV charging behaviors to address both user- and grid-related objectives to maximize the social welfare, by motivating mass EV adoption, improving EV users' QoE and ensuring grid stability against EV charging loads.

B. CONTRIBUTIONS OF THIS WORK

With the high mobility of EVs and the eliminated charging downtime through DWC, spatial online charging coordination helps achieve the desired load balancing objectives, and avoids delays in addressing the charging requirements of the EV users. This, however, may come at the price of potential increase in the driving distances and/or re-routing of EVs

FIGURE 2. Different network entities considered in this work.

from the shortest-distance path to charge at the most optimal charging lane. This is because, in an uncoordinated charging scenario, a closer charging lane has a higher probability of being selected by the EV user seeking energy. Using spatial coordination, however, introduces other charging possibilities for EV drivers, through which the charging load across all DWC lanes is balanced to achieve better grid stability.

Hence, in this work, an online, edge aggregator-based EV charging coordination strategy is proposed to achieve optimal allocation of the charging demand of on-the-move EVs among pre-deployed DWC lanes within the city infrastructure. The underlying assumption is that an optimal day-ahead non-EV load schedule is developed according to an efficient DSM program, as presented in an earlier work in [55], and is accurately followed. This work then formulates a Mixed Integer Non Linear Programming (MINLP) model that allocates EVs among the DWC lanes in an ECN, such that the peak-to-average energy supply ratio (PAER) of the ECN is minimized. This shall meet the EV charging requirements, through G2V energy transfer, while ensuring grid load balancing across different DWC lanes within the ECN. The discharge of EV stored energy back to the grid in V2G operation is excluded from the scope of this work. The proposed MINLP model is solved using a rule-based algorithm with parametric sweeps, and the performance is evaluated against shortest-distance-based EV allocation to assess the enhancement in PAER offered by the proposed model.

The key contributions of this work can be summarized as follows:

- This work proposes an online coordination strategy of on-the-move EVs requesting to charge from DWC lanes within an ECN to achieve grid- and user-related objectives including grid load balancing and maximal demand coverage.
- The proposed strategy incorporates a load-balancing EV-to-lane allocation algorithm to be executed by an EV aggregator. The EV aggregator offers edge computing capabilities to execute the coordination algorithm for EVs requesting charge within each time slot.
- This work also proposes an effective message exchange protocol, assuming an underlying low-latency and high-reliability communication network, to enable efficient execution of the proposed allocation algorithm.
- The proposed coordination strategy acknowledges the driving range, driving velocity and remaining mileage of EVs under consideration to account for vehicular mobility and arrival time to the DWC lanes.
- This work also develops a hypothetical case study of an ECN of DWC lanes within main cities in the United Arab Emirates (UAE), namely Dubai and Sharjah, to evaluate the performance of the proposed EV allocation algorithm.

To the best of the authors' knowledge, this work is the first to incorporate on-the-move charging lanes in EV demand management problems that achieve load balancing obj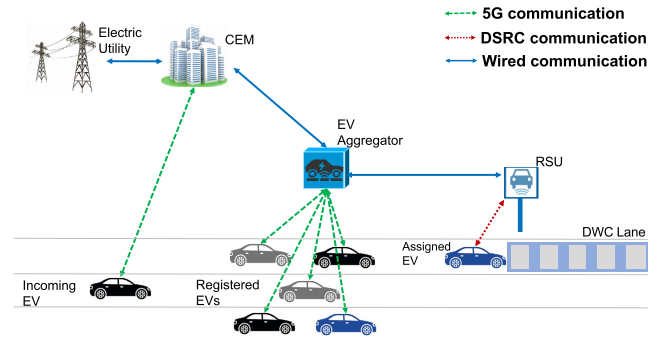ectives. Furthermore, the UAE case study presented in this work is first of a kind, which shall be further expanded as more empirical EV-related data becomes available. The rest of this paper is organized as follows: Section II provides details of the system model under consideration, consisting of DWC lanes and energy-demanding EVs in a ECN. The proposed spatial EV coordination strategy is then described in Section III with the associated message exchange protocol. Specifications of the EV allocation algorithm are provided in Section IV. The performance of the coordination strategy and the proposed algorithm is then evaluated using a UAE-based case study and the results are reported in Section V. The paper is finally concluded in Section VI.

II. SYSTEM MODEL

A simplified ECN is modeled in this work, consisting of M connected EVs and N DWC lanes of length L_j each. Each DWC lane consists of S charging segments connected in parallel to the power bus. The subscripts i and j are used to denote the indices of the EVs and the charging lanes, respectively, and the length of each charging segment within lane j, i.e. l_{sj} is designed that each segment can serve a maximum of one EV at a time. The ECN includes an EV aggregator that receives charging requests from different EVs and executes the online spatial EV allocation algorithm accordingly. A Centralized Energy Management (CEM) system is also included in the ECN, and is responsible for registering the different EVs within the network and for providing the day-ahead schedules of non-EV loads to the aggregator, based on the communication between the CEM and the utility provider. An outline of the different network entities and their corresponding communication links is shown in Figure 2.

As highlighted earlier, scheduling of the non-EV loads is assumed to take place separately and is not included within the scope of this work. Hence, the aggregator is an intermediate entity that interacts with the CEM system to obtain the predetermined consumption schedules and use them to calculate the energy supply available for EV charging at each DWC lane during each time slot. The aggregator then executes the spatial EV allocation algorithm and disseminates allocation information to the different EVs to address their charging demand. In this work, the DWC lanes are assumed to be geographically dispersed within the area of the ECN under
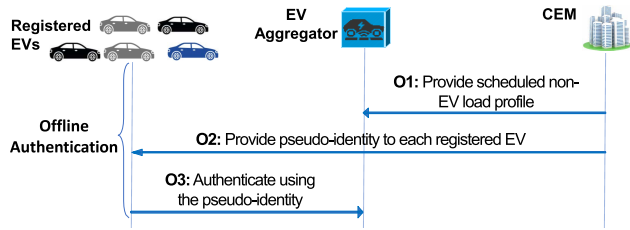
FIGURE 3. Message exchange sequence during offline authentication phase.

consideration, although they are all assumed to be electrically served by the same utility provider. Expectedly, the ECN also includes public and private plug-in charging stations but those are not considered in this work. It is assumed that the EV aggregator considered in this work only handles EVs requesting to be charged from DWC lanes.

The communication between the EVs and the aggregator is assumed to take place through low-latency and high-reliability 5G communication, to account for the high mobility of EVs and provide secure communication links [21], [56], [57]. In addition, road side units (RSU) are installed at the locations of the DWC lanes to enable radio communication between the EVs and the lanes through Dedicated Short Range Communication (DSRC), upon successful authentication with the EV aggregator. This reduces the physical layer latency and helps avoid interference from adjacent channels, given the short communication distance between the EVs and the charging lanes.

III. DWC COORDINATION STRATEGY

A. OFFLINE AUTHENTICATION PHASE

At the beginning of each day, the CEM provides the aggregator with the non-EV load schedules, X_{nE}, and rated supply at the power bus to which each DWC lane is connected, B_j (**O1**). For simplicity and without loss of generality, each power bus can only have a maximum of one DWC lane connected to it.

Each EV is pre-registered with the CEM system, and receives an EV ID, I_i, to be used for the first stage of authentication upon entering the ECN served by the CEM. The CEM then assigns a pseudo-identity, p_i, to each registered EV to be used for communication with the EV aggregator (**O2**). This ensures privacy of the EV information and reduces instances of identity theft. A fast, secure and lightweight authentication scheme is assumed to be employed for EV authentication to the different entities in the network including the EV aggregator (**O3**), following the authors' earlier work in [21]. A summary of the message exchange sequence with messages **O1**, **O2** and **O3** is shown in Figure 3.

B. CHARGING COORDINATION PHASE

At the beginning of each time slot, t, the EV aggregator predicts the hourly energy availability at each DWC lane location for the current day, $G_j(t)$ where $t = 1, 2, 3, \ldots, 24$ represents the 24 hours of the day, given the non-EV load profile, $X_{nE}(t)$,

and the rated bus power supply, $B_j(t)$, shared by the CEM. The rated power supply for each charging lane, P_j, is also provided by the CEM to the aggregator (**S1**).

As a pre-registered EV demands energy, it sends a charging request to the EV aggregator at the beginning of the time slot (**S2**). This request message includes the pseudo-identity of the EV, p_i, its current battery state-of-charge (SoC), b_i^t, the EV current location, which is also the origin (O) of the EV trip, o_i^t, the desired EV destination (D), d_i^t, the current EV traveling velocity, u_i^t, and its remaining mileage, m_i^t. The input to the load-balancing EV allocation algorithm is extracted from the charging request message as, $R_i^t = \{b_i^t, o_i^t, d_i^t, u_i^t, m_i^t\}$ in $\Re^5$. For each incoming request, the EV aggregator executes the EV-to-lane allocation algorithm, by evaluating the lengths of all possible routes from the origin to destination going through the charging lanes, as well as the current load on each lane and the energy demand of the requesting EV. The EV aggregator then assigns the EV to the charging lane such that the load across the lane is balanced while ensuring that the added distance to go through the assigned lane is less than the maximum distance threshold, λ. The algorithm is designed such that the execution time is significantly low, i.e. few milliseconds, to avoid delays in EV assignment. Furthermore, the algorithm is lightweight to allow the EV aggregator to simultaneously handle multiple EV requests with its computational capability as an edge device. In case of multiple EV requests, the EV aggregator prioritizes the EVs with lower SoC, i.e. lower b_i^t, to ensure better demand coverage and improve user satisfaction. Details of the EV-to-lane allocation algorithm are further detailed in Section IV)(**S3**). Since this paper particularly focuses on the spatial coordination of EVs among the available DWC lanes within a single time slot, the dependence on time is dropped from all the variables in the rest of this paper.

Upon executing the EV allocation algorithm, the EV aggregator determines the most optimum charging location to each EV requesting charge. Before communicating the ID of the assigned lane to each EV, the aggregator send a message (**S4**) to each EV, over a secure 5G communication channel, to confirm energy availability and provides the expected distance to be traveled by the EV on the route from its origin to destination through the assigned lane, r_{ij}, given the EV traveling velocity, u_i. The EV aggregator also provides the EV with the recommended on-lane traveling velocity, v_j, to ensure that the lane can address the energy demand of concurrently-charging EVs. Upon EV confirmation and approval (**S5**), the EV aggregator communicates the respective charger location and ID, I_j, to the EV over the same channel (**S6**). A summary of the message exchange process for this phase is shown in Figure 4, showing messages **S1**-**S6**.

C. CHARGING ACTIVATION & BILLING PHASES

As the EV approaches the specified charging location, it establishes a secure DSRC communication channel with the RSU to request the charging service with the specific
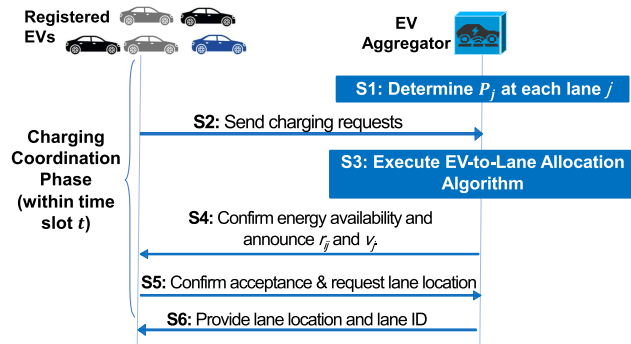
FIGURE 4. Message exchange sequence during charging coordination phase.

energy level allocated by the aggregator (**C1**). Upon receiving the message from the EV, the RSU communicates with the EV aggregator to confirm the charging request and verify the identity of the requesting EV along with the allocated energy level (**C2**). Upon verification with the aggregator, the RSU authenticates the EV and authorizes it to receive the charging service from the assigned DWC lane (**C3**). After successful authentication, the RSU sends a charging activation command to the respective charging lane (**C4**), and the charging process is initiated as soon as the EV is on the charging lane.

At the end of the charging process, each charging lane reports its supplied power and charging duration for each EV to the RSU (**B1**), which forwards this information to the EV aggregator (**B2**). Each EV also reports its received energy to the aggregator (**B3**), which compares both reports and generates the respective EV bill accordingly (**B4**). The message exchange during the charging activation and billing phases is summarized in Figure 5.

IV. SPATIAL EV ALLOCATION ALGORITHM

In the charging coordination phase shown in Figure 4, the EV aggregator starts by estimating P_j, then uses EV origin and destination data, i.e. o_i, d_i, to estimate the length of all possible routes from the origin to the destination going through each of the N charging lanes. This takes place by invoking Google Distance Matrix API [58]. The EV aggregator then creates a subset of feasible lanes for EV i, $N_{f,i} \subseteq N$, for which the trip is feasible, i.e. can be completed, given the current mileage of the EV, m_i. Within N_f, the EV aggregator evaluates the available supply at each feasible lane as well as the previous EV allocations to each lane within the same time slot. The aggregator allocates EVs to the most optimal lanes such that the load balance across the lanes is not disturbed. Hence, for each incoming EV, the aggregator assigns the EV to that lane that minimizes the difference between the peak energy supplied by each DWC lane, E_j, and the average energy supplied by all the lanes, E_{avg}, within the given time slot t_s acknowledging previously charged EVs within the same slot. That is, to minimize the peak-to-average energy ratio (PAER) supplied by the grid to the DWC lanes, which

can be expressed as,

$$\textbf{Minimize} \sum_{j=1}^{N} |E_j - E_{avg}|, \quad (1)$$

where,

$$E_j = \sum_{i=1}^{M} x_{ij} \eta_j P_j T_{c,ij}, \quad (2)$$

and,

$$E_{avg} = \frac{1}{N} \sum_{j=1}^{N} E_j. \quad (3)$$

x_{ij} is a binary decision variable responsible for the assignment of each EV i to lane j. This is set to 1 if EV i is assigned to lane j and is 0 otherwise. P_j is the power supply from each DWC lane j, η_j is the corresponding power transfer efficiency, and $T_{c,ij}$ is the effective charging time of EV i on lane j, which is related to the lane length and the recommended EV traveling velocity using, $T_{c,ij} = l_j / v_i$. Given the charging lane length, L_j, its rated power, P_j, and energy availability, G_j, the EV aggregator estimates the recommended traveling velocity, v_j, on each lane to ensure maximal demand coverage while achieving the load balancing conditions. A simplified, linear velocity estimation model is adopted in this work, as,

$$v_j = \frac{L_j P_j}{G_j}. \quad (4)$$

The following constraints are also applied:

- The route r_{ij} from the origin of the trip of EV i, o_i, to its destination, d_i, through each of the feasible DWC lanes should be less than the remaining mileage of EV i. Hence,

$$\sum_{j=1}^{N} x_{ij} r_{ij} < m_i, \quad \forall i \in M. \quad (5)$$

- The length of the route including the charging lanes should not be significantly higher than the original origin-to-destination route. This is controlled using a maximum distance threshold, λ_i, relating the length of the route through the lane, r_{ij}, to the direct O-D distance, q_i, as,

$$\sum_{j=1}^{N} x_{ij} r_{ij} \leq \lambda_i q_i, \quad \forall i \in M. \quad (6)$$

- Each EV can only be assigned to a single charger within the time slot, i.e.

$$\sum_{j=1}^{N} x_{ij} = 1, \quad \forall i \in M. \quad (7)$$

- The energy supplied by DWC lane j to all EVs within the time slot should be less than or equal to the total
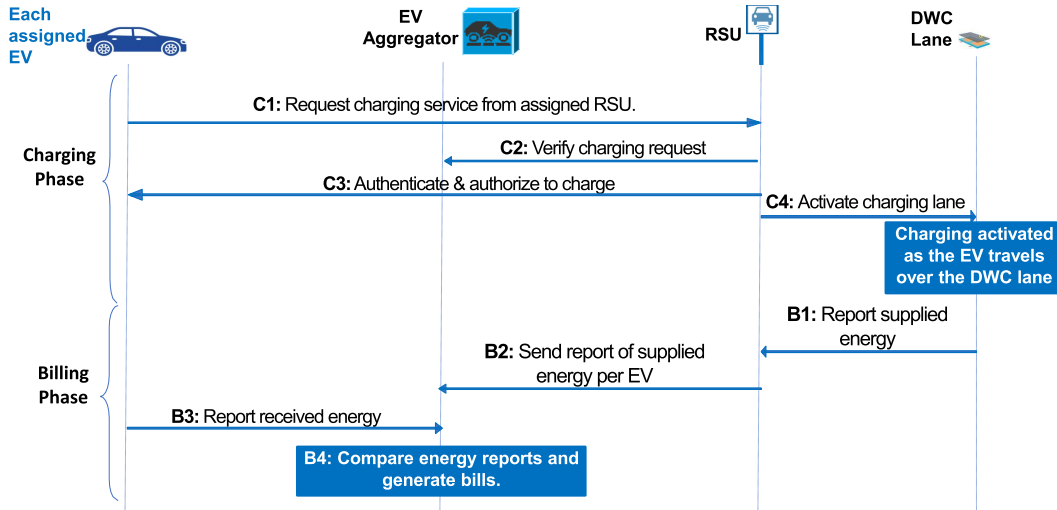
FIGURE 5. Message exchange sequence during charging activation and billing phases.

available energy supply at the location of j, G_j. This means,

$$E_j \leq G_j, \quad \forall j \in N. \tag{8}$$

Furthermore, due to lack of open-access empirical data on EV charging demand in the UAE and the currently low, but increasing, EV penetration levels, it is assumed that EVs demand to be charged with sufficient energy to cover their current trip from the origin to the destination, going through the assigned charging lane. Accordingly, the energy delivered by each lane to address EV demand is modeled as a constant multiple, α, of the expected energy consumption of EVs are they traverse through their respective trips between different O/D pairs, going through the selected charging lane. Assuming an average linear energy consumption factor of c_i kWh/km for each EV, the energy delivered per EV is modeled as,

$$e_i \leq \sum_{j=1}^{N} x_{ij} r_{ij} \alpha c_i, \quad \forall i \in M. \tag{9}$$

This assumption evolves from the main objective of introducing DWC systems, which is reducing range anxiety by compensating for the EV energy consumption during trips while eliminating charging downtime, to ensure reaching the destination without running out of charge. Hence, the energy multiplication factor, α, together with the distance threshold, λ, are used to assess the quality of experience (QoE) offered by the DWC infrastructure to the EV users by evaluating the additional distance traveled to charge through the allocated lane along with the allocated energy for each EV.

The EV-to-lane allocation algorithm is hence executed by the EV aggregator in real time for each incoming charging request, without having to perform day ahead predictions of EV load given the high mobility of EVs. This is shown in Algorithm 1.

Algorithm 1 Proposed EV Allocation Algorithm Among DWC Lanes

Given Locations and rated power of the DWC lanes.
Input X_{nE} and B_j, $\forall j \in N$ from CEM.
Input $r_i^t = \{b_i^t, o_i^t, d_i^t, u_i^t, m_i^t\}$.
Output Optimal EV allocation plan, χ^*.

1: **for** $i \in M$ **do**
2:     **for** $j \in N$ **do**
3:         Estimate hourly energy availability at each charging lane, G_j, using X_{nE} and B_j shared by CEM.
4:         Estimate the length of all possible routes from EV origin to destination through each DWC lane, r_{ij}.
5:         Determine the subset of feasible routes for each EV, $N_{f,i}$.
6:         Evaluate the current EV load on each lane j from previous assignments.
7:         Within the subset of feasible lanes, assign EV i such that (1) is achieved subject to (2), (5)-(8), using the energy demand model in (9) to establish an optimal allocation plan, χ^* that achieves load balancing within each time slot.
8:         Use lane energy availability and rated power to recommend the optimal on-lane traveling velocity, v_j, using (4).
9:     **end for**
10: **end for**

V. PERFORMANCE EVALUATION: UAE CASE STUDY

In order to evaluate the proposed charging coordination algorithm, DWC lanes are assumed to be optimally deployed on highly-congested arterial roads connecting the cities of Dubai and Sharjah, UAE. Heavy congestion is typically observed during early morning and late afternoon hours in areas surrounding schools and other educational institutions, as well as at the Sharjah-Dubai borders during employees' commute
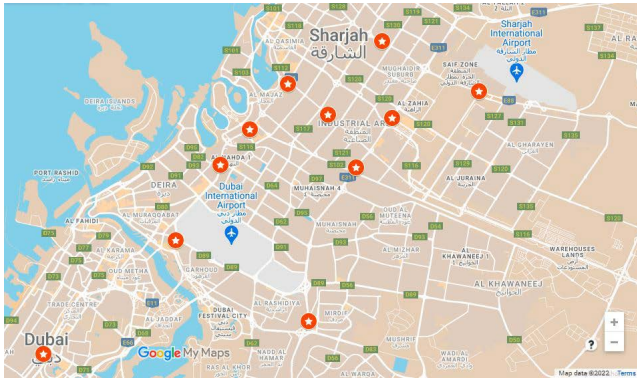
FIGURE 6. Locations of charging lanes used in the evaluation of the proposed EV allocation algorithm [60].
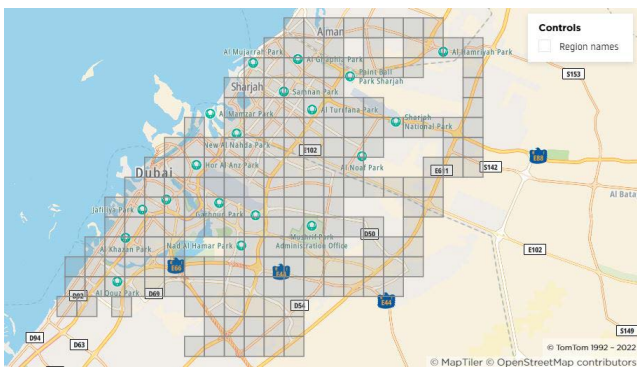

FIGURE 7. Regions used in origin-destination analysis to extract data on vehicular commutes [61].

FIGURE 8. Hourly trip count for trips commuted by EVs in each working day, sampled from the total hourly count extracted from TomTom Move O/D Analysis tool [61].

to and from work. EV charging networks are expected to be in high demand during these high congestion periods. Since there are currently no commercial deployments of DWC lanes within UAE, potential lane locations are used for the conducted analysis assuming an underlying deployment optimization model from earlier works in [54], [59]. Accordingly, the presumed-to-be optimal locations of the DWC lanes are pinned on the location map as shown in Figure 6. It should be noted that the actual locations of the charging lanes shall not impact the problem formulation nor the performance of the proposed allocation algorithm, as they are considered as inputs to the model.

In order to model the traffic flow of EVs, data on vehicular commutes between different origins (O) and destinations (D) within Sharjah and Dubai is first obtained from Tom-Tom Move O/D Analysis tool [61]. The map is divided into 200 equal-sized regions as shown in Figure 7.

The number of trips between all possible O-D pairs within the 200 regions is then extracted from the O/D Analysis portal for every hour during a working day. The only available data for the UAE at the time of study is for January 2021. Hourly trip counts for a working week are extracted and averaged to obtain the average number of trips on a typical working day. The announced EV roll-out plans in the UAE state that 30% EV penetration is expected on UAE roads by 2030 [62]. Since
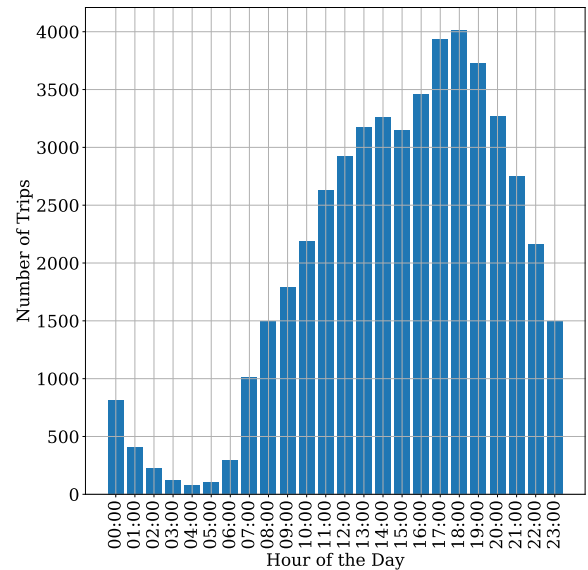
the distribution of EV users is expected to be concentrated in major cities, namely Abu Dhabi, Dubai and Sharjah, it is assumed that 60% of the EVs shall utilize the regions studied in this work covering Dubai and Sharjah. Hence, 18% of the hourly trip counts is assumed to be commuted by EVs, and is used to model the EV demand in this work. This is based on the underlying assumption that driving patterns are not expected to dramatically change between conventional ICE vehicles and electric ones, except for the routing through DWC lanes which is addressed by the allocation algorithm proposed in this work. Hence, by using empirical O/D trip data under this assumption, uncertainties in user driving patterns are inherently integrated in the EV demand model. Furthermore, the hourly resolution reflects actual traffic congestion levels during peak hours and improves the reliability of the proposed model. The distribution of hourly EV trips is shown in Figure 8.

In order to evaluate the performance of the proposed algorithm, the algorithm is executed for the EV trips during hours of highest congestion, i.e. 18:00 to 19:00, and the results are compared to those obtained with shortest distance based allocation, with which each EV is allocated to the charging lane that offers the least increase in the total trip length. A summary of the model parameters is shown in Table 1.

The proposed rule-based EV-to-lane allocation algorithm is executed on MATLAB [63], on an Intel core i7, 2.4 GHz machine. The average execution time for all 4009 requests is around 2 minutes, which indicates the time efficiency of the proposed algorithm. Since the algorithm allocates each incoming EV request independently, the average execution time per request is 0.0326 seconds. Three performance metrics are used to evaluate the performance of the proposed allocation algorithm against shortest distance allocation, namely:

TABLE 1. Model parameters.

Parameter	Symbol	Value
Time slot under study	t_s	18:00-19:00, work-day
Number of EVs requesting charge	M	4009
Number of DWC lanes	N	11
Length of each DWC lane	l_j	2.5 km
EV battery capacity	C	40 kWh
Maximum EV driving range	R	300 km
EV energy consumption rate	c	0.164 kWh/km
DWC lane power per EV	P_j	25 kW
Rated power at each DWC lane	B_j	3 MW

FIGURE 9. PAER of the proposed algorithm for different combinations of the distance threshold and energy multiplication factor.

FIGURE 10. Percentage demand coverage per EV of the proposed algorithm for different combinations of the distance threshold and energy multiplication factor.
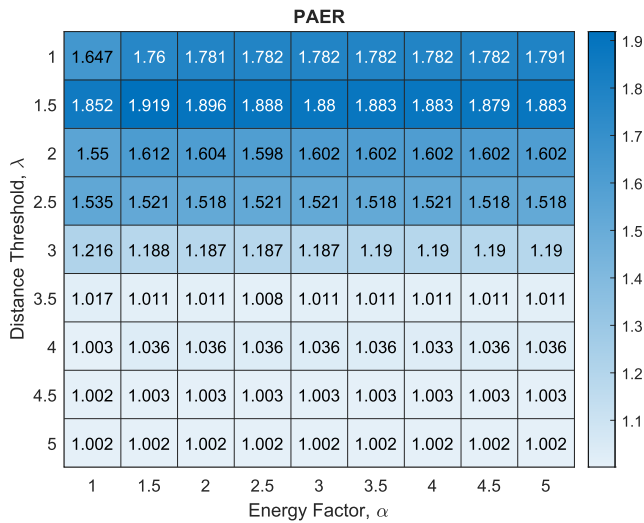

FIGURE 11. EV blocking rate of the proposed algorithm for different combinations of the distance threshold and energy multiplication factor.

PAER, EV blocking rate, and the percentage of energy allocated per EV, relative to the optimal allocation amount calculated using (9) for the given energy multiplication factor. This is equivalent to the percentage demand coverage per user, which is a measure of the quality of experience (QoE) offered to each EV driver. On the other hand, the EV blocking rate is the percentage of the number of EVs that were not assigned by the algorithm to any charging lane due to supply energy restrictions, i.e. because the lane has reached its maximum service capacity and has no more energy to address the demand of EVs.

To optimize the performance of the proposed algorithm, a parametric sweep is executed on the algorithm for different combinations of the distance threshold and energy multiplication factor. This is repeated for all EV trips data for the 24-hour span and the three performance metrics are evaluated. This aims to determine the best combination of values for the two parameters, α and λ, to achieve load balancing while maximizing the demand coverage per EV user and minimizing the number of unserved, i.e. blocked EVs. The results are shown in Figures 9, 10 and 11, respectively.

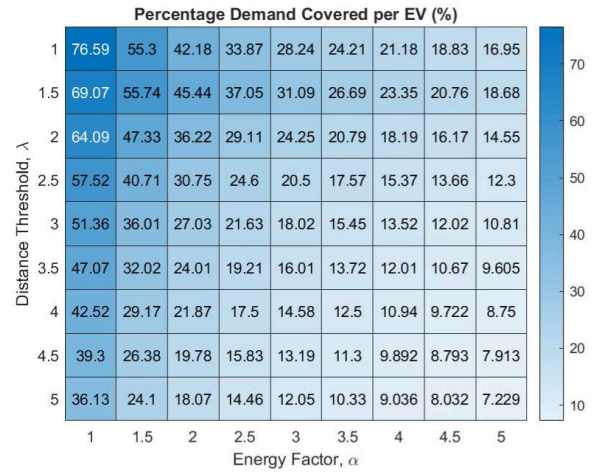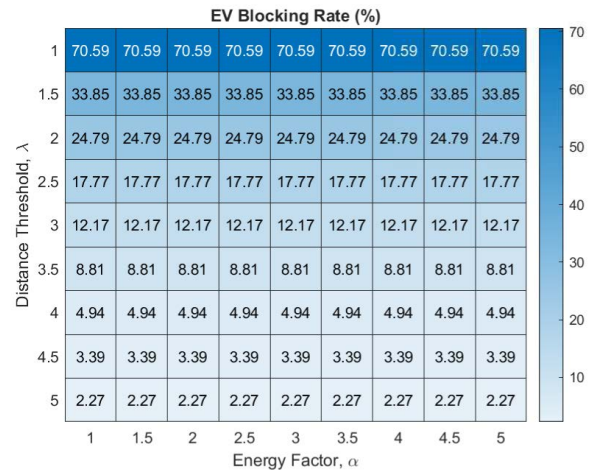Based on the results in Figures 9, 10 and 11, the following conclusions are made:

- The PAER values obtained using the proposed algorithm are very close to one for $3.5 \leq \lambda \leq 5$ for all values of α, which corresponds to a balanced load profile at DWC lanes within the IoEV.
- The percentage demand coverage values obtained using the proposed algorithm are greater than 50% for $1 \leq \lambda \leq 3$ when $\alpha = 1$, and for $1 \leq \lambda \leq 1.5$ when $\alpha = 1.5$.
- The EV blocking rate is less than 10% for $3.5 \leq \lambda \leq 5$ for all values of α.
- Depending on the desired objectives of the EV coordination problem, optimal choices of λ and α can be made by the system operator, i.e. the CEM.
- For this work, the optimal combination values of the distance threshold and energy compensation factor are selected to be $\lambda = 2$ and $\alpha = 1$. This ensures that the allocation algorithm is able to achieve an acceptable load balancing performance with PAER of 1.55, with
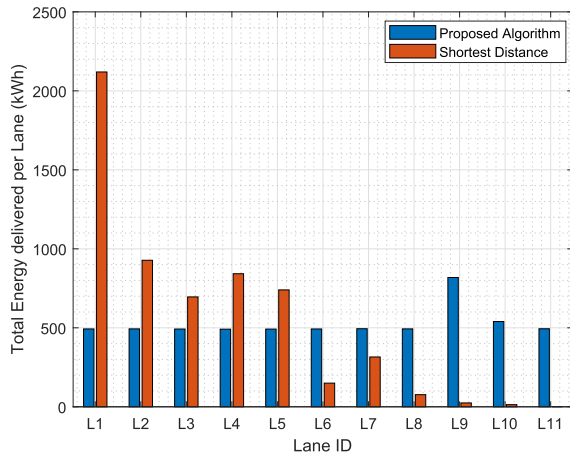
FIGURE 12. Energy supplied per lane to EVs allocated according to the proposed DWC coordination algorithm (blue bars) and those allocated based on shortest distance allocation (orange bars).
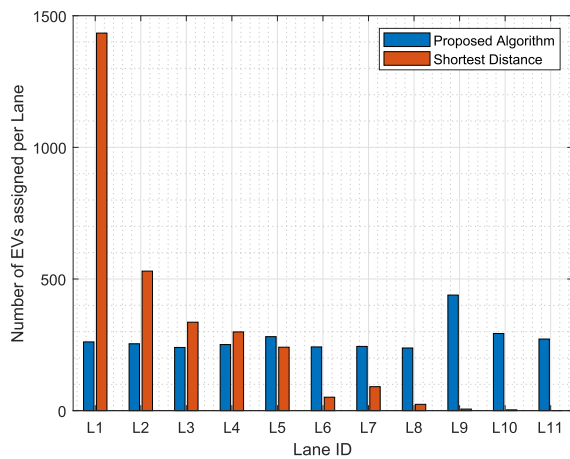

FIGURE 13. Number of EVs assigned per lane according to the proposed DWC coordination algorithm (blue bars) and those assigned based on shortest distance allocation (orange bars).

reasonable customer satisfaction levels through 64.1% demand coverage and 24.8% EV blocking rate.

Using $\lambda = 2$ translates to a maximum increase in trip length to be $2\times$ the length of the direct trip between the origin and destination. On the other hand, $\alpha = 1$ indicates that the model ensures that sufficient energy is delivered by the DWC to each assigned EV to compensate for the energy consumed to travel the route from origin to destination going through the assigned charging lane. Using $\lambda = 2$ and $\alpha = 1$, the PAER and the number of EVs allocated per lane are plotted in Figures 12 and 13, respectively, in comparison with shortest distance-based allocation.

As observed in Figures 12 and 13, the DWC load profile is significantly enhanced using the proposed algorithm in comparison to that obtained with shortest distance allocation. The PAER of the proposed allocation algorithm is around 44% less than that obtained using shortest distance-based allocation. This proves that the main objective of EV load balancing

is achieved with the proposed algorithm. Nevertheless, this comes at the cost of lower energy allocated per EV, with 64.1% demand coverage, calculated using the recommended EV on-lane traveling velocities obtained by the algorithm. For shortest distance based allocation, lanes $L1$, $L4$ and $L5$ are over-utilized, while lanes $L9$, $L10$ and $L11$ are under-utilized. This introduces significant load imbalance and impacts the overall stability of the power grid. Furthermore, the energy supply limitations of the charging lane and the recommended velocities are not incorporated in shortest distance based allocation. Hence, the percentage demand coverage and EV blocking rate cannot be assessed.

A. MODEL LIMITATIONS
In spite of the promising results obtained from the proposed model, few limitations need to be highlighted for further improvement in future works. These include:

- The energy demand and energy allocation calculations assume a linear relationship between the traveling distance and the energy consumption rate. This needs to be further expanded to address variations in EV energy consumption with velocity, driving patterns, etc.
- Constant energy consumption rate is assumed for all EVs in the presented model. Variations of EV energy profiles are inevitable and multiple EV models need to be considered in future analysis.
- The traveling velocity of EVs is calculated on average, which does not acknowledge the EV acceleration or deceleration. More accurate velocity models can be included in future works.
- A constant value is used for the distance threshold for all EVs under study. This assumption can be eliminated to allow for different distance thresholds based on EV driver's preferences.

In addition, since the EV-to-lane allocation algorithm is designed to run online, across different time slots and different grid supply profiles, further research can include the role of coordinated vehicle-to-grid (V2G) energy transfer to utilize excess energy in EV batteries to compensate for shortage in grid supply during times of high demand. The discharging of EVs through DWC lanes also needs to be further investigated to evaluate the efficiency and needed incentives for EV drivers to participate in V2G programs.

VI. CONCLUSION
Dynamic wireless charging systems form an integral part of the EV charging infrastructure, to address the range anxiety of EV drivers due to limited EV battery capacities and provide a seamless driving experience. In order to maximize the gains from the deployment of DWC lanes, this work proposes an effective DWC coordination strategy that assigns EVs demanding energy to the most optimal lanes, to reduce the peak-to-average energy ratio (PAER) supplied by the lanes to cover the demand of on-the-move EVs. This work presents details of the charging request scenario expected to

take place between EVs demanding energy and the charging infrastructure. A spatial EV-to-lane allocation algorithm is proposed to be executed by an EV aggregator, to stabilize the energy load profile across the DWC lanes in the EV charging network under consideration. The objective of the proposed algorithm is to minimize the load variation from EV charging across different charging locations within the charging network in the given planning horizon, while ensuring customer satisfaction through energy demand coverage.

The load-balancing EV allocation algorithm proposed in this work is proven effective when tested on a large volume of EV trips, predicted to take place between 18 : 00 and 19 : 00 on a typical working day in Dubai/Sharjah, UAE. Upon parameter optimization, the proposed algorithm almost flattens the load profile across the lanes and reduces the PAER by more than 44% in comparison with a shortest distance allocation algorithm, for a maximum increase in trip length to be $2\times$ the length of the direct trip between the origin and destination, and sufficient received energy to compensate for the energy consumed to travel the route from origin to destination going through the assigned charging lane. Future works shall address the limitations of the current model and shall expand on the charging network to include a larger number of DWC lanes, along with stationary wired and wireless charging points, to effectively coordinate the EV charging demand across different energy supply points. This also needs to be integrated with spatio-temporal scheduling of EV charging demand with the demand of other loads from residential, commercial and industrial areas within a smart grid to achieve overall grid load balancing.

ACKNOWLEDGMENT

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