Scheduling Mobile Charging Stations for Electric Vehicle Charging

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***Abstract*—Electric Vehicles (EVs) are being increasingly seen as an eco-friendly alternative to conventional internal combustion vehicles. EVs require periodic charging of their batteries and fixed charging stations (FCSs) have been used commonly to charge EV batteries. However, FCSs may not be able to charge many EVs during increased demands. Mobile charging stations (MCS) have been proposed for charging EVs at different spots, with an MCS carrying batteries travelling to the EV to charge its batteries. In this paper, we propose a framework for temporarily increasing the capacity of FCSs by scheduling MCSs to service additional EVs during increased demand. The problem of scheduling the MCSs to different FCSs based on EV charging demands is formulated, and is shown to be NP-hard. Two offline heuristic algorithms to solve the problem are proposed. Detailed simulation on a real-world map is presented to show that the algorithms perform well in realistic scenarios.**

***Keywords*—Electric Vehicle, Mobile Charging, Scheduling**

I. Introduction

Smart cities of tomorrow will need to address major environmental and energy management challenges. One of the primary sources of environmental pollution in urban areas is the transportation sector, which currently comprises of mostly internal combustion vehicles. To address this problem, Electric Vehicles (EV) are being increasingly seen as an eco-friendly and efficient alternative to traditional fossil fuel based vehicles. According to a study by BloombergNEF [2], light duty EV sales are expected to capture 28% of the global sales market by 2030 and 55% by 2040.

EVs are equipped with batteries that require periodic charging, and thus act as loads to the power grid. While EVs can be charged at home at low charging rates, public charging stations at different fixed locations are commonly being used for faster charging of EVs. With the very large number of EVs foreseen, uncoordinated charging of the EVs can overload the grid and have an adverse impact on its operation [4]. To alleviate this problem, many recent works have addressed the problem of charge scheduling of EVs. In this model, an EV sends its charge requirement to a central *aggregator*. The aggregator, based on the information provided by different EVs, decides the charge schedule (when and at what charging station the EVs will be charged) while satisfying different user and grid-level constraints. A good survey of some of the important works in the area of charge scheduling can be found in [11].

Fixed charging stations (FCS) have a limited number of charging outlets and may not be able to cope with sudden high demands for charging. High demand for charging can either cause service to be denied to some EVs, causing user dissatisfaction, or increase the waiting times of EVs at the charging stations. Mobile charging stations (MCS) have been proposed as a solution to these problems. A mobile charging station is a vehicle carrying a large number of batteries for energy storage which can be used to transfer charge to a number of EVs that require charging. They can be used to temporarily augment the capacity of these fixed charging stations and help in charging more EVs and in reducing the waiting time during high demand. Also, when an MCS is used to charge an EV, the charging does not directly affect the power grid. Thus, during peak hours, load demand from the grid for EV charging can be reduced by directing a larger number of EVs towards MCSs [9].

Given a set of charging requests from different locations at different times and a set of MCSs, deciding where the MCSs should be placed at different times to service the charge requests while optimizing different objectives such as number of EVs charged, reduced waiting time etc. is an important problem that has seen growing interest in recent years [9], [3], [6], [14]. Mobile charging stations can service charging demands in two ways, either by directly servicing vehicles anywhere in their routes or by servicing vehicles at fixed charging stations [10]. In this paper, we address the problem of optimal placement and scheduling of a set of MCSs at certain predesignated FCSs to service charging requests [13]. The placement of an MCS at an FCS can be seen as temporarily increasing the capacity of the corresponding FCS to handle excess demand to reduce waiting time and increase user satisfaction.

We first formally define the MCS allocation problem, and prove that the problem is NP-hard. A graph-theoretic formulation of the problem is proposed and two heuristic algorithms are then presented to solve the problem based on this formulation. The first algorithm is a single phase algorithm that charges a higher number of EVs with low average waiting time, but may have higher computation cost in some cases. The second algorithm is a two-phase algorithm that trades off the number of EVs charged with the computation cost. Detailed simulation results are presented on a real world scenario to show that the algorithms perform well.

II. Related Works

Most of the existing research in charge scheduling for EVs has focused on charging at FCS's only, with different works considering different grid-level, aggregator-level, and user-level constraints and objectives [11]. With growing demand and proliferation of electric vehicles, there has been an increased interest in providing charging services via mobile charging stations recently [5].

Li et al. [9] develop a novel approach of having a central repository of portable charging stations and using transport vehicles to drop these portable charging stations to specified locations. In [3], Chen et al. develop a network model for better communication between EVs and MCSs and address the problem of optimal placement of MCSs to reduce cost using a chaotic evolution particle swarm optimization algorithm. Huang et al. [6] investigate battery swapping and charging by mobile charging stations using a nearest job next policy for an urban environment. All these works try to directly service the EVs anywhere and does not address the problem of placing an MCS at an FCS to increase FCS capacity. Yang et al. [14] develop a simple algorithm to service additional demands of fixed charging stations on a highway by deploying mobile charging stations when required. However, their algorithm considers only a simple linear placement of FCSs. Also, in their algorithm, an MCS uses the power input of the FCS only and does not consider MCSs carrying their own energy source.

In this paper, we address the problem of placing mobile charging stations carrying limited energy sources at FCSs distributed at arbitrary locations over a a city to temporarily increase FCS's capacity.

III. The MCS Allocation Problem

Let F denote the set of FCSs in a region and M the set of available MCSs. Let V denote the set of EVs that are to be charged by the MCSs. The set V can be seen as the set of unscheduled EVs remaining after applying any charge scheduling algorithm on a set of EVs to be charged at the FCSs in F. Let r_c denote the charging rate provided by an MCS (same for all MCS) and cap_m denote the capacity of the MCS m expressed as the total time for which an MCS can provide charging at the rate r_c. Let T be the total time for which the MCSs are in operation. For simplicity, it is assumed that a MCS has only one charging outlet (so it can charge only one EV at one time), though the algorithm can be easily extended to include MCS with more than one charging outlets.

For any EV $v \in V$, let C_v denote the battery capacity of the EV in KWH. Let the term *State of Charge (SOC)* of an EV at any time refer to the battery charge remaining at that time as a percentage of total battery capacity. Let $soc_{v,t}$ denote the SOC of EV v at an arbitrary time t. Let $soc_{v,init}$ denote the initial SOC of v and $soc_{v,final}$ denote the final desired SOC of v after charging. We assume that each EV travels at a constant speed. Let d_v denote the discharge rate of the EV battery per unit time. We assume that the route of the EV and the locations of the FCSs are known, and hence the set of FCS that an EV passes by is known. This is not an impractical assumption in a smart urban environment as GPS-based routes are routinely used in vehicles. Assuming a constant speed for each EV, the arrival time of the EV at each FCS can also be estimated. Then, if the EV v starts it journey at time $t = 0$, and arrives at an FCS $f \in F$ at time $t_{v,f}$, its SOC $soc_{v,t_{v,f}}$ on arrival at f is given by

$$soc_{v,t_{v,f}} = \frac{(soc_{v,init} \times C_v) - (d_v \times t_{v,f})}{C_v}$$

Similarly, the charging time $ct_{v,f}$ for the EV v at FCS f is given by

$$ct_{v,f} = \frac{(soc_{v,final} - soc_{v,init}) \times C_v}{r_c}$$

Each vehicle is willing to wait a maximum duration of $t_{waitmax}$ at any FCS for an MCS to be allotted to it. Thus, when an EV v arrives at an FCS f, it can be charged using an MCS starting at any time in the interval $[t_{v,f}, t_{v,f} + t_{waitmax}]$. Each such charging interval $[t_{v,f}, t_{v,f} + ct_{v,f}], [t_{v,f}+1, t_{v,f} + ct_{v,f}+1], \ldots$ is termed as a *charging slot*. The EV v can be scheduled for charging at an MCS at any of these charging slots.

The problem is to compute a schedule for placing the set of MCSs at the set of FCSs for charging the vehicles in the set V such that the number of vehicles charged is maximized. The output of any algorithm for the MCS allocation problem is a $|M| \times |F| \times |V| \times T$ matrix R, where $R[m, f, v, t] = 1$ if and only if MCS m is placed at FCS f at time t for charging EV v, 0 otherwise. The objective is to maximize the number of EVs charged subject to the following constraints:

1) For each $m \in M$, the total charge provided to all EVs is less than or equal to its capacity c_m.

$$\forall m \in M \sum_{f\in F}\sum_{v\in V}\sum_{t\in T} R[m, f, v, t] \leq cap_m$$

2) Each MCS can charge at most one EV at any one time.

$$\forall m \in M\, \forall t \in [0, T] \sum_{f\in F}\sum_{v\in V} R[m, f, v, t] \leq 1$$

3) An EV can be charged only at one FCS by one MCS.

$$\begin{gathered}\forall v \in V\, (\exists m_1 \in M\, \exists f_1 \in F\, \exists t_1 \in [1, T] \\ R[m_1, f_1, v, t_1] = 1) \implies \\ \forall m \in (M - m_1)\, \forall f \in (F - f_1)\, \forall t \in [1, T] \\ R[m, f, v, t] = 0\end{gathered}$$

4) If an MCS starts charging an EV, it charges the EV fully (upto its desired final SOC) without interruption.

$$\begin{gathered}\forall v \in V\, (\exists m \in M\, \exists f \in F\, \exists t_1 \in [1, T] \\ R[m, f, v, t_1] = 0 \wedge R[m, f, v, t_1 + 1] = 1) \implies \\ \forall t \in [t_1 + 1, t_1 + ct_{v,f}]\, R[m, f, v, t] = 1 \wedge \\ \forall t \in [t_1 + ct_{v,f} + 1, T]\, R[m, f, v, t] = 0\end{gathered}$$

5) For any $m \in M$, if $R[m, f_1, v_1, t_1] = 1$ and $R[m, f_2, v_2, t_2] = 1$ where $f_1 \neq f_2$ and $t_1 < t_2$, then $t_2 - t_1$ is greater than or equal to the travel time of m from f_1 to f_2.

In the rest of this paper, we will refer to the problem as the *MCS-Allocation-Problem*, or *MCS-Allocation* in short.

A. NP-Hardness of MCS-Allocation

We consider the decision version of MCS-Allocation, referred to as *D-MCS-Allocation* which is defined as follows: Given the same inputs as for MCS-Allocation as defined in Section III, and a positive integer k, is there a schedule of the MCSs at the FCSs that charges at least k EVs? We prove the NP-hardness of D-MCS-Allocation by reduction from another known NP-hard problem, the *Wedding Seating Problem* [8], the decision version of which can be defined as follows:

Definition 1. Wedding Seating Problem (WSP): Consider that a set of guests, partitioned into groups, have to be seated at a set of K tables at a wedding. Each table can sit at most N guests. All members of the same group must sit in the same table. Also, some groups have conflicts (do not like each other), and therefore must be seated at different tables. Given a positive integer g, is there a way to sit at least g groups in the K tables?

The problem as stated above is slightly different than the one defined in the literature, which tries to find if all the groups can be seated in k or less tables. However, note that the solution of the problem as stated above by us, with g = total number of groups and $K = k$ can be used to solve the same problem. Wedding Seating Problem is known to be NP-hard [8]. We show that WSP $\leq_P$ D-MCS-Allocation.

Theorem 1. D-MCS-Allocation is NP-hard.

Proof: Given an instance of WSP, we form an instance of D-MCS-Allocation as follows. Let V = the set of groups, i.e., there is one EV for each group. Let $t_{waitmax} = 0$. i.e., there is only one posible charging slot of an EV at an FCS. Let M = the set of tables, i.e., each table represents an MCS, with $cap_m = N$ for each MCS $m \in M$. Let $F = \{f\}$, i.e., there is only one FCS. We can choose the routes and the average speeds of the EVs, and the charge and discharge rates so that (i) the charging time of each EV at f is the number of guests in the corresponding group, and (ii) the charging intervals of two EVs overlap if and only if the two corresponding groups have conflict. Let $k = g$.

Given a solution of D-MCS-Allocation, the EVs that are scheduled at an MCS correspond to groups that are allocated to a table. It is obvious that the capacity of a table is never exceeded and each group is seated as a whole in a table. It is also guaranteed that two conflicting groups are not seated at the same table, as the corresponding EVs have overlapping charging slots and hence cannot be charged by the same MCS. Thus existence of a solution of D-MCS-Allocation implies existence of a solution of WSP. Similarly, given a solution of the WSP problem, the groups that are seated at a table correspond to the EVs that are scheduled at the corresponding MCS. It is again easy to see that the charging intervals of the EVs do not overlap (and hence they can be charged by the same MCS) and the capacity of an MCS is not exceeded. Thus, if D-MCS-Allocation does not have a solution, WSP also does not have a solution. ■

IV. ALGORITHMS FOR MCS-ALLOCATION

The proposed algorithms are based on the well known *Bin Packing with Conflicts* problem, which can be reduced to a variation of graph coloring problem we refer to as the *Bin Packing Vertex Coloring* problem. We first define this problem and show how the MCS-Allocation problem can be mapped to a variation of that. We then modify an existing algorithm for the Bin Packing Vertex Coloring problem to propose two heuristics to solve the MCS-Allocation problem.

The Bin Packing Vertex Coloring problem is defined as follows:

Definition 2. Bin Packing Vertex Coloring Problem (BPVC): Given a graph G = ($\mathcal{V}$, $\mathcal{E}$), a non-negative integer weight w_i for each vertex, and a non-negative integer B, find a partition of $\mathcal{V}$ into k subsets such that the sum of the weights of the vertices assigned to the same subset is less than or equal to B, two vertices connected by an edge do not belong to the same subset, and k is minimum among all such partitions.

The BPVC problem attempts to pack the vertices of a graph in minimum number of bins of fixed capacity such that all vertices in a bin form an independent set.

To map the MCS-Allocation problem to a variation of the BPVC problem, we first form a graph $G = (\mathcal{V}, \mathcal{E})$ as follows:

- $\mathcal{V} = \{(v, f, t_{vf}^{start}, t_{vf}^{end}) | v \in V, f \in F, [t_{vf}^{start}, t_{vf}^{end}]$ is a possible charging slot of v at $f\}$. Thus, for each EV at each FCS it passes by, a vertex is added for each potential charging slot of the EV at the FCS.
- for each vertex $(v, f, t_{vf}^{start}, t_{vf}^{end}) \in \mathcal{V}$, assign a weight $w = (t_{vf}^{end} - t_{vf}^{start}) \times r_c$, i.e., the amount of charge needed by the EV v to charge in that charging slot.
- The edge set $\mathcal{E}$ is formed as follows. An edge is added between vertices $(u, e, t_{ue}^{start}, t_{ue}^{end})$ and $(v, f, t_{vf}^{start}, t_{vf}^{end})$ if
  1) $u = v$, or
  2) $[t_{ue}^{start}, t_{ue}^{end}]$ and $[t_{vf}^{start}, t_{vf}^{end}]$ overlap, or
  3) $e \neq f$, $t_{ue}^{end} < t_{vf}^{start}$, and the time required for MCS to go from FCS e to FCS f is greater than $t_{vf}^{start} - t_{ue}^{end}$

Thus, the vertex set covers all possible charging slots for charging all EVs at all FCS, and an edge between two vertices implies that the corresponding charging slots cannot be satisfied by the same MCS. We call this graph a *charge-conflict graph*.

The problem of finding a schedule for the MCSs is then similar to the Bin Packing Vertex Coloring Problem (BPVC). The BPVC problem attempts to pack the vertices of a graph in bins such that all vertices in a bin form an independent set, so finding an independent set in the charge-conflict graph can give a set of EVs that can be charged by a single MCS. Also, attempting to minimize the number of bins is similar to maximizing the number of EVs charged. However, the problems are not exactly the same, as unlike in the BPVC problem, not all vertices of the conflict graph need to be packed into (scheduled by) bins (MCS) in the MCS-Allocation problem; only one vertex per EV is to be selected. Also, rather than a presumed infinite supply of bins, we only have a select number of bins equal to the number of MCSs.

In order to solve the MCS-Allocation problem, we use the idea from an existing solution of the bin packing with conflicts problem by Gendreau et al. [1] to fill bins iteratively. In the following subsections, we propose two heuristics algorithms to solve the MCS-Allocation problem based on this idea, named *slotMCS-Allocation* and *reduced-slotMCS-Allocation*. The second algorithm is merely an extension of the first that reduces the size of the charge-conflict graph for faster execution, at the potential cost of charging lower number of EVs in some cases.

A. slotMCS-Allocation Algorithm

In this algorithm, we first construct the charge-conflict graph as described earlier. A maximum independent set I of the charge-conflict graph is then found. Since finding the maximum independent set is a NP-hard problem, I is found by first using a heuristic graph coloring algorithm to color the vertices of the conflict graph, and then choosing the maximum-sized set of vertices with the same color. Note that vertices with the same color in a valid graph coloring forms an independent set. Since there is no conflict between the vertices in I, the corresponding EVs are assigned to the MCS using solutions for the standard bin packing problem. Let M' be the set of MCSs with remaining charge less than a certain residual capacity, which is taken as the lowest charge requirement among the scheduled EVs; if no such MCS exists, M' is set to the MCS with the minimum remaining charge. For each vertex $(v, f, t_{vf}^{start}, t_{vf}^{end})$ in M', all vertices of the form $(v, *, *, *)$ are then removed from the charge-conflict graph, and the set of MCSs M' is also removed from the set of available MCS. This process is then repeated until either the conflict graph is empty (meaning that all EVs are scheduled) or the set of available MCSs becomes empty. The pseudocode of the algorithm is shown in Algorithm 1.

Algorithm 1 Algorithm for MCS-Allocation

procedure MCS-ALLOCATION-ALGORITHM
  $G \leftarrow$ Charge-conflict graph
  $M \leftarrow$ Set of MCSs
  $V \leftarrow$ Set of EVs
  while $V \neq null$ **and** $M \neq null$ **do**
    $I \leftarrow$ Independent set of G.
    Apply any algorithm for bin-packing to schedule
      EVs corresponding to vertices in I to M
    $c \leftarrow$ lowest charge requirement of any EV in I
    $M' \leftarrow$ bins with residual capacity greater than c
    if $M' = null$ **then**
      $M' \leftarrow$ MCS with minimum residual capacity
    $V' \leftarrow$ Set of EVs scheduled in M'
    $U \leftarrow$ Set of vertices in G corresponding to EVs in V'
    for $u \in U$ **do**
      $G \leftarrow G - u$
    $V \leftarrow V - V'$
    $M \leftarrow M - M'$

To find the independent set I, any valid graph coloring algorithm can be used; we use a heuristic based on [7] to compute I. The pseudocode is shown in Algorithm 2.

Algorithm 2 Algorithm for Finding Independent Set

procedure FIND-INDEPENDENT-SET
  $G \leftarrow$ input graph
  $V \leftarrow$ set of vertices in graph sorted by degree
  $E \leftarrow$ set of edges in graph
  $v \leftarrow$ vertex with maximum degree
  $v.color \leftarrow 1$
  $V \leftarrow V - v$
  while $V \neq null$ **do**
    $u \leftarrow$ vertex with maximum saturation degree
    $u.color \leftarrow$ least possible color
    $V \leftarrow V - u$
  $c \leftarrow$ color with maximum vertices
  $I \leftarrow$ vertices with color c
  return I

B. reduced-slotMCS-Allocation Algorithm

The size of the conflict graph can be very large since each EV may have many possible charging slots over multiple FCSs. In this subsection we introduce a two phase algorithm to solve this problem. The first phase of the algorithm reduces the size of the graph by assigning a single potential FCS to each EV for charging. In the second phase, the slotMCS-Allocation algorithm described earlier is applied on this reduced graph. We next give a description of the algorithm to reduce the size of the conflict graph.

We construct a bipartite graph G between the sets V and F such that an edge exists between an EV $v \in V$ and an FCS $f \in F$ if and only if v passes by f in its route. Let edges of this graph be denoted by (v, f), $v \in V$ and $f \in F$. Given this bipartite graph, we attempt to fix a possible FCS for each EV. The allocation of the FCSs should be such that least overlap between charging schedules exists. To do so, we attempt to keep FCS allocation as sparse as possible. To do this, a maximum cardinality matching of the bipartite graph is found, and EVs are assigned to FCSs as per this matching. The set of EVs allotted an FCS is then removed from the set of vertices V and the bipartite graph is updated. This process is repeated until all EVs are allotted an FCS. The pseudocode for this algorithm is shown in Algorithm 3.

Algorithm 3 Algorithm for FCS Allocation to EVs

procedure ALLOT-FCS
  $V \leftarrow$ set of EVs
  $F \leftarrow$ set of FCS
  $G \leftarrow$ bipartite graph between V and F
  while $V \neq null$ **do**
    $V' \leftarrow$ set of EVs in maximum cardinality matching
    $E \leftarrow$ set of edges in maximum cardinality matching
    for $(v, f) \in E$ **do**
      $C[v] \leftarrow f$
    $V \leftarrow V - V'$
    Update bipartite graph G
  return C

Algorithm 3 gives one possible charging location for each EV. The algorithm returns an array C where $C[i]$ denotes the FCS where vehicle i can be charged. Once the possible charging location of each EV is known, charge intervals for each EV can be generated only for that FCS. This can be used to generate a charge-conflict graph as before and the slotMCS-Allocation algorithm can then be applied on it.

V. SIMULATION RESULTS

The performance of the two proposed algorithms are evaluated by extensive simulation. We use the road map and charging station locations in the city of Los Angeles collected from OpenStreet maps [12]. Since the present day proliferation of charging stations is not very high, conventional gas station coordinates extracted from OpenStreet map are also taken as coordinates for charging stations. This gives a total of around 3000 FCSs, although only a small subset of them are actually used as most of them do not fall in the route of any EV. The starting times of the routes for EVs are generated between a fixed period referred to as the *start time window*. The typical journey time of an EV is around 40-45 minutes. The density of the FCSs is such that on randomly generated routes, the average number of FCSs per route was between 2 and 3. It was assumed that vehicles start with an initial SOC of 50-60%.

The MCSs are assumed to carry batteries whose rate of charge is such that it can fully charge a single EV battery in around 30 minutes. Each MCS is assumed to carry enough batteries to fully charge three EV batteries. Five such MCSs were taken for the simulation. The MCSs are assumed to start off with their own battery fully charged. The desired SOC of an EV on departure from an FCS (if the EV is charged at that FCS) is randomly chosen to be between 20-25% more than the SOC at arrival at that FCS. This corresponds to the expected use of MCS to provide just enough charge to vehicles to help them either complete their journey or reach another FCS where they can be fully charged. MCSs seldom act as primary sources of charge for vehicles. Note that with these parameters, the maximum number of EVs that can be charged by a single MCS is 15 (since an MCS can provide 100% charge to 3 vehicles and the minimum charge to be provided to each EV is 20% of its full charge). Thus, the maximum number of EVs that can be charged with this set of parameters (five MCS) by any possible schedule is 75. The value of $t_{waitmax}$ is taken as 20 minutes. While this gives 21 possible charging slots, we assume that two charging slots must differ by 5 minutes to reduce the number of slots. Therefore, for any EV, at any given FCS, five charging slots exist (at time 0, 5, 10, 15, and 20 from the arrival time).

We measure the following metrics to evaluate the performance of the algorithms: the total number of EVs charged, the average wait time of an EV for charging as a fraction of the total journey time of the EV, and the percentage utilization of MCSs battery charging capacity. We also measure the utilization of the MCSs own battery for its travel between FCS, which is an indication of the distance travelled by the MCSs.

A. Results

Figure 1 shows the number of EVs charged for varying number of EVs. The start time window is kept at 2 hours. It is seen that the slotMCS-Allocation algorithm performs better the the reduced-slotMCS-Allocation algorithm in terms of the number of EVs charged. This is expected as the graph reduction step in Phase 1 of the reduced-slotMCS-Allocation algorithm reduces the number of possible charging slots for a vehicle as each EV is pre-allocated to only one FCS. The charging slots at other FCS that are removed in Phase 1 may have less conflicts than the slots that are chosen.

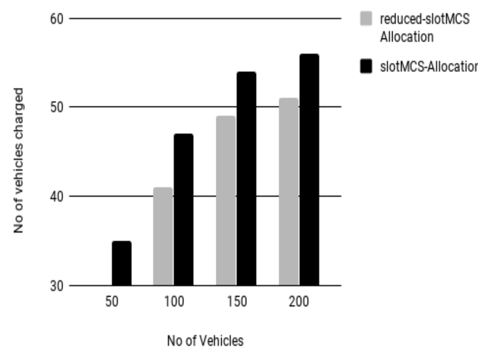

Fig. 1: Number of EVs charged

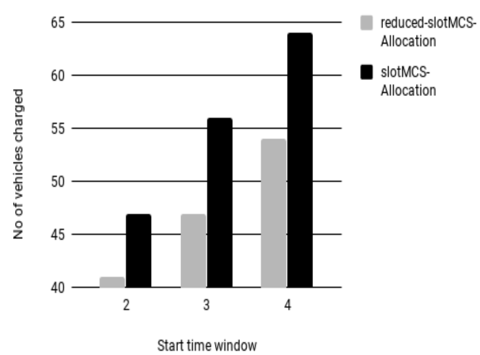

Fig. 2: No. of EVs charged for different start time windows

However, reduced-slotMCS-Allocation algorithm runs much faster, computing the schedules around 25 to 35 times faster on a standard PC than the slotMCS-Allocation algorithm for different number of EVs. For both algorithms, though the absolute number of EVs charged increases with the number of EVs, the percentage of EVs charged drops from around 60-70% for smaller number of EVs to around 25-30% for larger number of EVs. There are two reasons for this. A larger number of EVs causes more EVs to pass by the same FCS at overlapping times and hence more slot conflicts, causing many of them to remain uncharged. Also, as discussed earlier, an upper bound of 75 exists on the number of EVs that can be charged, and thus with 150 and 200 EVs, the maximum percentage of EVs that can be charged is 50% and 37.5%. The upper bound of 75 EVs discussed earlier neglects conflicts and assumes that vehicles demand only a minimum possible charge requirement of 20% of SOC, even though EV charge demands are generated randomly between 20% to 25%. Given these observations, charging around 60 vehicles for a 2 hour start time window shows that the slotMCS-Allocation algorithm performs quite well.

To see the effect of the start time window on the performance, we vary the start time window from 2 hours to 4 hours. The number of EVs is kept at 100. Figure 2 shows the number of EVs charged. It is seen that the number of EVs charged increases significantly if the start time window is increased, charging 64 EVs for a start time window of 4. Also, more number of EVs charged implies a better utilization of the

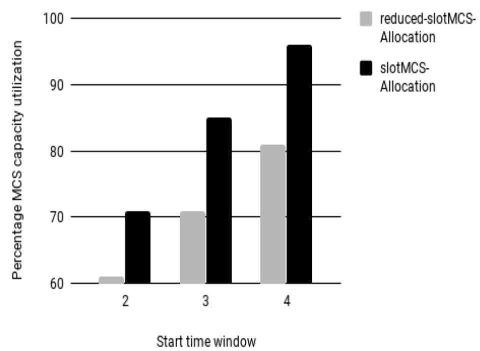

Fig. 3: Utilization of MCS charging capacity

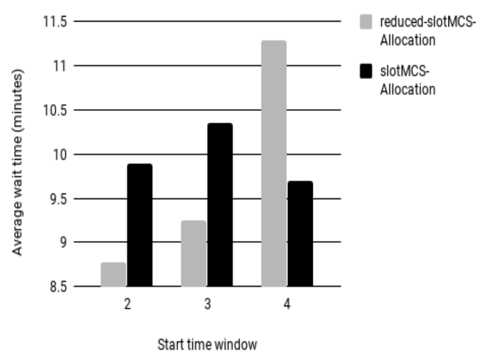

Fig. 4: Average waiting time

charging capacity of the MCS. Figure 3 shows the percentage of MCS charging capacity utilized for different values of the start time window. The increased number of vehicles charged increases the utilization of the MCS charging capacity, giving nearly 96% utilization for slotMCS-Allocation algorithm for a start time window of 4 hours, which is very good.

Figure 4 shows the average waiting time of an EV that is charged at an MCS as a percentage of its total journey time for 100 EVs. While no discernible pattern exists for the average waiting time, it is seen that the average waiting time stays within 20-25% of the total journey time of an EV. It is seen that an EV on an average has to wait for about 10 minutes after arrival at an FCS till it starts getting charged.

Since an MCS have to travel between different FCS, and it can also be an EV, it will also use its own batteries. Note that this battery is separate from the batteries carried to charge the EVs. An MCS is assumed to carry the same type of batteries as an EV and discharge at the same rate. Figure 5 shows how much of its own battery is used by an MCS for travelling between FCSs. As the number of vehicles charged increases, MCSs have to travel more and therefore the battery consumption increases with increase in start time window. However, it is seen that MCSs never use up their entire battery for travelling between FCSs, and thus the distance travelled by an MCS is not a constraint for charging the EVs.

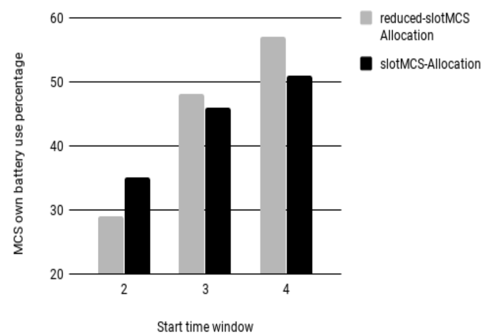

Fig. 5: MCS battery use for own travel

VI. Conclusions

In this paper, we have proposed two algorithms for scheduling mobile charging stations to charge EVs at designated fixed charging stations. Detailed simulation results are presented to show that the algorithms perform well. The work can be further extended to consider charging EVs at arbitrary spots rather than only at fixed charging stations.

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