Charging-expense Minimization through Assignment Rescheduling of Movable Charging Stations in Electric Vehicle Networks

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***Abstract*—Electric vehicles (EVs), as promising components of the sustainable and eco-friendly transportation systems, are being widely adopted to reduce the consumption of fossil fuel and pollution of environments. EVs are usually equipped with wireless modules to support the vehicle to vehicle communications, by which an electric vehicular network (EVN) is formed. In EVN, some EVs are with insufficient battery energy and may exhaust the battery energy before arriving at their destinations, and these EVs are referred to as IEVs. More seriously, IEVs probably cannot find any fixed charging facilities nearby. With the development of mobile charging technology, some movable charging stations (MCSs) are deployed into EVN, and MCSs can actively navigate to charge IEVs. In this paper, an assignment rescheduling mechanism of movable charging stations (ARMM) is proposed, where the MCS assignments are dynamically rescheduled. In ARMM, in order to reduce the charging expenses of IEVs and enhance the proportion of charged IEVs, the assigned IEVs of some MCSs could be switched to other MCSs, while the charging positions of MCSs are selected by minimizing the charging expenses of IEVs and are dynamically altered. Besides, the incentives of assigned IEVs to reduce the charging expenses of unassigned IEVs are proven. Simulation results demonstrate the preferable performance of ARMM, i.e. ARMM can reduce the charging expenses of IEVs and enhance the proportion of charged IEVs effectively.**

***Index Terms*—Electric vehicle network; movable charging station; assignment rescheduling; charging-expense minimization.**

I. Introduction

Recently, electric vehicles (EVs) refueled by electricity have received considerable attention, along with the increasing concerns over the environments and ever stringent emission regulations [1], [2]. Vehicle manufacturers have equipped EVs with wireless modules to support the vehicle to vehicle communications provided by IEEE 802.11p standard, and thus EVs constitute an electric vehicular network (EVN) [3].

In EVN, an EV usually suffers from a limited battery capacity, especially when it takes a long-distance travel, and it must be charged before the exhaustion of battery energy. EVs with insufficient battery energy are referred to as IEVs and can be charged by some charging infrastructures, such as the fixed charging stations deployed roadside. However, to the best of our knowledge, quite a few countries/cities have constructed a mature system of fixed charging stations due to the expensive cost. Fortunately, with the rapid development of mobile charging technology, movable charging stations (MCSs) [4], [5], [6], [7] (as shown in Fig. 1) have emerged. Especially, MCSs are much easier to be deployed, and IEVs are charged by MCSs more conveniently, since MCSs can actively navigate to charge IEVs.

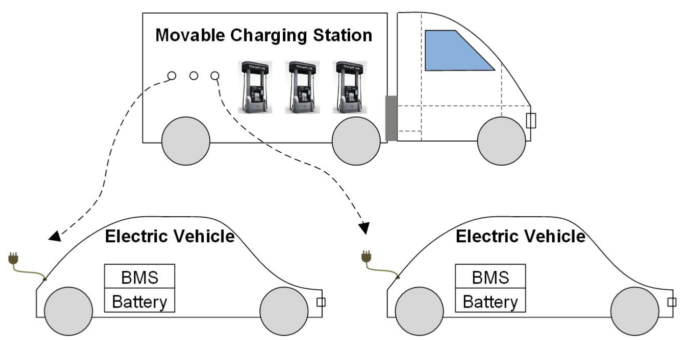

Fig. 1: A movable charging station.

Similar to gasoline vehicles, EVs turn into IEVs when they detect the low battery states. In the zones without (or with few) fixed charging stations, such as suburbs or villages, MCSs are deployed as public infrastructures. Thus, we consider the following charging scenario: some traveling EVs detect the low battery states, and then they turn into IEVs. IEVs request the charging services from neighboring MCSs. The charging positions are selected by minimizing the charging expenses of IEVs, because MCSs are deployed as the non-profit public transportation facilities (e.g. railways, metros, and buses). Evidently, each IEV wants to be successfully charged by an MCS at a small charging expense. Therefore, in this charging scenario, the charging expenses of IEVs need to be reduced, and the proportion of charged IEVs needs to be increased.

Note that the characters of IEVs and EVs are varied over time, i.e. at every time slot some EVs could detected the low battery states and turn into IEVs, while some IEVs could be charged by MCSs and turn into EVs. Naturally, the charging expenses of IEVs can be reduced, if new IEVs are allowed to be charged by neighboring MCSs which have been assigned to charge other IEVs, and then several

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IEVs are charged by the same MCSs simultaneously. Such mechanism can make more IEVs charged by MCSs and promote the charging efficiency of MCSs.

Motivated by the above considerations, we propose an assignment rescheduling mechanism of MCSs (ARMM) to dynamically reschedule the MCS assignments, through the negotiations among MCSs, assigned IEVs, and unassigned IEVs. In ARMM, the assigned IEVs of some MCSs could be switched to other MCSs, while the charging positions of MCSs are selected by minimizing the charging expenses of IEVs and are dynamically altered. Thus, the charging expenses of IEVs are reduced, and the proportion of charged IEVs is enhanced.

The remainder of this paper is organized as follows: Section II briefly surveys some existing related studies. Section III proposes a system model to describe the problem of MCS assignments. Section IV provides an analysis framework for this problem. Section V presents the assignment rescheduling mechanism of MCSs (ARMM). Section VI covers some further analyses on ARMM, including the computation efficiency and the incentives of assigned IEVs to reduce the charging expenses of unassigned IEVs. Simulation results for performance evaluation of ARMM are reported in Section VII. Finally, Section VIII concludes the paper.

II. Related Work

In EVN with fixed charging stations, there are two critical issues to be addressed:

(i) The optimal layout of fixed charging stations is the prime issue. The layout of fixed charging stations should be appropriately arranged to minimize the deployment cost of fixed charging stations and/or the travel time of EVs. This issue has been investigated in some literatures, such as [3], [8], [9], [10]. In [3], a genetic programming approach is employed to find a virtually-optimal charging station deployment, and thus the travel time of EVs is minimized. In [8], the optimal sites of charging stations are identified according to the environmental factors and the service range of charging stations. The proposed method reduces the network loss and improves the voltage profile. Two charging station placement cases, i.e. with and without considering the limited battery size, are investigated in [9]. By the solutions, the electric buses are recharged with long continuous service hours. In [10], a multi-objective, multi-stage collaborative planning model is proposed for the coupled charging station infrastructure to minimize the investment and operation cost of the distribution system, while the captured traffic flow is maximized. The above works consider the proper placements of fixed charging stations rather than the routes of MCSs.

(ii) With regard to the reduction of electric energy consumption, the route scheduling of mobile EVs to the fast-charging stations remains another concerned issue. To avoid the overload of power system during the peak time, the load management strategies are indispensable to distribute the EV charging loads temporally and spatially [11]. However, the reliability of the distribution networks of EVs has not been taken into account. In [12], a VANET-enhanced EV charging strategy is developed to improve the energy consumption and reduce the travel cost, while averting the overload of power system. Nevertheless, the incentive mechanisms for motivating EVs to follow the charging decisions are not analysed or proven. In [13], a mixed-integer programming technique is used to facilitate an EV classification scheme, and this scheme can reduce the cost of energy trading of the charging stations. With regard to the problem of minimizing the cost of charging stations, an online centralized scheduling algorithm is proposed to obtain a Pareto-optimal solution, as described in [14].

Some relevant research has been conducted on charging techniques or MCS assignments, such as [4], where some key techniques regarding MCSs are validated, and an energy storage system is provided to facilitate battery and ultra-capacitor to be installed in MCS truck. In [15], a special kind of MCS dedicated for urban and resort areas is presented to charge EVs. References [4], [15] focus on the charging techniques of MCSs, such as electric battery or energy storage units, while the issue of MCS assignments is not considered. A novel heterogeneous network model is presented to improve the communications between EVs and MCSs by using macro cells and small cells [16], and an algorithm is designed to determine the optimal placements of MCSs based on the charging demand and the maintenance cost, while the incentives in the placements of MCSs are not investigated. Reference [5] proposes a Lyapunov-based optimization algorithm to maximize the long-term profits of MCSs, through formulating a stochastic optimization problem to decide the optimal strategy of power management. However, the MCS assignments are not dynamically rescheduled according to the time-variant charging demand of IEVs. [17] provides a framework of scheduling MCSs to charge EVs. The problem of scheduling MCSs based on the charging demand is first formulated, and then a heuristic algorithm (SlotMCS-Allocation) is proposed to solve this problem. In this work, MCSs are placed at some fixed charging stations to temporarily increase the capacity of the fixed charging stations, which restricts the agile placements of MCSs seriously. Besides, Wang $et\ al.$ formulate a nonlinear flow-refueling location model to optimize the MCS locations based on the network designed by Nguyen and Dupuis [18]. The scale of charging facilities' deployment is not verified, and the travel routes of MCSs and EVs are not scheduled.

The solutions of some problems motivate us, although these problems seem different from the problem of MCS assignments. In [19], a multi-objective iterated local search algorithm with adaptive neighborhood selection (MOILS-ANS) is given to solve the multitrip pickup and delivery problem. In this problem, the delivery nodes can be mapped into the charging positions of MCSs. Likewise, [20] proposes a multi-objective bike repositioning approach, and an artificial bee colony (ABC) algorithm is modified to find the optimal solutions. The positions of bike stations in this approach can be mapped into the charging positions of MCSs as well.

In the problem of MCS assignments, the characters of IEVs and EVs are varied over time, i.e. EVs having detected low battery states turn into IEVs, and IEVs having been charged by MCSs turn into EVs, which implies that the charging demand of IEVs is varied over time. This fact is neglected in the above works. Thus, to reduce the charging expenses of IEVs and enhance the proportion of charged IEVs, the MCS assignments should be dynamically rescheduled to cope with the time-variant charging demand of IEVs.

The purpose of this work is to investigate the assignment rescheduling of MCSs. To this end, four cases of available assignment schemes are discussed, and then we propose ARMM, where the assigned IEVs of some MCSs could be switched to other MCSs. Besides, the charging positions of MCSs are selected by minimizing the charging expenses of IEVs and are dynamically altered. Specially, we prove that ARMM can endow the assigned IEVs with incentives to reduce the charging expenses of unassigned IEVs. The contributions of this work are summarized as follows:

- In our proposed ARMM, according to the time-variant charging demand IEVs, MCSs which have been assigned to charge some IEVs can be dynamically rescheduled, and some assigned IEVs could be switched to other MCSs.
- The charging expenses of IEVs are effectively reduced through the negotiations (regarding the charging expenses and/or charging profits of IEVs) among MCSs, assigned IEVs, and unassigned IEVs.
- The incentives of assigned IEVs to reduce the charging expenses of unassigned IEVs are proven to verify the feasibility of our proposed ARMM.

III. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, the problem of MCS assignments is formulated. The explanations of main notations are provided in TABLE I.

TABLE I: Description of main notations

Parameter	Description
$\mathcal{I}$	Set of road intersections
$\mathcal{S}$	Set of road segments
$\mathcal{E}$	Set of EVs
$\mathcal{M}$	Set of MCSs
l	Length of each road segment
$m_s(v_i)$	Traveling speed of EV v_i
R	Communication range of each EV
$e_i^{(t)}$	Battery energy of EV v_i at the t-th time slot
$p(v_i)^{(t)}$	Current position of EV v_i at the t-th time slot
$cp(\psi_j)^{(t)}$	Charging position of MCS ψ_j at the t-th time slot
$E_m(v_i)$	Extra travel of IEV v_i
$\Delta E_m(v_i)$	Increased extra travel of IEV v_i
$\mathcal{V}(\psi_j)$	Set of IEVs assigned to MCS ψ_j
$t_w(v_i, cp(\psi_j)^{(t)})$	Waiting duration of IEV v_i at $cp(\psi_j)^{(t)}$
$t_w(v_i)$	Cumulative waiting duration of IEV v_i
$Q(v_i)$	Charging expense of IEV v_i
$q(v_i, \psi_j)$	Charging expense of IEV v_i paid to MCS ψ_j
$q(v_i, v_k)$	Charging expense of IEV v_i paid to IEV v_k
$G(v_k)$	Charging profit of IEV v_k
r_0	Price of unit electricity transferred from an MCS to an IEV
r_m	Maximum price of increased extra travel

A. System Model

Some definitions are first given as follows:

Definition 1. Road lattice. A road lattice $\mathcal{L}(m, n)$ is constructed with segments parallel to the x and y axes for notation convenience, as shown in Fig. 2. There are $(m+1)\cdot(n+1)$ road intersections in the road lattice. The set of road intersections is denoted by $\mathcal{I}$. The set of road segments is denoted by $\mathcal{S}$, and each road segment is of the same length l.

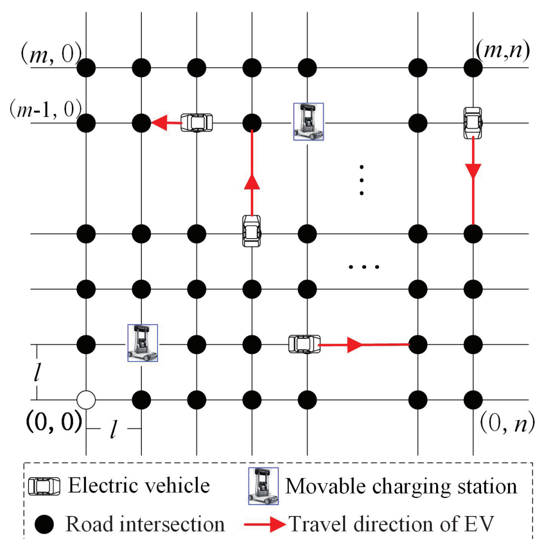


Fig. 2: A road lattice.

Definition 2. Electric vehicles. There are N EVs, and the set of EVs is denoted by $\mathcal{E}$. Each EV is with the same communication range R. The departure position and the destination of an EV v_i are denoted by s_i and d_i, respectively, where $s_i, d_i \in \mathcal{I}$. At the t-th time slot, the battery energy and position of v_i are denoted by $e_i^{(t)}$ and $p(v_i)^{(t)}$, respectively. v_i travels at a speed of $m_s(v_i)$, and c unit of battery energy is consumed for traveling through a road segment.

Definition 3. Movable charging stations. There are M MCSs, and the set of M MCSs is denoted by $\mathcal{M}$. With regard to an MCS ψ_j, the set of IEVs which are assigned to ψ_j is denoted by $\mathcal{V}(\psi_j)$, and the charging position at the t-th time slot is denoted by $cp(\psi_j)^{(t)}$.

Definition 4. Rule of EV travels. If an EV v_i has enough battery energy to travel from s_i to d_i (i.e. there is $e_i^{(0)} \geq c \cdot |s_i - d_i|$), and then v_i travels along the shortest Manhattan path [28], [29]; Otherwise, when v_i detects the low battery state ($e_i^{(t)} \leq \frac{e_i^{(0)}}{\gamma}$, where $\gamma > 1$) at the t-th time slot, v_i

turns into an IEV. Suppose v_i is assigned to an MCS ψ_j to be charged at the position $\widetilde{p}$, and the extra travel undertaken by v_i is computed by:

$$E_m(v_i) = \left|p(v_i)^{(t)} - \widetilde{p}\right| + |\widetilde{p} - d_i| - \left|p(v_i)^{(t)} - d_i\right|, \quad (1)$$

where $|\cdot|$ denotes the number of road segments on a Manhattan path, and thus $\left|p(v_i)^{(t)} - \widetilde{p}\right| + |\widetilde{p} - d_i|$ denotes the future travel distance of v_i via the charging position $\widetilde{p}$, as illustrated in Fig. 3.

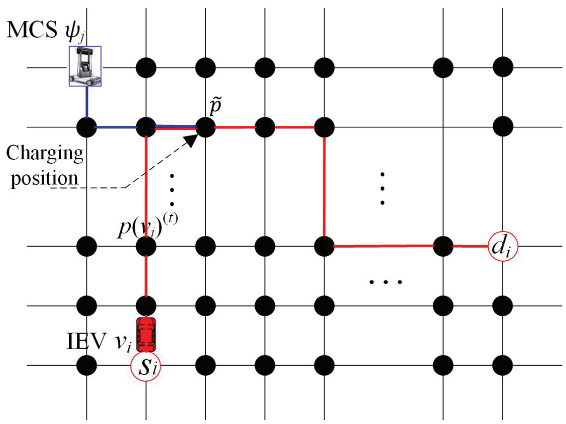


Fig. 3: Extra travel of an IEV.

Definition 5. An MCS charges an IEV. Suppose an IEV v_i is assigned to an MCS ψ_j and is charged at $\widetilde{p}$, the quantity of electricity transferred from ψ_j to v_i is expressed as:

$$\triangle e_i = c \cdot \{|s_i - d_i| + E_m(v_i)\} - e_i^{(0)}, \quad (2)$$

where $\triangle e_i$ is calculated as the insufficient electricity of v_i. Besides, the waiting duration of v_i is calculated as:

$$t_w(v_i, \widetilde{p}) = \begin{cases} 0, & if\ \frac{\left|p(v_i)^{(t)} - \widetilde{p}\right|}{m_s(v_i)} \geq \frac{\left|p(\psi_j)^{(t)} - \widetilde{p}\right|}{m_s(\psi_j)}, \\ \frac{\left|p(\psi_j)^{(t)} - \widetilde{p}\right|}{m_s(\psi_j)} - \frac{\left|p(v_i)^{(t)} - \widetilde{p}\right|}{m_s(v_i)}, & otherwise. \end{cases} \quad (3)$$

The cumulative waiting duration of each IEV should not be larger than a waiting duration threshold T to avoid a long-term waiting, i.e. there should be $t_w(v_i) \leq T$. Note that T can be set according to the requirements of EV drivers, because the value of T measures the charging experience of charged IEVs. Typically, a smaller T gives rise to a better charging experience of charged IEVs.

B. Problem Objective

In order to reduce the charging expenses of IEVs and enhance the proportion of charged IEVs, the problem objective is formally presented as follows:

$$\begin{cases} \min \ \frac{\sum_{i=1}^{N} Q(v_i)}{N}, \\ \max \ \frac{N_c}{N_I}, \end{cases} \quad (4)$$

where N_c, N_I, and N denote the number of charged IEVs, the number of IEVs, and the number of EVs, respectively. $Q(v_i)$ denotes the charging expense of IEV v_i. Specially, if v_i is not an IEV, and there is $Q(v_i) = 0$.

There are two constraints for an MCS charging an IEV: (*i*) The IEV has enough residual battery energy to travel to the charging position; (*ii*) The cumulative waiting duration of each IEV is not longer than the waiting duration threshold T.

IV. Analysis Framework

As aforementioned above, the characters of IEVs and EVs are varied over time. Hence, the MCS assignments should be dynamically rescheduled to reduce the charging expenses of IEVs and charge more IEVs.

Moreover, the number of MCSs is typically smaller than that of IEVs, and thus an MCS should charge several IEVs simultaneously, which is practical because an MCS has multiple charging interfaces (as illustrated in Fig. 1). With regard to an MCS with some assigned IEVs, before it arrives at the charging position, some unassigned IEVs could be assigned to it. The unassigned IEVs must be admitted by the IEVs which have been assigned to the MCS, and the charging position could be accordingly altered, which leads to the increased extra travels of these assigned IEVs.

Suppose an EV v_i detects the low energy state at the t-th time slot, and then v_i turns into an IEV. After that, v_i requests the neighboring MCSs in the communication range R for the possible charge. Suppose ψ_j is a neighboring MCS (the distance is smaller than R, i.e. $d(v_i, \psi_j) \leq R$), and an available assignment scheme should satisfy one of the following cases:

Case 1: $\mathcal{V}(\psi_j) = \emptyset$ (MCS ψ_j does not have any assigned IEVs), and the charging position $cp(\psi_j)^{(t)}$ is selected by:

$$cp(\psi_j)^{(t)} = \arg\min_{\widetilde{p} \in \mathcal{I}} \left\{E_m(v_i) \middle|\ e_i^{(t)} \geq c \cdot \left|p(v_i)^{(t)} - \widetilde{p}\right|\ and\ t_w(v_i, \widetilde{p}) \leq T\right\}, \quad (5)$$

which indicates that $cp(\psi_j)^{(t)}$ is selected by minimizing the extra travel of v_i. After v_i is charged by ψ_j at the position $cp(\psi_j)^{(t)}$, the expense $q(v_i, \psi_j)$ is paid to ψ_j:

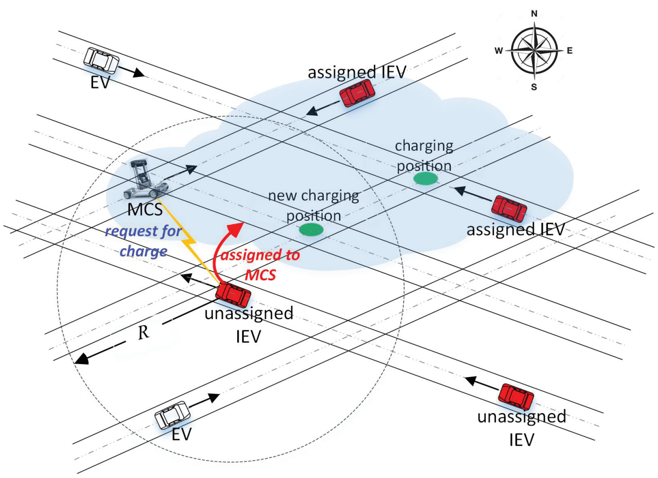
$$q(v_i, \psi_j) = r_0 \cdot \triangle e_i = r_0 \cdot \left\{c \cdot [|s_i - d_i| + E_m(v_i)] - e_i^{(0)}\right\}, \quad (6)$$

where r_0 denotes the price of unit electricity transferred from an MCS to an IEV. Under Case 1, we have $Q(v_i) = q(v_i, \psi_j)$.

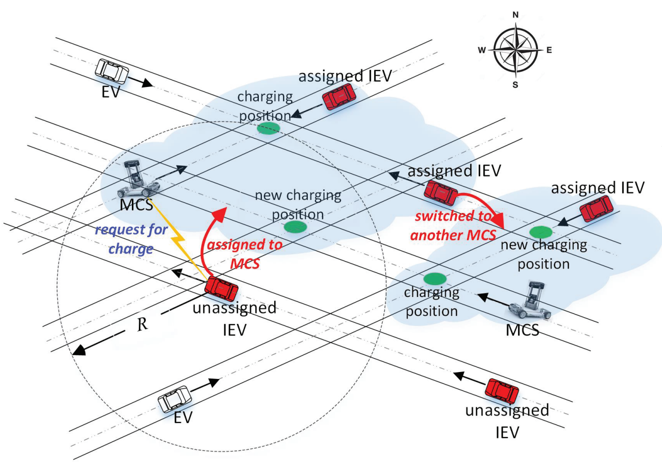
Case 2: $\mathcal{V}(\psi_j) \neq \emptyset$, and v_i is assigned to MCS ψ_j, as shown in Fig. 4(a). The new charging position $cp(\psi_j)^{(t)}$ is determined by:

$$cp(\psi_j)^{(t)} = \arg\min_{\widetilde{p} \in \mathcal{I}} \left\{Q(v_i) \middle|\ e_i^{(t)} \geq c \cdot \left|p(v_i)^{(t)} - \widetilde{p}\right|\ and\ t_w(v_i, \widetilde{p}) \leq T\right\},$$
$$\forall v_k \in \mathcal{V}(\psi_j),\ s.t. \begin{cases} e_k^{(t)} \geq c \cdot \left|p(v_k)^{(t)} - \widetilde{p}\right|, \\ t_w(v_k) + t_w(v_k, \widetilde{p}) \leq T, \end{cases} \quad (7)$$

where v_k is an assigned IEV of ψ_j, and $t_w(v_k)$ denotes the waiting duration having been spent by v_k. Equation (7) implies that each assigned IEV of ψ_j has enough electric energy to travel to the new charging position $cp(\psi_j)^{(t)}$, and the cumulative waiting duration of each assigned IEV is still not longer than the waiting duration threshold T.



(a) An IEV assigned to an MCS



(b) An assigned IEV switched to another MCS

Fig. 4: Two available assignment schemes (Case 2 and Case 3).

The charging expense of v_i is comprised of two parts: (i) The expense paid to ψ_j; (ii) The expenses paid to the assigned IEVs of ψ_j. Thus, $Q(v_i)$ is expressed as:

$$Q(v_i) = q(v_i, \psi_j) + \sum_{\forall v_k \in \mathcal{V}(\psi_j)} q(v_i, v_k), \tag{8}$$

where $q(v_i, \psi_j)$ is obtained by (6), and $q(v_i, v_k)$ is expressed as:

$$q(v_i, v_k) = \begin{cases} 0, & if\ \Delta E_m(v_k) \leq 0, \\ r_k \cdot \Delta E_m(v_k), & otherwise, \end{cases} \tag{9}$$

where r_k denotes the price of increased extra travel of v_k. The price of different assigned IEVs may be different due to their different travel intentions and travel emergencies.

In (9), $\Delta E_m(v_k)$ denotes the increased extra travel of v_k, which is caused by the charging position alteration:

$$\begin{aligned} \Delta E_m(v_k) = & \left| p(v_k)^{(t)} - cp(\psi_j)^{(t)} \right| + \left| cp(\psi_j)^{(t)} - d_k \right| \\ & - \left| p(v_k)^{(t)} - cp(\psi_j)^{(t-1)} \right| - \left| cp(\psi_j)^{(t-1)} - d_k \right|. \end{aligned} \tag{10}$$

Besides, when $\Delta E_m(v_k) > 0$, the expense $c \cdot r_0 \cdot \Delta E_m(v_k)$ is paid for the increased electricity consumption of v_k, and hence the charging profit of v_k is calculated by:

$$G(r_k) = \begin{cases} -c \cdot r_0 \cdot \Delta E_m(v_k), & if\ \Delta E_m(v_k) \leq 0, \\ (r_k - c \cdot r_0) \cdot \Delta E_m(v_k), & otherwise. \end{cases} \tag{11}$$

Case 3: $\mathcal{V}(\psi_j) \neq \emptyset$, and a new charging position cannot be found by (7) when v_i is assigned to ψ_j. There is another MCS $\psi_{j'}$ around ψ_j, and v_i can be charged by ψ_j when one or several assigned IEVs of ψ_j are switched to $\psi_{j'}$, as shown in Fig. 4(b). The new charging position of ψ_j is selected by minimizing the charging expense of v_i:

$$\begin{aligned} & cp(\psi_j)^{(t)} = \\ & \arg\min_{\widetilde{p} \in \mathcal{I}} \left\{ Q(v_i) \middle|\ e_i^{(t)} \geq c \cdot \left| p(v_i)^{(t)} - \widetilde{p} \right| \ \ and\ t_w(v_i, \widetilde{p}) \leq T \right\}, \\ & \forall v_k \in \mathcal{V}(\psi_j) \setminus \overline{\mathcal{V}}(\psi_j, \psi_{j'}),\ s.t. \begin{cases} e_k^{(t)} \geq c \cdot \left| p(v_k)^{(t)} - \widetilde{p} \right|, \\ t_w(v_k) + t_w(v_k, \widetilde{p}) \leq T, \end{cases} \end{aligned} \tag{12}$$

where $\overline{\mathcal{V}}(\psi_j, \psi_{j'})$ denotes the set of assigned IEVs switched to $\psi_{j'}$. Likewise, $cp(\psi_{j'})^{(t)}$ should be updated.

Besides, $Q(v_i)$ is calculated by:

$$\begin{aligned} Q(v_i) = & q(v_i, \psi_j) + \sum_{\forall v_k \in \mathcal{V}(\psi_j) \setminus \overline{\mathcal{V}}(\psi_j, \psi_{j'})} q(v_i, v_k) \\ & + \sum_{\forall v_{k'} \in \mathcal{V}(\psi_{j'}) \bigcup \overline{\mathcal{V}}(\psi_j, \psi_{j'})} q(v_i, v_{k'}). \end{aligned} \tag{13}$$

Because some assigned IEVs of ψ_j are switched to $\psi_{j'}$, and the charging position of $\psi_{j'}$ could be altered, which leads to the increased extra travels of IEVs in the set $\mathcal{V}(\psi_{j'}) \bigcup \overline{\mathcal{V}}(\psi_j, \psi_{j'})$.

Thus, (13) indicates that the charging expense of v_i is comprised of three parts: (i) The expense paid to ψ_j; (ii) The expenses paid to the assigned IEVs of ψ_j; (iii) The expenses paid to the assigned IEVs of $\psi_{j'}$.

Case 4: $\mathcal{V}(\psi_j) \neq \emptyset$, and there are several MCSs around ψ_j. Some assigned IEVs of ψ_j could be switched to several different MCSs. Then, v_i can be charged by ψ_j. Similar to Case 3, the new charging position of ψ_j is selected by minimizing the charging expense of v_i. Case 4 is taken as a derivative of Case 3.

V. Assignment Rescheduling Mechanism of MCSs

To reduce the charging expenses of IEVs and enhance the proportion of charged IEVs, we propose an assignment rescheduling mechanism of MCSs (ARMM) to dynamically reschedule the MCS assignments. ARMM is a completely distributed mechanism, and the global computations and message interactions are not needed. In ARMM, the dedicated short range communications (DSRC) can be applied to realize the vehicle to vehicle communications, and the maximum communication range specified in DSRC standard [30] is up to several thousand meters.

The operation of ARMM is described in terms of eight stages: initialization, IEVs request for charges, MCS receives request from IEVs, MCS negotiates with assigned IEVs, MCS negotiates with neighboring MCSs, IEVs select optimal assignment schemes, MCS and IEVs reschedule routes, and MCS charges IEVs, as illustrated in Fig. 5, where the symbol $(t-1)^+$ denotes some (small) time after the end of the $(t-1)$-th time slot, and $(t)^-$ denotes some (small) time before the start of the t-th time slot, such that there is $(t-1)^+ < (t)^- < (t) < (t)^+ < (t+\tau)$.

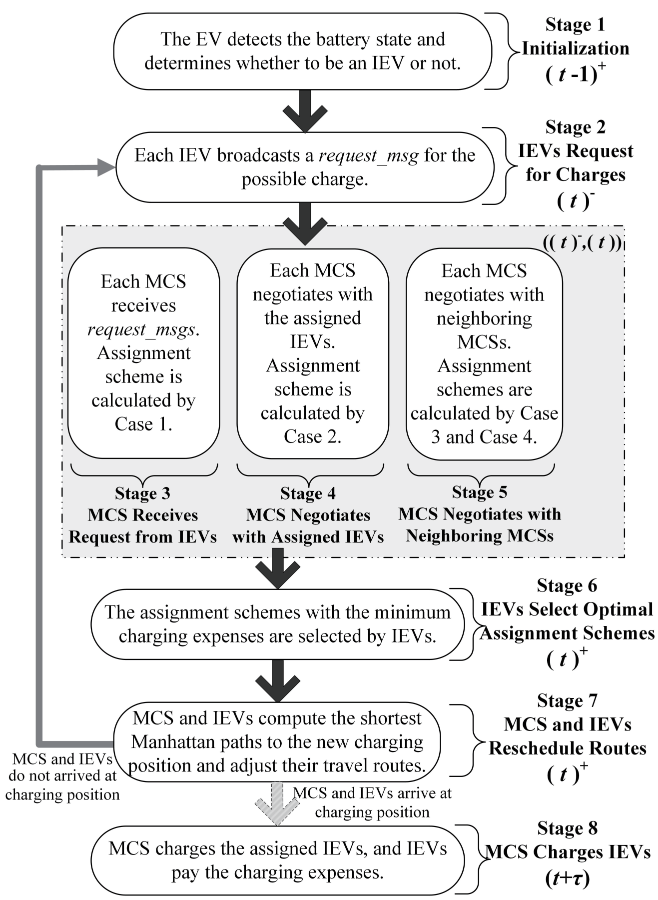


Fig. 5: The stages of ARMM.

A. Stages of ARMM

The detailed stages of ARMM are provided as follows:

Stage 1. *Initialization*. With regard to each EV v_i, when $e_i^{(t)} \le \frac{e_i^{(0)}}{\gamma}$, v_i should determines whether it is an IEV by the following inequality:

$$\left\lfloor \frac{e_i^{(0)}}{c} \right\rfloor < |s_i - d_i| \,. \tag{14}$$

When (14) is satisfied, v_i is an IEV; Otherwise, v_i is not an IEV, and it can travel to the destination without any charges.

Stage 2. *IEVs Request for Charges*. Suppose at the t-th time slot, v_i turns into an IEV, and then v_i broadcasts a charging request $request\_msg$ in the communication range R. The structure of $request\_msg$ is depicted in Fig. 6.

Stage 3. *MCS Receives Request from IEVs*. With regard to each MCS ψ_j which receives the $request\_msg$ from v_i, if there are not any IEVs assigned to ψ_j, i.e. $\mathcal{V}(\psi_j) = \emptyset$, and then the assignment scheme including $cp(\psi_j)^{(t)}$ and $q(v_i, \psi_j)$ is calculated by Case 1. A $response\_msg$ including $cp(\psi_j)^{(t)}$ and $q(v_i, \psi_j)$ is sent to v_i. If there is an IEV or some IEVs having been assigned to ψ_j, i.e. $\mathcal{V}(\psi_j) \neq \emptyset$, and then Stage 4 is carried out.

Stage 4. *MCS Negotiates with Assigned IEVs*. ψ_j sends an $inquire\_msg$ to the assigned IEVs. After receiving the $inquire\_msg$ from ψ_j, each assigned IEV replies with a $reply\_msg$ to ψ_j. A $reply\_msg$ includes the current position, residual battery energy, cumulative waiting duration, and price of increased extra travel, as shown in Fig. 6. These $reply_msg$s are forwarded to v_i. Then, the assignment scheme including the new charging position and the charging expense is calculated by Case 2.

Stage 5. *MCS Negotiates with Neighboring MCSs*. If there are some neighboring MCSs around ψ_j, and then all the $reply_msg$s sent from the assigned IEVs of ψ_j and the neighboring MCSs are forwarded to v_i. The assignment schemes (the new charging positions and the charging expenses) are calculated by v_i according to Case 3 and Case 4.

Stage 6. *IEVs Select Optimal Assignment Schemes*. Upon receiving the assignment schemes, the assignment scheme with the minimum charging expense is selected by v_i, and then the selected assignment scheme is encapsulated into an $assign\_msg$ and notified to MCS ψ_j, IEVs in $\mathcal{V}(\psi_j)$ and neighboring MCSs. After that, the set of assigned IEVs of ψ_j is updated by:

$$\mathcal{V}(\psi_j) \leftarrow \mathcal{V}(\psi_j) \bigcup v_i \setminus \bigcup_{\psi_{j'}} \overline{\mathcal{V}}(\psi_j, \psi_{j'}), \tag{15}$$

where $\bigcup_{\psi_{j'}} \overline{\mathcal{V}}(\psi_j, \psi_{j'})$ denotes the set of assigned IEVs switched to neighboring MCSs.

Stage 7. *MCS and IEVs Reschedule Routes*. ψ_j and assigned IEVs compute the shortest Manhattan paths to the new charging position and adjust their travel routes. Besides, the extra travels of the assigned IEVs are updated, e.g. the extra travel of v_k is updated by:

$$E_m(v_k) \leftarrow E_m(v_k) + \Delta E_m(v_k), \tag{16}$$

Message Type	ID	Sender Type	Time Slot	Position	Battery Energy	Waiting Duration	Price
request_msg	v_i	IEV	t	$p(v_i)^{(t)}$	$e_i^{(t)}$	0	r_i
response_msg / *inquire_msg*	ψ_j	MCS	t	$p(\psi_j)^{(t)}$	N/A	N/A	r_0
reply_msg	$\mathcal{V}(\psi_j)$	Assigned IEVs	t	Positions of $\mathcal{V}(\psi_j)$	Energies of $\mathcal{V}(\psi_j)$	Waiting durations of $\mathcal{V}(\psi_j)$	Prices of $\mathcal{V}(\psi_j)$
assign_msg	v_i	IEV	t	Selected assignment scheme			

Fig. 6: Structures of messages in ARMM.

where $\Delta E_m(v_k)$ is obtained by (10).

Stage 8. *MCS Charges IEVs*. When ψ_j and the assigned IEVs arrive at the charging position, and then ψ_j charges these IEVs. Then, the charged IEV v_i pays the expense $Q(v_i)$, which could be comprised of: the expense paid to ψ_j for the electricity transferred from ψ_j; the expenses paid to the early assigned IEVs which admit the charge of v_i, for their increased extra travels due to the charging position alterations and/or the MCS switches.

Note that some new IEVs are assigned to MCSs every time slot, and thus the process from Stage 2 to Stage 7 is repeated, i.e. the MCS assignments are dynamically rescheduled every time slot. A sequential diagram concerning the message interactions in ARMM is given in Fig. 7, and the pseudo-code of ARMM is depicted in Algorithm 1.

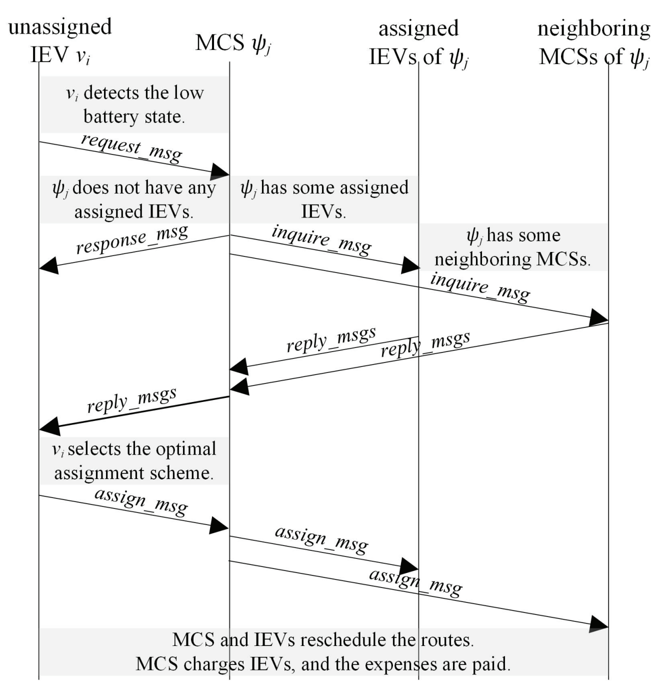


Fig. 7: Sequential diagram of ARMM.

Algorithm 1 Pseudo-code of ARMM

```
t ← 1;
while The t-th time slot falls into an observation period do
    Each EV determines whether it is an IEV;
    for Each EV v_i turning into an IEV at the t-th time slot do
        v_i broadcasts a charging request;
        for Each MCS ψ_j which receives the charging request from v_i do
            if V(ψ_j) = ∅ then
                The assignment scheme is calculated by Case 1.
            end if
            if V(ψ_j) ≠ ∅ then
                ψ_j negotiates with the assigned IEVs in the set V(ψ_j), and the assignment scheme is calculated by Case 2.
                ψ_j negotiates with neighboring MCSs, and the assignment schemes are calculated by Case 3 and Case 4.
            end if
            The available assignment schemes are forwarded to v_i.
        end for
        The assignment scheme with the minimum expense is selected by v_i and notified to MCS.
        The routes of v_i, MCS, and some assigned IEVs are rescheduled.
        v_i and MCS move towards the charging position.
    end for
    t ← t + 1;
end while
```

B. Conflicts in MCS Assignments

The conflicts in MCS assignments happen when several IEVs select an MCS as the optimal MCS simultaneously. However, this MCS cannot be assigned to charge all of these IEVs. In ARMM, the IEV with the minimum charging expense can preferentially select this MCS, and other IEVs should select their sub-optimal MCSs.

VI. Mechanism Analysis

A. Computation Efficiency

The computation efficiency of ARMM is analysed in terms of the computation complexity in Case 1 to Case 4:

- In Case 1, the number of computations is at most $(m+1)\cdot(n+1)$ $(m, n << N)$, and thus the computation complexity is $O(1)$;

- In Case 2, the computation complexity is $O(1)$ as well;
- In Case 3, the number of assigned IEVs of ψ_j is denoted by $|\mathcal{V}(\psi_j)|$, and then the number of potential sets of switched IEVs is written as $2^{|\mathcal{V}(\psi_j)|}-1$, which implies that the computation complexity is expressed as $(m+1)\cdot(n+1)\cdot\left(2^{|\mathcal{V}(\psi_j)|}-1\right)$;
- In Case 4, suppose there are ξ ($\xi < M-1$) neighboring MCSs around ψ_j, and the computation complexity of obtaining the optimal assignment scheme is $(m+1)\cdot(n+1)\cdot\sum_{\kappa=1}^{|\mathcal{V}(\psi_j)|}\left\{\binom{|\mathcal{V}(\psi_j)|}{\kappa}\cdot\xi^{\kappa}\right\}$.

Typically, the number of IEVs and the number of MCSs are much smaller than the number of EVs, i.e. there are $|\mathcal{V}(\psi_j)| << N$ and $M << N$. Therefore, the computation complexity of ARMM is $O(1)$.

B. Incentives in ARMM

In this subsection, the incentives of assigned IEVs to reduce the charging expenses of unassigned IEVs are analysed.

Suppose there are K available assignment schemes, where two assigned IEVs v_k and $v_{k'}$ are involved in two available assignment schemes $\mathcal{AS}_1$ and $\mathcal{AS}_2$, respectively. When $\Delta E_m(v_k) = \Delta E_m(v_{k'})$, the probability of $\mathcal{AS}_1$ outperforming $\mathcal{AS}_2$ is expressed as:

$$\begin{aligned} Pr\left(q(v_i,v_k)\le q(v_i,v_{k'})\right) &= 1-Pr\left(q(v_i,v_{k'})<q(v_i,v_k)\right)\\ &= 1-Pr\left(r_{k'}<r_k\right)=1-\mathcal{F}\left(r_k\right), \end{aligned} \tag{17}$$

where $\mathcal{F}(\cdot)$ denotes the probability distribution function of $Pr(\cdot)$.

By (11), when $\Delta E_m(v_k)>0$, the charging profit of v_k is written as:

$$G\left(r_k\right)=q(v_i,v_k)-c\cdot r_0\cdot\Delta E_m(v_k). \tag{18}$$

Because EVs are considered to be selfish, the charging profit of each assigned IEV is expected to be maximized:

$$\begin{aligned} &\max_{v_i\in\mathcal{E}\setminus v_k}\left\{\ G\left(r_k\right)\cdot\prod\left[1-\mathcal{F}\left(r_k\right)\right]\ \right\}\\ =&\max_{v_i\in\mathcal{E}\setminus v_k}\left\{\left[q(v_i,v_k)-r_0\cdot c\cdot\Delta E_m(v_k)\right]\cdot\left[1-\mathcal{F}\left(r_k\right)\right]^{K-1}\right\}, \end{aligned} \tag{19}$$

and there is at least one internal solution in (19), implying that the first order of $G\left(r_k\right)\cdot\prod\left[1-\mathcal{F}\left(r_k\right)\right]$ with respect to $q(v_i,v_k)$ is equal to 0:

$$\left\{\begin{array}{l}\left[1-\mathcal{F}\left(r_k\right)\right]^{K-1}-(K-1)\cdot\left[1-\mathcal{F}\left(r_k\right)\right]^{K-2}\\ \cdot f\left(r_k\right)\cdot\left[q(v_i,v_k)-c\cdot r_0\cdot\Delta E_m(v_k)\right]\cdot\frac{dr_k}{dq(v_i,v_k)}\end{array}\right\}=0, \tag{20}$$

where $f(\cdot)$ denotes the probability density function of $\mathcal{F}(\cdot)$.

Without loss of generality, suppose $\mathcal{F}(\cdot)$ obeys a uniform distribution $U(c\cdot r_0, r_m)$, and the following equations can be obtained by (20):

$$\begin{aligned} q(v_i,v_k) &= c\cdot r_0\cdot\Delta E_m(v_k)+\frac{\int_{r_k}^{r_m}\left[1-\mathcal{F}\left(x\right)\right]^{K-1}dx}{\left[1-\mathcal{F}\left(r_k\right)\right]^{K-1}}\\ &= c\cdot r_0\cdot\Delta E_m(v_k)+\frac{\int_{r_k}^{r_m}\left(1-\frac{x-c\cdot r_0}{r_m-c\cdot r_0}\right)^{K-1}dx}{\left(1-\frac{r_k-c\cdot r_0}{r_m-c\cdot r_0}\right)^{K-1}}\\ &= c\cdot r_0\cdot\Delta E_m(v_k)+\frac{r_m-r_k}{K}, \end{aligned} \tag{21}$$

which indicates that a smaller price of increased extra travel gives rise to a larger charging profit. Especially, when K is large enough, the price of increased extra travel is very close to the price of unit electricity transferred from an MCS to an IEV (r_0). Likewise, when $r_k = r_{k'}$, a larger increased extra travel leads to a smaller charging profit.

Therefore, the incentives in ARMM can motivate the assigned IEVs to reduce their prices to increase their charging profits, and the assignment schemes (where the assigned IEVs are with smaller increased extra travels) are prone to be selected. Therefore, the incentives in ARMM can reduce the charging expenses of IEVs.

VII. Performance Evaluation

In this section, we provide a thorough performance evaluation of our proposed ARMM, along with comparisons with other algorithms (Lyapunov-based optimization [5], SlotMCS-Allocation [17], MOILS-ANS [19], ABC algorithm [20], and optimal centralized solution). Specially, the optimal centralized solution assumes the future charging demand of IEVs is completely foreknown, and thus the optimal MCS assignments can be decided.

The price of increased extra travel of each IEV is randomly selected from a price interval $[c\cdot r_0, r_m]$. In real charging scenarios, the price interval is determined by the electricity trading market. The initial battery energy of each EV obeys a normal distribution $\mathcal{N}(\mu,\delta^2)$, where the value of μ indicates the average initial battery energy of EVs, and the value of δ indicates the deviation of initial battery energy among EVs. The normal distribution $\mathcal{N}(\mu,\delta^2)$ reflects the battery diversity of the electric vehicles which are produced by different manufacturers. We develop a simulator using C++ language, and the simulation results are averaged over 500 runs.

The main parameter settings are shown in TABLE II. Note that the parameter values given in TABLE II are taken as the default values, i.e. the default values of parameters are adopted in the following simulations when the parameter values are not explicitly varied. Besides, the simulation results are obtained on the premise that several neighboring MCSs can provide their available assignment schemes to an IEV simultaneously, and the assignment scheme with the minimum charging expense is selected.

A. Number of IEVs and Proportion of Charged IEVs

We first observe the number of IEVs and the number of charged IEVs. Fig. 8 illustrates the impacts of N and M

TABLE II: Simulation Parameters

Parameter	Description	Value
N	Number of EVs	800
M	Number of MCSs	45
$m \times n$	Size of road lattice	60×60
l	Length of each road segment	0.4 km
T	Waiting duration threshold	200 s
R	Communication range of each EV	1.0 km
m_s	Travel speed of each EV and each MCS	16.7 m/s
μ	Average battery energy of EVs	90 kwh
δ	Standard deviation of battery energy	15 kwh
c	Energy consumption of traveling through a road segment	0.5 kwh
γ	Low battery parameter	3
r_0	Price of unit electricity transferred from an MCS to an IEV	2.4/kwh
r_m	Maximum price of increased extra travel	12.5/km

on the number of IEVs and the number of charged IEVs, respectively.

Three observations are obtained as follows: (i) Both the number of IEVs and the number of charged IEVs raise with the increase of N. This is because when more EVs are traveling in the road lattice, more IEVs exist and are charged by MCSs. (ii) When N is fixed, a larger M leads to a larger number of charged IEVs, since more MCSs can charge more IEVs. (iii) With the increase of N, the bars of the number of IEVs ascend more rapidly than those of the number of charged IEVs, which implies that when the number of IEVs becomes very large, MCSs cannot charge all of these IEVs, and some IEVs fail to be charged.

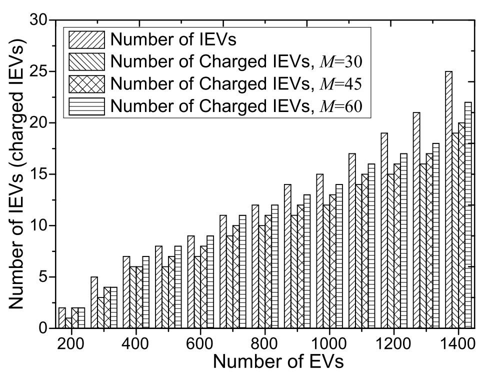


Fig. 8: Number of IEVs (charged IEVs) vs. N and M

Furthermore, the proportion of charged IEVs under different μ is observed in Fig. 9. In Fig. 9, the curves decrease with the increase of N, which is attributed to the fact that more IEVs cannot be charged when the number of IEVs has exceeded a maximum workload of MCSs, and thus the proportion of charged IEVs is decreased. Besides, the curve with a larger μ is higher than that with a smaller μ. The reason is that μ is related with the initial battery energy of EVs, and a larger μ indicates that more EVs have enough battery energy to complete their travels and do not turn into IEVs. Thereby, IEVs can be charged by MCSs more easily.

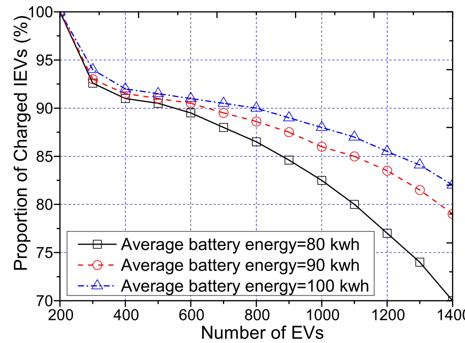


Fig. 9: Proportion of charged IEVs vs. N and μ.

B. Average Extra Travel Distance and Average Waiting Duration

As shown in Fig. 10(a), the average extra travel distance of IEVs is reduced by increasing the number of MCSs, and this is because some nearer MCSs can be found to charge IEVs, when more MCSs are deployed into the road lattice. Besides, the curve with a smaller μ is much higher than that with a larger μ, due to the fact that with a smaller μ more IEVs exist and could be assigned to the same MCSs, thus enlarging the extra travel distance of IEVs.

In Fig. 10(b), the curves of average waiting duration for charges rise up with the increase of N. The reason is that some IEVs are possible to wait other IEVs (assigned to the same MCSs) for longer durations, when more IEVs are assigned to the same MCSs. Moreover, the curve with a larger R is much higher than that with a smaller R, and this is because IEVs with a larger communication range can request the charging services from farther MCSs, and then more IEVs can be charged by MCSs, although some IEVs wait for longer durations.

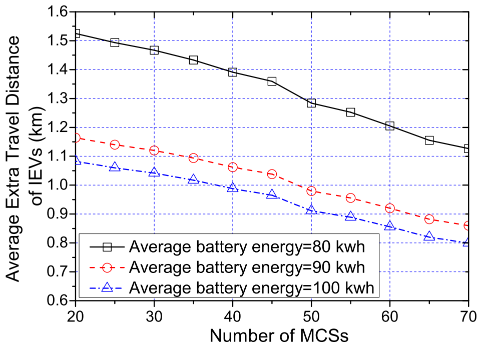
C. Average Charging Expense and Average Charging Profit

As depicted in Fig. 11, both the average charging expense and the average charging profit of IEVs are reduced with the increase of M or μ, which is attributed to the fact that a larger M or a larger μ indicates fewer IEVs are assigned to the same MCSs. Thus, the extra travel distance of IEVs is decreased (in Fig. 10(a)), which reduces the average charging expense of IEVs accordingly.

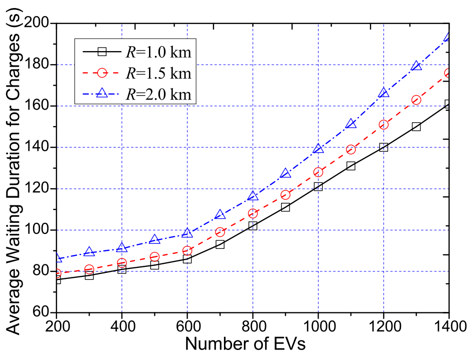
When $M = 70$ and $\mu = 100$, the average charging expense and average charging profit are 11.375 and 6.497, respectively. Note that the average charging profit is always smaller than the average charging expense, because some charging expenses should be additionally paid for the increased extra travels of some early assigned IEVs.

D. Algorithm Comparisons

To further analyse the merits of ARMM, we compare ARMM with Lyapunov-based optimization, SlotMCS-Allocation, MOILS-ANS, ABC algorithm, and optimal centralized solution. In Lyapunov-based optimization, the

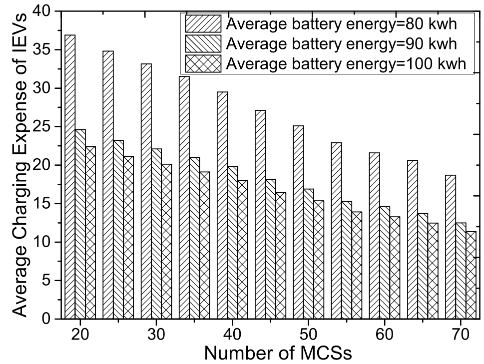


(a) Average extra travel distance vs. M and μ

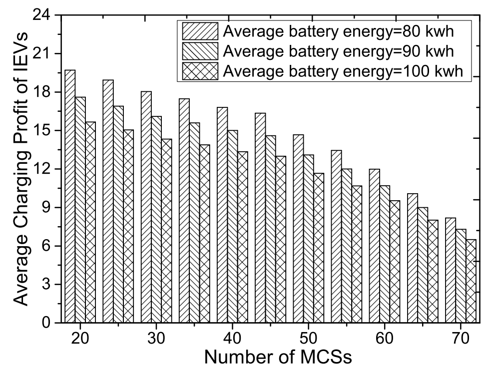


(b) Average waiting duration vs. N and R

Fig. 10: Average extra travel distance and average waiting duration.



(a) Average charging expense vs. M and μ



(b) Average charging profit vs. M and μ

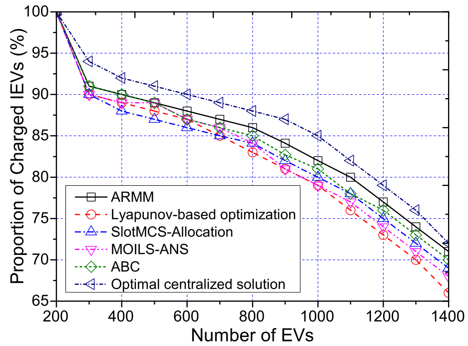
Fig. 11: Average charging expense and average charging profit.

renewable power and the traditional power are not differentiated, and the IEVs assigned to an MCS are considered to fall into the same charging queue. In SlotMCS-Allocation, the obtained placements of MCSs are mapped into the charging positions of MCSs.

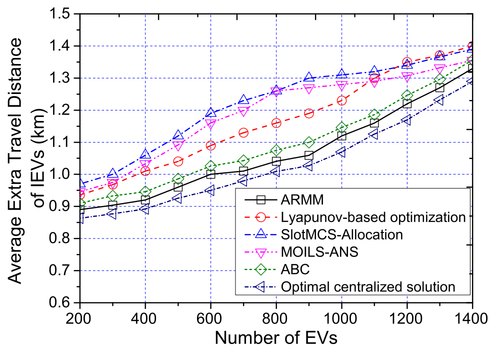
The simulations are conducted on a real dataset comprised of taxis' trajectories [31] in Chengdu city, China. In this dataset, there are about 10,000 taxis, and their trajectories were produced during the period from Oct. 1, 2018 to Oct. 31, 2018. Each trajectory point is represented by a set of time stamp, latitude, longitude, and taxi ID. The total number of trajectory points in the dataset is about 11 million. The trajectories of N taxis are randomly selected to simulate the movements of EVs.

These algorithms are compared in terms of the proportion of charged IEVs, average extra travel distance of IEVs, average charging expense of IEVs, and average computation time for charging an IEV. The simulation results are given in Fig. 12 and Fig. 13, which suggest that ARMM outperforms other algorithms by an obvious margin except the average computation time. The reason for these phenomena is that ARMM attempts to charge IEVs as much as possible through the dynamic assignments of MCSs. In order to charge more IEVs, the assigned IEVs of some MCSs can be switched to other MCSs, and thus the proportion of charged IEVs is larger than other algorithms. To reduce the charging expenses of IEVs, the charging positions are selected by minimizing the charging expenses of IEVs and are dynamically altered. Thus, ARMM reduces the extra travel distance and charging expenses of IEVs. Fig. 13(b) illustrates that the mechanism of dynamic assignments of MCSs prolongs the average computation time slightly. However, the average computation time of ARMM falls into a small numerical interval $[5.269, 5.373]$, which is tolerable in real charging scenarios.

Fig. 12 and Fig. 13 indicate that the gaps between the results of ARMM and the results of the optimal centralized solution are not very large, especially in terms of the average charging expense of IEVs and average extra travel distance of IEVs. Besides, the average computation time of the optimal centralized solution is much longer than other algorithms because of its complex computation (all potential cases are traversed to find the optimal assignments). Note that the optimal centralized solution is not available in real charging scenarios, due to the strong assumption that the future charging demand of IEVs must be completely foreknown.

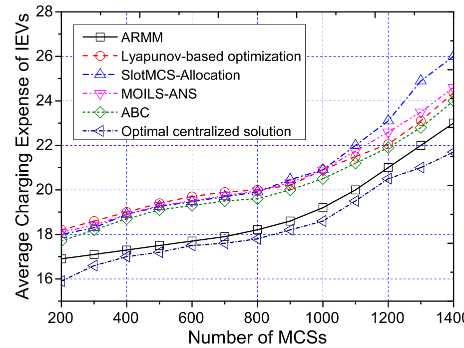


(a) Proportion of charged IEVs

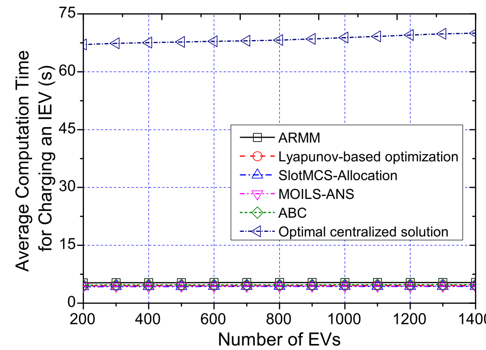


(b) Average extra travel distance

Fig. 12: Algorithm comparisons in terms of proportion of charged IEVs, and average extra travel distance.



(a) Average charging expense



(b) Average computation time

Fig. 13: Algorithm comparisons in terms of average charging expense, and average computation time.

VIII. Conclusion

We have studied the problem of MCS assignments in EVN, and an assignment rescheduling mechanism of M-CSs (ARMM) has been introduced. In ARMM, the MCS assignments are dynamically rescheduled. Especially, the assigned IEVs of some MCSs could be switched to other MCSs, while the charging positions of MCSs are selected by minimizing the charging expenses of IEVs and are dynamically altered. Therefore, ARMM can reduce the charging expenses of IEVs and enhance the proportion of charged IEVs effectively.

In this work, the idle MCSs (which do not have any assigned IEVs) are considered to stop and wait at the current positions, and the placements of idle MCSs according to real-time traffic flows will be investigated in future to improve the IEV charges. Besides, the charging positions cannot be selected from any positions in a practical road network, and the selections of charging positions should be restricted by a set of designated charging positions where MCSs are allowed to charge IEVs, such as some charging parks. Furthermore, MCSs can carry some batteries which have been fully charged, and thus they can charge IEVs by swapping the batteries. The battery swapping manner (such as [32]) can be adopted in ARMM to shorten the charging durations significantly.

Acknowledgments

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