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A smart system combining real and predicted data to recommend an optimal electric vehicle charging station

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ABSTRACT

The electric vehicle (EV) is considered an attractive alternative to a conventional vehicle, due to its potential beneficiation in decreasing carbon emission. But the battery range anxiety is a key challenge to its wide adoption and also the EV drivers spend so much time in public charging stations (CS) to charge especially during peak times. In this paper, we propose a charging station selected system (C3S) to control and manage EVs charging plans. Moreover, the C3S system proposed consists of a set of algorithms that are proposed to recommend a suitable CS for EV charging requests. The CS selection is based on minimizing travel time and takes into account in real-time the queuing time at CS, EVs' charging reservations, and the predicted time of EVs' future charging requests. Besides, we proposed three different strategies for predicting the EVs incoming and controlling the uncertainty matter of the dynamic arrival of EV charging requests. As part of the Helsinki City scenario, the evaluation results demonstrate the performance, especially at peak times, of our proposed C3S with regard to the CS recommendation which has the minimum total trip duration.

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1. INTRODUCTION

Over the last few years, the government has become more encouraging of policy action related to climate change [1]. With the rapid development of cities and associated vehicle numbers, the transportation sector has become responsible for a large increase in the world's energy consumption and therefore its air pollution levels [2]. electric vehicles (EVs) have been playing an ever-more important role in urban transportation systems for their capability of energy-saving, carbon reduction, environmental protection, promoting renewable energy, and introducing a sustainable transportation system [3], [4]. Compared to traditional internal combustion engine (ICE) vehicles, EVs are more efficient and could provide a 45% reduction in carbon emissions [5], [6]. Many countries around the world put up suitable policies to facilitate the EV industry development and its popularization [7]. Therefore the EV market will be rapidly growing, it is expected that more than 130 million EVs will get in the market by 2030 [8], [9], and also the public charging stations (CS), a large number of EVs can be connected to a power grid for charging such as fast-charging stations and parking lots [10], [11], will be playing an important role in charging EVs compared with home charging, due to the most of EV owners do not have the capacity to charge their EVs at home. On the other hand, the limited range of the battery capacity, the frequently charging especially in long-distance travel, the high peak charging demand due to the large use of EVs in a specific time period, and therefore, a long-time spending by EV owners at CSs for charging unlike gas stations where the internal combustion engine (ICE) vehicles can get refueled in minutes are considered one of the main EV challenges that causing great inconvenience. Furthermore, the simple solution of increasing the CS network capacity by deploying more stations is impractical in view of the addition to the power needs and the constraints on the power grid [12], [13], there also exists a limited physical space and the CSs number can be increased to a limited number. Therefore, the optimal solution is how to make the EVs charging process more efficient, by better managing both the scheduling of charging stations and EV on-road that have planned the charging reservation and those can make in the near future charging reservation requests.

Many works have proposed different EV charging schemes to effectively manage the electric vehicles charging plans using optimization problems. Yang *et al*. [14] propose an EV navigation system that is based on autonomic computing and a hierarchical architecture over vehicle ad-hoc network, this system improves the EVs travel time based on traffic information center (TIC), which works as a brain that analyzes the traffic information including traffic flow, state of charge (SOC), average speed, and vehicle route, and then plans routes.

Razo *et al.* [15] presented a smart scheduling approach based on the A* algorithm and a peer-to-peer scheduling system. This method aims to minimize the total travel time for each EV by considering the estimated state of the charging stations and the individual EV information. Yang *et al.* [16] proposed an optimal model is proposed for EV route selection and charging navigation strategy, it is based on real-time crowd sensing and the data collected from EV drivers' mobile devices, and a mathematical model is proposed by using the queuing theory to estimate the waiting time at CSs. Cao *et al.* [17] proposed CS-selection scheme for managing EVs' charging plans, the selection is depended on the knowledge of those electric vehicles locally parking at charging stations and those remotely sending requests of charging reservations, and therefore, the charging reservations of electric vehicles take into account their arrival and expected charging time at charging stations selected. Liu *et al.* [18] presented a charging control algorithm to solve shortest path problem, by formulating a route charging navigation problem according to pricing time varying, the decisions of routing and charging are impacted by electricity prices of time-dependent, in deterministic utilizing online information and a stochastic traffic network. Zhang *et al.* [19] proposed a charging management framework for optimal choice between battery swapping/charging stations. The proposed framework is composed by electric vehicles, battery swapping stations, charging stations, and global controller entity, which is responsible for CS-selected decision.

However, the uncertainties due to the dynamically waiting time of the charging stations and changing traffic conditions are also another important factor. A few works have tried to address this issue, the CS recommendation based on the EVs reservations and the real state of CSs and the prediction of the future EVs charging requests in real-time, by using reinforcement learning such as the study presented in [20], here the authors present their proposed algorithms to recommend an appropriate charging station by minimizing the EV travel time. Lee *et al.* [21] proposed an RCS algorithm to select the optimal charging station, the selection based on minimizing the total EVs trip time with considering the unknowing future charging requests, which are predicted by using the deep reinforcement learning. In contrast, to make the good predictive based on machine learning model and also deep neural networks machine, the model must operate under a big and high quality of the dataset. This latter is considered as the main challenges which include the absence or lack of high dimensional datasets contain EVs driver's charging behavior [22].

In addition, we have also proposed a strategy to mitigate the impact of future unknown EVs charging demands caused by the dynamic change of traffic conditions on the roads in [23], [24]. Our method based on the dynamic change of the charging plans of all EVs that have a charging reservation, the updating charging plans are made at each impact in the CSs states due to a new EV charging request. However, some EVs may receive significant recommendations for changing charging plans, especially at peak times [25].

In this paper, we propose CS selected system (C3S) to recommend the appropriate charging station for electric vehicles that send a charging reservation request. The C3S system consists of a collection of proposed algorithms to control and manage the EVs charging requests, EVs charging reservations, and queuing time at CSs, and also to predict the future EVs charging demands. Moreover, the selection of CS, which is recommended for an EV that has sent a charging request, is based on the total travel time, including the arrival time, the waiting and charging time, and the expecting time due to other future incoming EVs. In addition, we propose three strategies each one presented under an algorithm to predict the incoming EVs that may send the charging requests in the near future when a new EV driver need to charge it EV battery and then makes a charging reservation request. Eventually, we presented in section 2 the proposed C3S system model, and we detailed all these algorithms and the strategy that have been adopted by each one in section 3. Finaly, the performance comparison with previous work and conclusion are presented in sections 4 and 5 respectively.

2. THE PROPOSED C3S SYSTEM MODEL

2.1. Network entities and assumptions

Electric vehicle: vehicle uses electric motor for propelling, it receives electricity by plugging into the electric grid and store it in batteries. If the EV is below the minimum of state of charge (SoC), the EV connects to the global aggregator (GA) in order to select a suitable charging station. Charging station: an EV charging station is an element in an infrastructure deployed geographically in a smart city to charge EVs in parallel. Therefore, each CS is equipped with many charging sockets. The CSs condition, i.e. waiting time for charging and number of electric vehicles parking at the charging stations, is supervised by GA.

Global aggregator: a centralized unit to manage and control the EVs charging reservations and the CSs' and the EVs' state that are required to make CS-selection decision. In this work, we consider that all EVs are equipped with a global position system global positioning system (GPS) that contains its own movement information and tooled up with wireless communication devices such as 4G or 3G/LTE, which allows them to communicate with the GA through road-side unit (RSU) to find an appropriate CS for charging. We also assume that the CSs are geographically deployed in a city, and each CS equips with multiple charging ports with the result that a number of EVs can be charged in parallel. The EV charging scheduling at the CS is based on the first come first serve (FCFS) policy. Then if a CS is fully occupied, arriving EVs need to wait until one of its charging sockets is free.

2.2. EV charging management system cycle

Based on Figure 1, the model procedure for our proposed EV charging management system is listed in:

- Step 1: the EVs are on their journey. If an EV, namelyEV_r, needs charging service as a result of a low energy status or the EV driver wants to make a charging plan along the trip path; it informs the GA by sending its status report including the information about its SOC, speed, location, and trip destination.
- Step 2: when GA receipts the reservation request, it sends to all CSs located in the same geographical area of the EV across the RSU to inform it about their current queuing state.
- Step 3: each CS runs Algorithm 1 to get the list, contains the waiting time of each charging socket in CS, and sends it into GA.
- Step 4: based on running Algorithm 2 inside of Algorithm 3, GA recalculates all lists that are receipted taking into account the reservation table, and before deciding which the better CS for EV in terms of the minimized trip times including charging times, GA runs one of our three proposed algorithm (Algorithm 4, 5, or 6) to predicts the EVs on-the-move that can send a reservation request and can arrive at CS selection before like EV_{10} or EV_{12} in Figure 1, to select the appropriate CS to EV_r, and to add them to the reservation table. After all, the decision is sent back toEV_r.
- Step 5: EV_r moves across to its destination by following the path that including proposed CS for recharging.
- Step 6: CS notices GA for canceling reservation of EV_r when this latter arrival at CS, then EV_r starts waiting in queue if there is not a vacant charge socket.

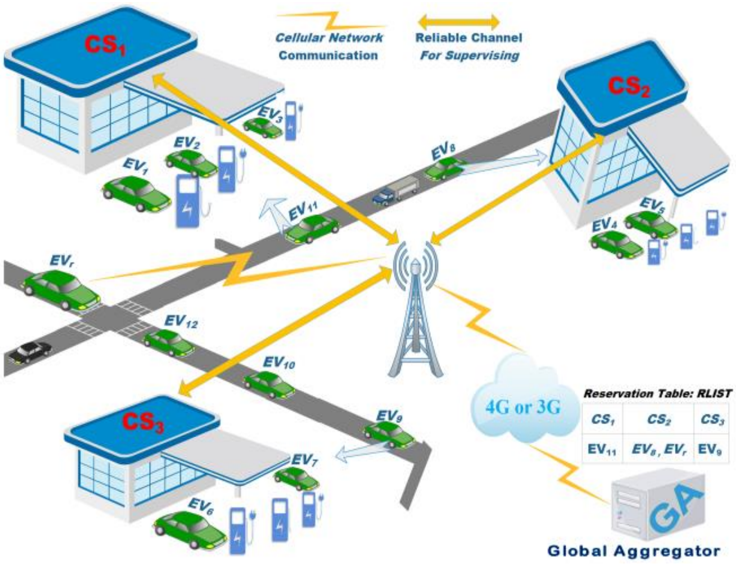

Figure 1. C3S architecture

3. THE PROPOSED C3S SCHEDULING ALGORITHMS

In this section, we have described our proposed model. Moreover, we have detailed each algorithm of the proposed scheduling algorithms which represent the core of the proposed model and are also responsible for the recommendation decision-making. Table 1 defines the meaning of all the variables that are used in these algorithms and also in the explaining of their functioning way.

Table 1. List of nomenclatures

Symbol	Description
EV_i	EV of index i
CS_j	CS of index j
N_{slot}	Number of charging socket at FCS or MCS
N_{CS}	Number of CS in smart city
N_{ev}	Number of EVs in charging queuing parked at CS
Tslot	Output including available time per charging socket at CS
RLIST	The reservation list which contains in each line an EV and the CS selected for charging.
PLIST	Temporary list of EVs with best choice of CS
CSLIST	List contains the LST array of all CS with reservations
E_i^{curr}	Current volume of EV_i battery
E_i^{max}	Full volume of EV_i battery
$E_{i,j}^{trans}$	Estimation of the energy consumed for moving the EV_i to the CS_j
T_i^{fin}	Charging finish time of EV_i
T^{curr}	Current time in city
$T_{i,j}^{trip}$	The time required for the EV_i to reach its final destination, including the time spent at CS_j for charging
$T_{i,j}^{arr}$	The time required for the EV_i to arrive at the station CS_j
$T_{i,j}^{wait}$	The waiting time for the EV_i to pass inside the CS_j before starting the charging process
$T_{i,j}^{char}$	The time required to charge the EV_i battery at CS_j
$T_{i,j,d}^{trans}$	The time spent by EV_i between CS_j and its final destination
$T_{i,j}^{trans}$	The time spent by EV_i between CS_j and its current position
T_j^Q	The waiting and charging time at the CS_j estimated by GA including all EVs charging reservation
β_j	Charging power at CS_j
S_i	Moving speed of EV_i
α	Electric energy consumed per meter

3.1. Presentation

The total EV trip duration by way of an intermediate CS for charging, is estimated by taking into account EV information state, previous reservations, CSs status, and other incoming EVs' charging reservations to predict the future CSs status. We decouple our proposed model into four steps: Algorithm 1 details the estimation charging time at CS, on which Algorithm 3 details to make decision for optimal CS-selection to each EV sending a reservation request. The decision based on Algorithm 4, 5, or 6 for predicting the incoming EV into CSs in the near future and Algorithm 2 to assign each those incoming EV to an appropriate CS by taking into account FCFS policy.

3.2. Estimated charging time at CS

Algorithm 1 allows calculating the queuing time at each CS according to the EVs currently parking at these CSs. Given the parallel charging procedure through multiple charging slots, we define a list Tslot to contain the estimation of the available charging time for each charging slot. Then, we initialize all slots by current time, denoted by T^{curr}, using a loop operation with N_{slot} iterations from line 1 to line 3, and N_{slot} indicates the number slots in CS.

To distribute the EVs parked lot at a CS for charging, the loop operation starts from sorting the queue, based on FCFS order at line 5, and processing each EV_i in the queue, which has N_{ev} vehicle, from line 6 to 10. Furthermore, the charging finish time T_i^{fin} of each EV_i is expressed as line 7, where $\frac{E_i^{max} - E_i^{curr}}{\beta}$ is the time for EV_i to be fully recharged and $Tslot\ get(0)$ represents the earliest available time for charging seeing all charging slots at a CS. $Tslot.get(0)$ is at the head of Tslot that will be sorted, with ascending order, once processing the EV_i for each loop, line 8 and 9. The above operations are repeated until all EVs in the queue are assigned to charging slots. Finally, Algorithm 1 returns the Tslot that including the minimum waiting time at a CS given $Tslot.get(0)$, line 12.

Algorithm 1. Charging time at CS

Require: list of EV, N_{ev} and N_{slot}
Ensure: Tslot sorted
for k=1 to N_{slot} **do**
  $\mathrm{Tslot} \cdot \mathrm{add}(T^{curr})$
end for
if $N_{ev} > 0$ **then**
  sort the queue of N_{ev} according to FCFS
  for i=1 to N_{ev} **do**
    $T_i^{fin} = \mathrm{Tslot} \cdot \mathrm{get}(0) + \frac{E_i^{max} - E_i^{curr}}{\beta}$
    replace $Tslot \cdot get(0)$ with T_i^{fin} in Tslot
    sort Tslot with ascending order
  end for
end if
Return Tslot

3.3. CS update per EV for minimizing travel time

Algorithm 2 is an intermediate algorithm. Itt is used to update the CS of each EV in the PLIST list, a list of predictions which is an array of dictionary type in the form of an (EV→CS) pair. The selection of the appropriate CS is based on the minimizing of trip time that is expressed as (1).

$$T_{i,j}^{trip} = T_{i,j}^{trans} + T_{i,j}^{wait} + T_{i,j}^{char} + T_{i,j,d}^{trans} \quad (1)$$

Algorithm 2. EVs reservations updating algorithm

Require: PLIST
Ensure: PLIST contains the new CS recommendation
for i=1 to $\mathrm{PLIST} \cdot \mathrm{Size}(\ )$ **do**
  $CS_{j_{min}} = CS_k$, such as $T_{i,k}^{arr} = \arg_{m<N_{CS}} \min(T_{i,m}^{arr})$
  $T^{min\,Trip} = T_{i,k}^{trip}$ according to Eq.1
  for j=1 to N_{CS} **do**
    if $E_i^{curr} \geq E_{i,j}^{trans}$ **then**
      Calculate $T_{i,j}^{trip}$ according to Eq.1
      if $T_{i,j}^{trip} < T^{min\,Trip}$ **then**
        $T^{min\,Trip} = T_{i,j}^{trip}$
        $CS_{j_{min}} = CS_j$
      end if
    end if
  end for
  $\mathrm{PLIST} \cdot \mathrm{set}(EV_i, CS_{j_{min}}())$
end for
return PLIST

$$T_{i,j}^{wait} = \begin{cases} 0, if\ T_j^Q < T_{i,j}^{arr} \\ T_j^Q - T_{i,j}^{arr}, otherwise \end{cases} \quad (2)$$

With T_j^Q indicate the estimation of the waiting time at CS_j, including the queuing times at CS_j and all EVs having a charging reservation to it and $T_{i,j}^{arr}$ expressed as (3).

$$T_{i,j}^{arr} = T^{curr} + T_{i,j}^{trans} \quad (3)$$

As well, the charging time expressed as (4).

$$T_{i,j}^{char} = \frac{E_i^{max} - E_i^{curr} + E_{i,j}^{trans}}{\beta_j} \tag{4}$$

$$\text{with } E_{i,j}^{trans} = S_i \times T_{i,j}^{trans} \times \alpha \tag{5}$$

In Algorithm 2, lines 2 and 3, we used two variables $CS_{j_{min}}$ and $T^{minTrip}$ to keep successively the optimal station and the minimum value of the EV_i trip time, and they are initialized with values obtained by using the nearest CS toEV_i, then the browsing of all CSs, the loop lines 4 to 12, in order to find where there is the minimum $T_{i,j}^{arr}$. Moreover, the clause between lines 5 and 11 is to eliminate the CSs where the current energy of EV_i is not enough to move towards them. At the end of the iteration, the $CS_{j_{min}}$ obtained is assigned to the EV_i in the PLIST, the line 13. Finally, PLIST is returned with each EV has a CS by which their trip time is the minimum, line 15.

3.4. Decision algorithm to making EVs charging reservations

When a charging request is received by GA, the latter executes Algorithm 3 whose status of EVs having a charging reservation, LR list, will be updated, line 1, also the ascending order of EVs in LR list will be carried out according to the arrival time, T_{ev}^{arr} , in order to serve those who will arrive first at their destination, first come first serve basis, line 2. Then GA sends to all CSs for updating their queuing times by executing algorithm 1, these queuing times will be stored in CSLIST list, line 3. The queuing time will be estimated for each CS only when taking into account the charging reservations previously made by EVs, stored in LR list. For that, a loop, between line 4 and 10, set up to extract each reservation i.e. EV_i and their reservation CS_j, line 5 and 6, and to update the queuing time for CS_jin the CSLIST list, line 9, thereafter $CSLIST(CS_j)$ list, Tslot list ofCS_j, are sorted with ascending order to obtain the minimum queuing time that will be used for the next iteration. Eventually, CSLIST is used by one of the Algorithms 4, 5 or 6 which is responsible for selecting the best charging station taking into account the forecast of EVs which may request a charging reservation after which is being in the process, line 11, and the EV charging reservation with its optimal CS selected for charging is added to LR list of reservations, line 12.

Algorithm 3. Decision algorithm of EV charging reservation

Require : LR, EV_r, CSLIST updated
Ensure : Notify $EV_r$by CS_rrecommended
1: **Update** parameters of all EVs in LR
2: Sort LR with ascending order of T_{ev}^{arr}
3: CSLIST given by all CS using Algorithm 1
4: **for** k=1 to $LR \cdot Size(\ )$ **do**
5: $EV_i = LR \cdot getEV(k)$
6: $CS_j = LR \cdot getCS(k)$
7: **Calculate** $T_{i,j}^{arr}$, $T_{i,j}^{wait}$ and $T_{i,j}^{char}$ according to Eq. 3, Eq. 2 and Eq. 4 , respectively
8: $CSLIST(CS_j) \cdot get(0) = T_{i,j}^{arr} + T_{i,j}^{wait} + T_{i,j}^{char}$
9: $CSLIST(CS_j) \cdot sort(\ )$ with ascending order
10: **end for**
11: $CS_r = CS$ returned by Algorithm 4, 5 or 6
12: $LR \cdot add(EV_r, CS_r\ )$

3.5. Detail of the optimal CS selection for EV charging request

To select the optimal charging station based on the minimum journey time, most selection strategies are taken into account waiting time, charging time, arrival time, the time between charging station and the destination, and the number of EVs that already have a charging reservation. Furthermore, the impact between EVs serviced by the GA and the uncertainty of future EVs charging demands was not considered. Therefore, we propose three algorithms with different strategies to select CS by considering all previous parameters and also dynamic arrival charging requests. All these algorithms, in the first line, start by calculating the number of future charging requests, which is calculated by (6):

$$PN_{ev} = \left(T_{r,j}^{arr} - T^{curr}\right) \times \omega + \delta \tag{6}$$

where $T_{r,j}^{arr}$ the arrival time value of EV_r, EV charging request, to CS_j, the farthest charging station, defined as (7).

$$T_{r,j}^{arr} = arg_{k<N_{cs}} max\left(T_{r,k}^{arr}\right) \tag{7}$$

Moreover, T^{curr} is the current time when the reservation request is sent to GA, ω is the EV flow rate defined as the number of EV (named λ) per time unit (named τ), and δ represents the incertitude and is calculated as (8).

$$\delta = \begin{cases} 0, if \left(\left(T_{r,j}^{arr} - T^{curr}\right) \times \lambda\right) mod\ \tau = 0 \\ 1, otherwise \end{cases} \tag{8}$$

Subsequently, the detailed description of each Algorithm 4. The idea of Algorithm 4 is to select the charging station which will have the maximum occurrence in the CS recommendation process for EV_r charge request, i.e. the most frequent CS selected.

Algorithm 4. Maximum frequency of CS selected

Require: CS_j, CSLIST list contains all CS queuing time and reservations.
Ensure : CS_r recommended
1: Calculate PN_{ev} according to Eq. 6
2: **for** k=1 to n **do**
3: PLIST · add(allEVinS, null), S is Calculated according to Eq. 9
4: PLIST · add(EV_r, null)
5: TCSLIST = CSLIST · clone( )
6: **While** PLIST · size( ) > 0 **do**
7: PLIST, returned by Algorithm 2
8: PLIST · sort( ) with ascending order of T_{ev}^{arr}
9: CS_j = PLIST · getCS(0)
10: EV_i = PLIST · getEV(0)
11: TCSLIST(CS_j) · set(0, $T_{i,j}^{arr} + T_{i,j}^{wait} + T_{i,j}^{char}$) according to Eq. 3 , Eq. 2 and Eq. 4 respectively
12: CSLIST(CS_j) · sort( ) with ascending order
13: **if** $EV_r = EV_i$ **then**
14: $RK_j = RK_j + 1$
15: **Exit** while loop
16: **end if**
17: PLIST · remove(0)
18: **end while**
19: PLIST · removeALL( )
20: **end for**
21: $CS_r = argmax_{k<N_{CS}}(RK_k)$

The loop, between lines 2 and 20, has for goal to perform several operations of CS recommendation by making a new prediction of EV future charging requests, line 3, which will be recorded in the PLIST list with EV_r , line 3 and 4. The expectation of EVs incoming calculated as (9).

$$S = \left\{EV_i \mid i \in [1, PN_{ev}]\ and\ T_i^{req} \in \left[T^{curr}, T_{r,j}^{arr}\right]\right\} \tag{9}$$

where, T_i^{req} is the expected time for an EV_i to send a charge request, it will be randomly obtained.

At the line 5, the queuing time of all CS with all reservations of charging requests are copied in a virtual list TCSLIST, which will be used to accumulate the expected EVs incoming charging requests from PLIST list, line 11, after recommending a CS at each EV in PLIST list and served the first EV coming at it CS selection, line 7 and 8. The operation will be repeated, loop between line 6 and 18, until the EV_r will be served, line 13, then the rank of CS selected to EV_r will be increased, line 14, and an exit loop, line 15, to extract another recommendation. Moreover, to obtain high precision predictions, the CS selection operation will be performed several times, loop between lines 2 and 20, and finally, CS_r that has a maximum frequent will be returned, line 21.

Algorithm 5 works the same way of Algorithm 4, only the strategy of CS selection changed, where here the CS selection based on the minimum of the average of travel times which will be calculated and saved for each CS_j selected in CST list, list in form (CS→list) pair to save $T_{r,j}^{trip}$ predicted, line 14 and 15. To make high precision predictions and measurements, and that the quality of the CS selection will be improved the operation will be performed several times, loop between lines 2 and 21. Finally, the optimal CS_r will be returned when the minimum of trip time average of each CS will have calculated, line 22.

Algorithm 5. Minimum trip times average of CS selected

Require : CS_j , CSLIST list contains all CS queuing time and reservations.
Ensure : CS_r recommended
1: Calculate PN_{ev} according to Eq. 6
2: **for** k=1 to n **do**
3: $PLIST \cdot add(allEVinS, null)$, S is Calculated according to Eq. 9
4: $PLIST \cdot add(EV_r, null)$
5: $TCSLIST = CSLIST \cdot clone(\ )$
6: **while** $PLIST \cdot size(\ ) > 0$ **do**
7: PLIST, returned by Algorithm 2
8: $PLIST \cdot sort(\ )$ with ascending order of T_{ev}^{arr}
9: $CS_j = PLIST \cdot getCS(0)$
10: $EV_i = PLIST \cdot getEV(0)$
11: $TCSLIST(CS_j) \cdot set(0, T_{i,j}^{arr} + T_{i,j}^{wait} + T_{i,j}^{char})$ according to Eq. 3 , Eq. 2 and Eq. 4 respectively
12: $CSLIST(CS_j) \cdot sort(\ )$ with ascending order
13: **if** $EV_r = EV_i$ **then**
14: **Calculate** $T_{r,j}^{trip}$ according to Eq. 1
15: $CST(CS_j) \cdot getList(\ ) \cdot add(T_{r,j}^{trip})$
16: **Exit** while loop
17: **end if**
18: $PLIST \cdot remove(0)$
19: **end while**
20: $PLIST \cdot removeAll(\ )$
21: **end for**
22: $CS_r = argmin_{k<N_{CS}}\left(avg\left(CST(CS_k) \cdot getList(\ )\right)\right)$

The approach implemented by Algorithm 6 to recommend the optimal CS is the same as that presented in the previous algorithms in terms of determining the number of future charging requests, the parameters of the expected EVs such as location, and battery level, as well as the method of estimating waiting time in the CSs. Except, the way distribution of charging requests' activation times is planned regularly, line 2, with the set of the expected EVs are calculated as (10).

$$S' = \left\{EV_i \middle| i \in [1, PN_{ev}] \text{ and } T_i^{req} = T^{curr} + \left(\frac{T_{r,j}^{arr} - T^{curr}}{PN_{ev}}\right) \times i\right\} \tag{10}$$

Where, T_i^{req} times when the predicted incoming EV_i send the charging request.

Algorithm 6. Regularly distribution of future EVs charging request

Require : CS_j , CSLIST list contains all CS queuing time and reservations.
Ensure : CS_r recommended
1: Calculate PN_{ev} according to Eq. 6
2: $PLIST \cdot add(allEVinS', null)$, S' is Calculated according to Eq. 10
3: $PLIST \cdot add(EV_r, null)$
4: $TCSLIST = CSLIST \cdot clone(\ )$
5: **while** $PLIST \cdot size(\ ) > 0$ **do**
6: PLIST, returned by Algorithm 2
7: $PLIST \cdot sort(\ )$ with ascending order of T_{ev}^{arr}
8: $CS_j = PLIST \cdot getCS(0)$

$EV_i = PLIST \cdot getEV(0)$

$TCSLIST(CS_j) \cdot set(0, T_{i,j}^{arr} + T_{i,j}^{wait} + T_{i,j}^{char})$ according to Eq. 3, Eq. 2 and Eq. 4 respectively

$CSLIST(CS_j) \cdot sort(\ )$ with ascending order

if $EV_r = EV_i$ **then**

$CS_r = CS_j$

Exit while loop

end if

$PLIST \cdot remove(0)$

end while

4. RESULTS AND DISCUSSION

4.1. Simulation configurations

In order to simulate and evaluate the C3S proposed system, we built and deployed the proposed system in the opportunistic network environment (ONE), a Java-based simulator for evaluation [26]. Moreover, we present, in this section, a detailed description of the environment parameters setting for the system simulations. The default scenario is represented as the city center of Helsinki city in Finland with an area of 4500×3400 m2 as shown in Figure 2.

Figure 2. Simulation scenario deployed on Helsinki city

Here, we assume that we have four charging stations supplied with sufficient electrical energy, and each of them has equipped with five charging slots using the fast-charging rate of 80 kW, level 3. In addition, 300 EV are initialized randomly in the network with (40-80) kW as maximum electricity capacity of a battery and at the start with (10%-40%) as a SOC threshold. Furthermore, the variable moving speed of each EV is initialized by a value within 30 and 50 km/h, and with (0.12-0.18) kWh/Km as the average energy consumption. Furthermore, the locations and destinations of EVs are chosen randomly by the ONE simulator, and Dijkstra's shortest path algorithm is applied for the movement of nodes on the map to obtain the path towards EVs' destination. Eventually, we set up ONE simulator to update positions, energy, and speeds of the electric vehicles at each second in the charging stations or on the road.

C3S proposed system consists of three methods noted by Ag2M1, Alg2M2 and Alg2M3 is compared with the previous strategy, noted by Alg1, which based on the updating periodically of EV charging reservations at each change due to a new EV charging demand [23]-[25]. In addition, to show the performance of C3S system algorithms we adopted average trip time (ATT), the average time that EVs spend on their trip including spending time at CSs selected for charging, as a metric of evaluation.

4.2. Result and discussion

Figure 3 shows the simulation results obtained after we had run the simulator 100 times at each experience, in which the simulator was set up to make a defined number of charging requests as a rate of EV number per hour that needed to have a charging reservation. It is obvious from the obtained results that all the methods proposed in this strategy are better with regard to trip duration than the previous strategy, and their effectiveness increase with the increase in the number of EVs charging requests. However, the previous strategy is more preferable of all methods proposed in this strategy when the flux of EVs charging requests is lower and the ATT is more significant particularly when the number EV charging request is very high. Therefore, we can conclude that this proposed strategy can be used at peak times and the previous one at off-peak times.

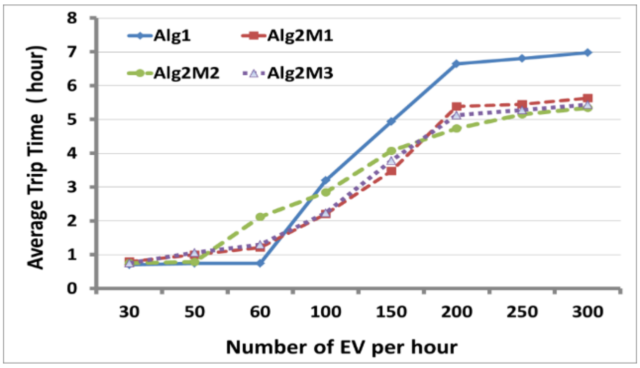

Figure 3. AVG trip time by charging request flow

Likewise, Figure 4 shows the results when we change the number of charging stations, with the setting of the global number of charging sockets in city to 30 charging sockets (see Table 2), and set up the rate of EV charging demands per hour to 300 EV, which is an EV charging request almost every 12 seconds. The curve indicating the previous strategy appears above all methods curves proposed in this strategy when the number of bounds increases and vice versa. Therefore, algorithms proposed in this work are more performance of what is proposed in the previous work in terms of minimizing trip time, as a consequence of the loss of time due to the change of direction of electric vehicles according to the periodic update of the charging plans, especially when the number of CS deployed in the city is greater. Finally, we can say that the strategy proposed in this work is more adapted than the proposed in previous work in big cities and more effective in peak times.

Table 2. Number of charging sockets at charging stations

CS Number	Socket number at each CS
3	10
6	5
10	3
15	2

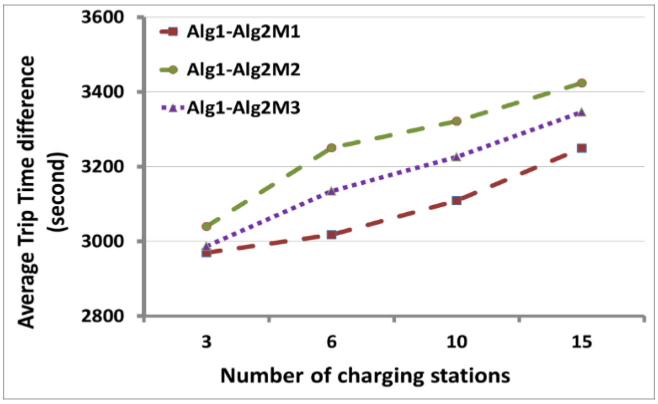

Figure 4. AVG trip time lag between the two strategies at each change of CS number

5. CONCLUSIONS

We proposed in this paper C3S which aims to recommend a suitable charging station for an EV charging request en route to its destination. The selection based on the minimum time spending along the EV trip which includes waiting and charging time, charging time of the previous EVs charging reservations, and an additional time of the future EVs incoming. The proposed C3S combines with the current data of CSs state and EVs conditions that had a charging reservation and the expected data of EVs that can send charging requests due to the uncertainty of EVs driver behaviors and traffic jams. Moreover, the absence of good dimensional datasets of the charging requests demeanors of EVs' drivers that can let us use machine learning to obtain the high precision about the future EVs conditions, we proposed three different strategies to achieve this goal, and each strategy was developed in form of a proposed algorithm. The evaluation of C3S algorithms compared with the previous work algorithms, based on the updating periodically of the EVs charging plans, shows its performance and its effectiveness in terms of the selection of the optimal charging station, particularly in peak times.

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