Mobile Edge Computing for Big Data-Enabled Electric Vehicle Charging

Yue Cao, Houbing Song, Omprakash Kaiwartya, Bingpeng Zhou, Yuan Zhuang, Yang Cao and Xu Zhang

***Abstract*—As one of the key drivers of smart grid, Electric Vehicles (EVs) are environment-friendly to alleviate CO_2 pollution. Big data analytics could enable the move from Internet of EVs, to optimized EV charging in smart transportation. In this paper, we propose a Mobile Edge Computing (MEC) based system, in line with a big data-driven planning strategy on which Charging Station (CS) to charge. The Global Controller (GC) as cloud server further facilitates analytics of big data, from CSs (service providers) and on-the-move EVs (mobile clients), to predict the charging availability of CSs. Mobility-aware MEC servers interact with opportunistically encountered EVs, to disseminate CSs' predicted charging availability, collect EVs' driving big data, and implement decentralized computing on data mining and aggregation. The case study shows benefits of MEC based system in terms of communication efficiency (with repeated monitoring the traffic jam), concerning the long term popularity of EVs.**

I. Introduction

THE application of Electric Vehicles (EVs) [1] has been recognized as a significant means to reduce CO_2 emissions, and attracted numerous attention from both academia and industry. In November 2016, the United States government announced new actions to accelerate the deployment of EVs and charging infrastructures, including the designation of 48 national EV charging corridors. The charging facilities can be installed not just in the commercial Charging Stations (CSs), but also in the public service areas such as shopping malls and parking lots etc. EVs will converge in those places and they must be served according to the well-defined reservation and scheduling strategy [2], meanwhile without unpleasant experiences of long waiting time to discourage driver's comfort.

Different from previous works [3] addressing "when" EVs should be charged while they are parked at CSs (namely charging scheduling), we focus on "which CS" that EVs should plan for charging while they are *on-the-move* during journeys (namely CS-selection). Due to the relatively long charging time, to optimize CS-selection problem has become a critical issue. Firstly, how to optimally plan charging at CS based on the EV's charging demand, will have strong impact on charging efficiency at the CS side. This is particularly the case where a grid operator deploys multiple CSs, and aims to optimize the electricity utilization across them. Secondly, EV drivers can experience a better Quality of Experience (QoE), in terms of a shorter charging waiting time at CSs [1].

The centralized cloud based system [4] is widely applied in existing works. It normally relies on ubiquitous cellular network and real-time information for optimization. Previous work [5] adopted a cloud-based Global Controller (GC) connecting to all CSs and on-the-move EVs. Whenever an EV requires for charging, it will send a request to the GC for seeking the best CS recommendation, and further report its charging reservation[1]. The latter information is useful to predict the load congestion level at a CS.

However, by seamlessly collecting data from all EVs and CSs, it is very time-consuming for the GC to achieve optimization. The complexity and computation load of this centralized solution, increases exponentially (depends on those request charging and those have made charging reservations) with the number of EVs. Moreover, the cellular network is costly and sometime is over-congested, which degrades the communication quality. Therefore, a decentralized EVs charging management solution is desired. Besides, delay tolerant charging reservations need finer grained control, rather than just an established connection to a large and remotely centralized GC.

In this paper, we propose a Mobile Edge Computing (MEC) [6] based system which integrates big data analytics, to opportunistically disseminate the outcome from GC and collect driving big data from mobile clients. The MEC servers implement big data mining and aggregation in a decentralized way, to alleviate the size of data to be processed by the GC. This is different from the resource-consuming cloud based system, which solely relies on the GC to ubiquitously and seamlessly interact with CSs and EVs.

II. Related Works

A. On-the-move EV Charging Planning

Compared to numerous works reviewed in [3] which investigate *Parking Mode*, the works in [1], [5] have proposed the centralized EVs charging information management infrastructures for *On-the-move Mode*, where EVs need to send charging requests to the cloud-based GC, such that the GC can calculate the optimal solution and make decision on where to charge EVs. While these mechanisms are both using the conventional cellular network as the communications infrastructure, and the infrastructure-based mobile networks are becoming increasingly overloaded due to the growing number of EVs, other communication devices associated with their computing and communications demands. Previous work [1] has attempted to utilize additional infrastructures in urban city, via Road Side Units (RSUs) to enable the Publish/Subscribe (P/S) communication paradigm.

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[1]The charging reservation includes arrival time (when the EV will arrive at a CS) and expected charging time at the selected CS (how long its charging time will be).

The cost of maintaining and extending these infrastructures is high, due to the increased geographical density of users (and also with their mobility). The increased density puts a high load on both infrastructure-based networks including wired and wireless networks. This ultimately increases the energy demands and leads to CO_2 emissions, thus could finally harm the environment.

B. Urban Data in Smart Transportation

Smart transportation can fundamentally change urban lives at many levels, such as less pollution, garbage, parking problems and more energy savings. Exploring big data analytics via an ubiquitous, dynamic, scalable, sustainable ecosystem offers a wide range of benefits and opportunities. Most of the techniques require high processing time using conventional methods of data processing. Therefore, novel and sophisticated techniques are desirable to efficiently process the big data generated from stakeholders, from a distributed manner through ubiquitously disseminated and collected information, in order to understand the city wide application in a whole picture.

C. Cloud Computing vs Mobile Edge Computing

The rapid growth of Internet of Things (IoT) devices and mobile applications have placed severe demands on cloud infrastructure, which has led to moving computing and data services towards the edge of cloud, resulting in a novel MEC [6] architecture. MEC could reduce data transfer times, remove potential performance bottlenecks, and increase data security and enhance privacy while enabling advanced applications such as smart functioned infrastructure.

The major difference between cloud computing and MEC, is on the location awareness to support application services. This is because the cloud server locates in a centralized place, behaves as a centralized global manager to compute tasks (with information collected ubiquitously). Note that, MEC servers at different locations are owned and managed by separate operators and owners. With the collaboration among different operators, they can form a collaborative and decentralized computing system in the wide region.

III. Provisioning of MEC Based System

A. Centralized vs Distributed Charging Management

The centralized manner relies on the cloud server GC to advance the resource efficiency, by taking the advantage of potential economies of scale. This brings much privacy concern, as EV status (e.g., location and trip destination) included in charging request will be released to the GC.

In comparison, the decentralized manner benefits to much improved privacy protection [7], where the charging management is executed by the EV individually. It is an attempt to betterment the speed and flexibility by reorganizing the locations of users, so as to enable control and execution of a service in the local.

B. Charging Planning

The prevalence and accessibility of big data are changing the way people see their cities. Dedicated authorities should carefully consider which indicators were meaningful or how they should be analyzed. Here, the charging planning strategy certainly benefits, via analytics of big data from CSs and EVs (that ideally should be captured ubiquitously and timely):

- **CS's Location Condition** refers to number of EVs being parked, with their required charging time [8]. A longer service queue implies a worse QoE (in terms of how long to stay at CS) for incoming EVs, as they may experience additional time to wait for charging.
- **Charging Reservation at CS** indicates which CS to charge, and includes the arrival time, and expected charging time upon arrival at that CS.
- **Trip Destination** refers that EVs would end up with journeys. Inevitably, selecting a CS that is far away from the drivers' trip destination, is user unfriendly.
- **Traffic Condition** [9] on the road fluctuates the EV's arrival time at CS, and energy consumed towards that CS. The EV within a certain range of traffic congestion will slow down its speed, while it will accelerate the speed once leaving from that range.

C. Communication Technologies

As shown in Fig. 1, the communication technology adopted between the GC and CSs can be simply based on reliable Internet or cellular network, as they are fixed network entities. However, there is a necessity to scalably and ubiquitously disseminate CSs' charging availability (computed by the GC) to EVs, and collect EVs' driving big data.

Although 3G/LTE can be applied thanks to ubiquitous coverage, EVs' charging requests are just on-demand while CSs condition is fluctuated after a certain periods (e.g., minutes-level). Besides, EVs' charging reservations are generated, only when they have charging intention. Motivated by above, the opportunistic communication paradigm, e.g., Delay/Disruption Tolerant Networking (DTN) [10] between EVs and MEC servers is desirable, which alleviates the burden of relying on cellular network. TABLE I summarizes communication technologies applicable in MEC and cloud based systems.

D. Network Entities

1) Stakeholders: The popularization of EVs and deployment of CSs is a classic chicken and egg problem. CSs are essential for EVs to charge, but at the same time the deployment of CSs does not make sense in the absence of EVs.

- **Electric Vehicle (EV)** which is below the Status Of Charge (SOC) threshold (a value under which the EV should seek for charging), needs to travel towards a CS for charging. As long as the EV has an intention on where to charge, it further makes a charging reservation associated with that CS.
- **Charging Station (CS)** is located at a certain location (normally with high EVs penetration), and equipped with

TABLE I
SUMMARY OF FEASIBLE COMMUNICATION TECHNOLOGIES APPLIED IN MEC AND CLOUD BASED SYSTEMS

	GC↔MEC Server	GC↔CS	MEC Server↔EV	GC↔EV
MEC Based System	Internet, Cellular network	Internet, Cellular network	Opportunistic WiFi communication	N/A
Cloud Based System	N/A	N/A	N/A	Cellular network

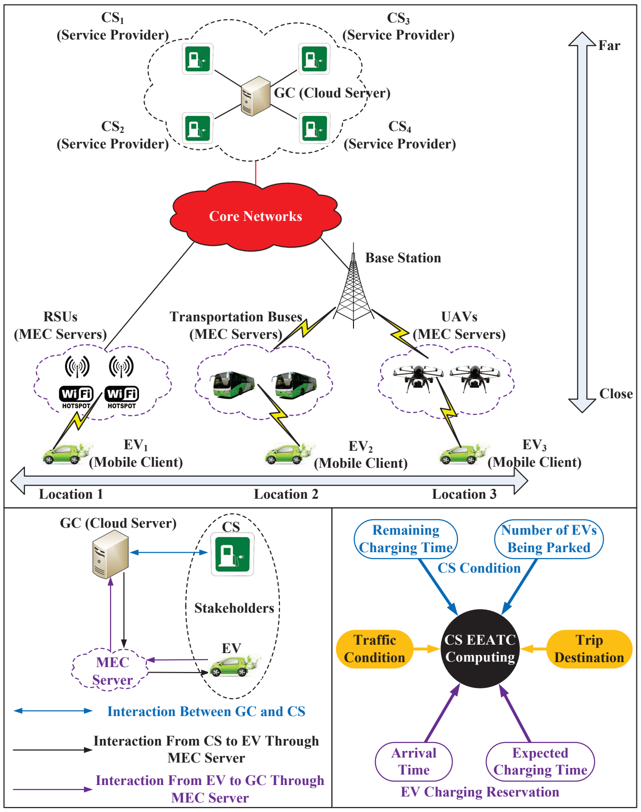

Fig. 1. Big Picture of MEC Based System for EV Charging

a number of plug-in charging slots to charge multiple EVs in parallel. Particularly, its local condition is monitored by the the cloud server GC, to compute the Expected Earliest Available Time for Charging (EEATC)[2] [11].

2) Cloud Server: It is a logical server that is built and delivered through a cloud computing platform, over CSs and EVs. Here, the **Global Controller (GC)**[3] manages the CSs' EEATC dissemination, based on the monitored CSs local condition and EVs' charging reservations collected by MEC servers.

3) MEC Server: The MEC server provides a set of middleware services associated to applications, wherein it implements two key operations:

- Disseminate CSs' EEATC (computed by the GC) to EVs.
- Enable data mining, aggregation (possible with authentication) for opportunistically collected EVs' charging reservations.

[2]It refers to when a CS is expected to be available for charging an EV.

[3]It also schedules the amount of electricity among CSs, depending on the anticipated charging demands (identified from received EVs' charging reservations). This operation is mainly involved in the *Parking Mode* use case.

Envisioning for smart transportation use case, we provision three types of MEC servers:

- **Road Side Unit (RSUs)** [1] are strategically deployed for providing infrastructure support as RSUs limit information to be disseminated within a certain area, thus resulting in smaller message delay, better information security, and possibly lower communications cost.
- **Transportation Buses** [12] provide typical public transport services based on regular operation along a route calling at agreed bus stops (according to timetable on when and how long to stop).
- **Unmanned Aerial Vehicles (UAVs)** [13] are flying aircrafts which can either be controlled remotely or autonomously. Despite the fact that relatively large UAV platforms are playing increasingly prominent roles in strategic and defense programs, technological advances in the recent years have led to the emergence of smaller significantly and cheaper UAVs.

E. Proposed MEC Based System

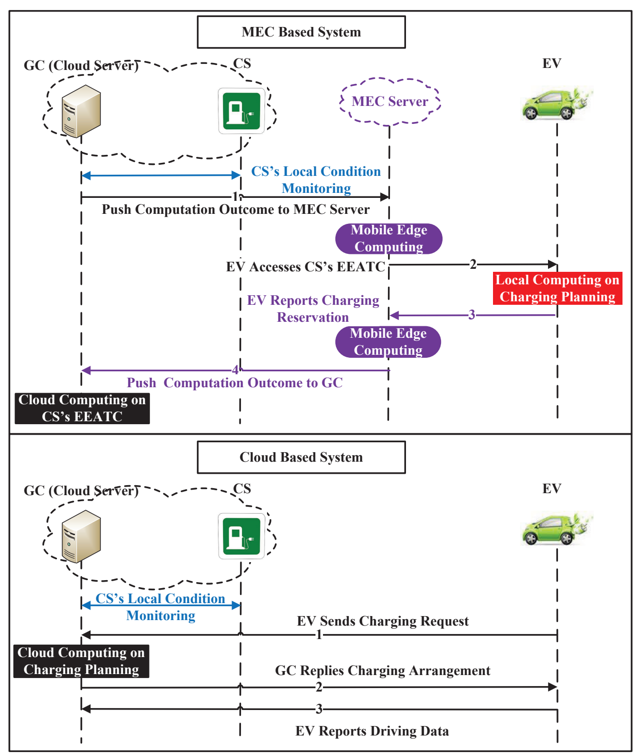

Fig. 2. Signallings Process for Charging Management

All CSs are geographically deployed under a city scenario, and their locations are available for all EVs through their embedded GPS. EVs opportunistically access CSs' EEATC from MEC servers, make charging planning and further report charging reservations (through MEC servers to the GC). The GC analyzes the EVs' charging reservations together with CSs' local condition, to compute CSs' EEATC. Note that, the provisioning of MEC servers would have influence on how fast the CSs' EEATC can be accessed by EVs, as well as how possible EVs' charging reservations can be collected. Fig. 2 illustrates a typical procedure:

Step 1: The GC periodically (with time interval T) disseminates its computed CSs' EEATC to all legitimate MEC servers, and get cached there. Note that the information received at the previous time interval, will be replaced with that associates to current T, to guarantee the freshness of CSs' EEATC maintained at MEC servers.

Step 2: The EV opportunistically encounters a MEC server, then accesses the cached information. If with a charging demand, the EV makes planning on where to charge, based on its accessed information.

Step 3: The EV which is in the planned trip towards the selected CS, further generates its charging reservation. This is normally collected by an opportunistically encountered MEC server, which analyzes and mines valid information[4] from collected EVs' charging reservations.

Step 4: At the time slot approaching $(T + L)$, the MEC server aggregates those mined charging reservations, and reports to the GC once. The GC next makes computation and notifies CSs regarding their EEATC to be published at $(T+L)$.

F. Analysis on MEC Based System

1) Cloud Based System: The charging planning is implemented in a centralized manner in cloud system.

Step 1: The EV which needs charging, sends its request to the GC, through the cellular network.

Step 2: The GC makes CS-selection decision, based on the continuously monitored CSs' local condition and charging reservations reported from other EVs. The decision on where to charge, is replied from the GC to that pending EV.

Step 3: The EV acknowledges the CS-selection decision, further reports its charging reservation to the GC.

2) Communication Cost: Denoting N_{ev}, N_{mec} and N_{cs} as number of EVs, MEC servers and CSs, the communication costs of MEC and cloud based systems are analysed as below:

- **MEC Based System**: The GC experiences a communication cost of $O\left(\frac{N_{mec}}{T}\right)$. This is because within interval T, it disseminates CSs' EEATC dissemination to N_{mec} MEC servers, and processes (aggregated and mined) charging reservations from N_{mec} MEC servers.
- **Cloud Based System**: The GC experiences a cost of $O(N_{ev})$ for handling the charging requests/reservations from N_{ev} EVs.

3) Computation Cost: The computation complexity of MEC based system is scaled by $O\left(\frac{N_{cs}+N_{mec}}{T}\right)$, as it interacts with CSs and MEC servers within T. In comparison, that for cloud based system is given by $O\left(N_{cs} + N_{ev}\right)$.

[4]The charging reservation of EV with an earlier arrival than $(T+L)$ (where L is the previous time slot for GC dissemination), will not be reported to the GC. This is because the EV's charging reservation will be deleted by its selected CS, upon once parking before $(T + L)$.

G. Discussion

The cloud based system suffers from privacy concern, in which the driving big data (e.g., trip destination, location) has to be released through its charging request (Step 1 in Fig. 2). In reality, it is common that $(N_{mec} \ll N_{ev})$, while the number of charging services is higher than N_{ev} (meaning that each EV needs to charge more than once in long term). As such, we claim that the communication and computation efficiency of MEC based system.

Even though RSUs have been widely applied in Vehicular Ad hoc NETworks (VANETs), the deployment introduces additional economy cost. In addition to deployment cost, effectiveness and utilization of RSUs may also depend on the number of EVs that are presented in a given area. Although applying transportation buses envisions for a more flexible way than RSUs, the bus mobility limited by regulated routes (only covers majority areas of a city) may degrade the coverage of information dissemination. Even if the mobility of UAVs is not limited by any route, the energy constraint is a primary concern for operating a large number of UAVs, where the interaction between UAVs and EVs leads to massive network overhead and can eventually undermine the UAVs' energy (thus its average lifetime) [14]. Inevitably, to frequently recharge UAVs degrades the network connectivities.

IV. Proposal of Big Data Driven EV Charging

A. System Cycle

Fig.3 describes four phases involved in the EV charging management cycle.

Driving: The EV is travelling towards its trip destination, opportunistically accesses CSs' EEATC from MEC servers.

Charging Planning: The EV reaching its SOC threshold, needs to make planning on where to charge. Based on its recorded CSs' EEATC information, the EV locally selects a CS as charging recommendation. Upon that decision, the EV's charging reservation is also reported to the MEC server in the same way (updating is needed in case of traffic congestion). In this phase, the data from on-the-move EVs is collected.

Charging Scheduling: Upon arrival at the selected CS, the underlying charging scheduling concerning when to charge EV is determined by the CS. The First Come First Serve (FCFS) is applied, that the EV with the earliest arrival time is scheduled as the highest priority. Here, the data from those EVs being parked is collected.

Battery Charging: The EV is being charged via the plug-in charger at the CS, where its charging data is captured by CS. Once the EV has been fully charged, it will resume its movement and turn to the **Driving Phase**.

B. Charging Planning Logic

If with charging demand, the EV moving during journey is required to firstly travel towards a recommended CS for charging, after which it heads towards the trip destination. Intuitively, the charging planning logic aims to select one of Θ CSs, through which the EV will experience the minimum

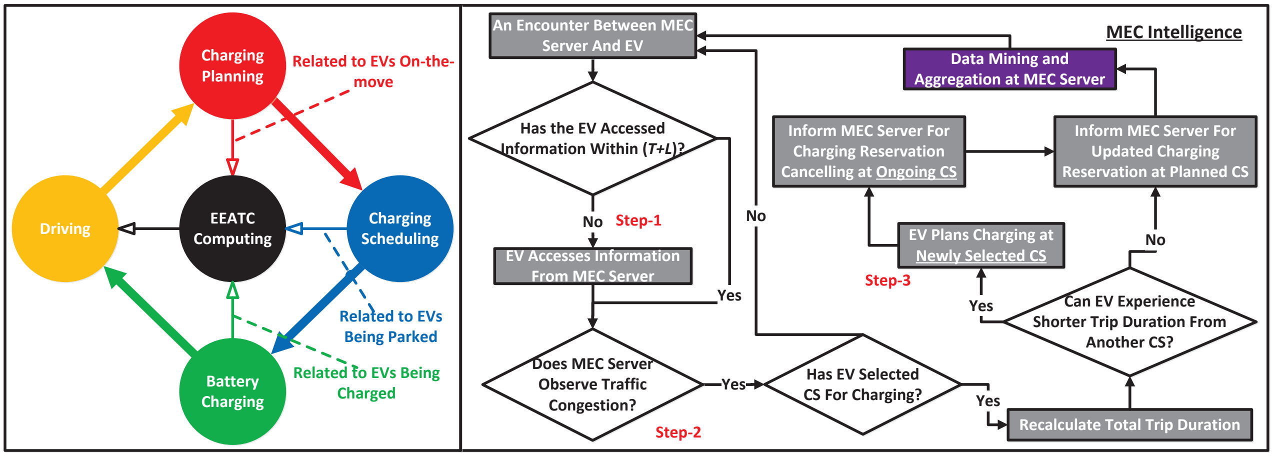

Fig. 3. System Cycle of EV Charging Management

total trip duration:

$$\arg\min_{cs\in\Theta}\left(T^{tra}_{ev,cs} + \mathrm{ST}_{cs} + T^{min}_{cs,d}\right) \tag{1}$$

This includes:

- Travelling time from the location of EV to a CS, denoted by $T^{tra}_{ev,cs}$.
- Time to stay at a CS, given by ST_{cs}. Specifically, this value consists of the EV's expected charging time $T^{cha}_{ev,cs}$, and how long it needs to wait for charging. In Equation (2), the first subcase implies that the EV will be immediately scheduled for charging upon its arrival, as such ST_{cs} equals to $T^{cha}_{ev,cs}$. This happens when there is still unoccupied charging slot at CS. Alternatively, if all charging slots of a CS are currently occupied, the incoming EV needs to wait until one of them is free. In the second subcase, $\mathrm{EEATC}_{cs} - (T^{tra}_{ev,cs} + T_{cur})$ refers to the additional time to wait for charging, where T_{cur} is the current time in network.
- The estimated minimum travelling time from the selected CS to the trip destination of EV, given by $T^{min}_{cs,d}$. We assume that upon a fully recharged service at the selected CS, EV will start to travel towards its destination, with the maximum moving speed, e.g., speed acceleration.

C. MEC Intelligence

Fig. 3 illustrates the intelligence running at MEC server:

Step-1: A service discovery protocol is implemented between the EV and MEC server. The EV which has already accessed CSs' EEATC, will not access that associated with the same T more than once. This reduces the redundant communication cost, since the CSs' EEATC released from GC has not been updated.

Step-2: Due to the traffic congestion, components in Equation (2) are fluctuated. As long as the MEC server observes traffic congestion, it triggers the EV (has charging intention) in proximity to report an updated charging reservation, and checks the fitness of ongoing charging plan (by re-running CS-selection decision).

Step-3: If the newly selected CS benefits to a shorter trip duration than that of previously selected CS, the EV informs the MEC server to cancel its current charging reservation, then arranges another charging reservation at the newly decided CS. At the MEC server side, it implements the data mining, aggregation (possible with authentication) operations on the collected EV's charging reservations.

V. Case Study

A. Scenario Configuration

In Opportunistic Network Environment (ONE) [15], the underlying city scenario is based on the Helsinki in Finland with 8300×7400 m^2 area, containing four main districts A-D. Every district is assigned with its own bus route as shown in Fig. 4. The trip destinations of EVs are randomly determined within the city.

400 EVs with $[2.7 \sim 13.9]$ m/s variable moving speed are initialized considering road safety in a city. The configuration of EVs follows the charging specification {Maximum Electricity Capacity (MEC), Max Travelling Distance (MTD), SOC}. Here, the electricity consumption for the Traveled Distance (TD) is calculated based on $\frac{\mathrm{MEC}\times\mathrm{TD}}{\mathrm{MTD}}$. We configure the following EVs with 100 for each type:

- **Coda Automotive** {33.8 kWh, 193 km, 30%}
- **Wheego Whip** {30 kWh, 161 km, 40%}
- **Renault Fluence Z.E.** {22 kWh, 160 km, 50%}
- **Hyundai BlueOn** {16.4 kWh, 140 km, 60%}

Besides, 9 CSs are provided with sufficient electric energy and 3 charging slots through entire simulation, using the fast charging rate of 62 kW. The CS publication frequency is 300s by default. 5 MEC functioned transportation buses with $[7 \sim 10]$ m/s variable moving speed are eventually configured on each route. Buses will stop for $[0 \sim 120]$s once a destination on their routes is reached. We consider a 300m transmission range for EVs to communicate with buses. 50 randomly generated traffic congestions happen within each 600s and last for 300s, while the congestion range is 300m.

Both MEC and cloud based systems (discussed in Section IV) are implemented. Note that, for fair comparison, the cloud

$$\mathrm{ST}_{cs} = \begin{cases} T^{cha}_{ev,cs} & \text{if } (\mathrm{EEATC}_{cs} < (T^{tra}_{ev,cs} + T_{cur})) \\ \mathrm{EEATC}_{cs} - (T^{tra}_{ev,cs} + T_{cur}) + T^{cha}_{ev,cs} & \text{else} \end{cases} \tag{2}$$

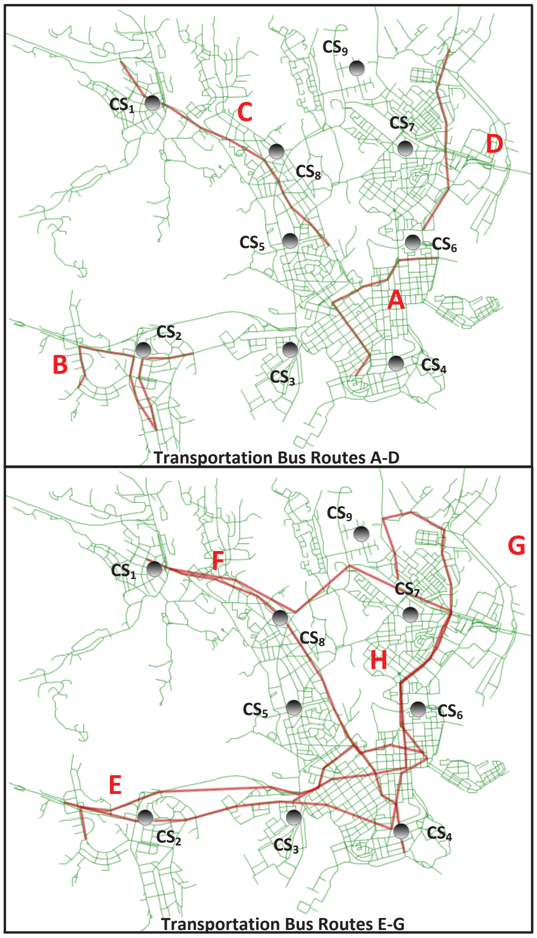

Fig. 4. The Helsinki City Scenario

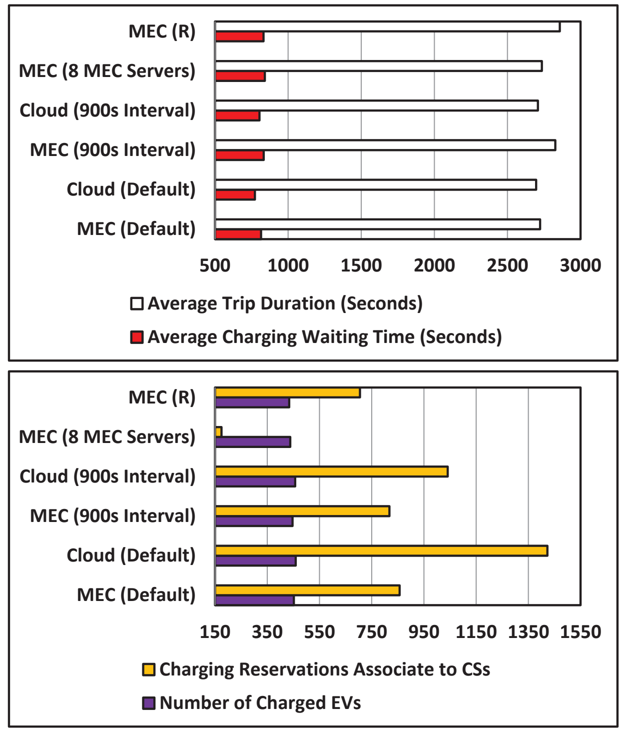

Fig. 5. Performance Results

based system enables a periodical (set to be consistent with GC dissemination interval in case of the MEC based system) charging reservation updating mechanism. The simulation time is 43200s = 12 hours. For charging performance at EV side, we concern the **Average Charging Waiting Time** reflects the average period between the time an EV arrives at the selected CS and the time its battery recharging is finished. The **Average Trip Duration** reflects the average time that an EV experiences for its trip, through the recharging service at an intermediate CS.

B. Performance Results

We observe that the MEC and cloud based systems achieve a close charging performance. This implies the the decentralized MEC based system, with $T = 300$s to disseminate CSs' EEATC dissemination and collect EVs' charging reservations, is able to achieve a comparable charging performance to that of cloud based system (requiring real-time and ubiquitous communication). Besides, a longer T from 300s to 900s degrades charging performance in both MEC and cloud based systems. Due to the same reason, if reducing the number of MEC servers (1 per route, 8 in total), the charging performance is degraded.

In addition, the MEC based system reduces the communication costs to report EVs' charging reservations, thanks to aggregation enabled at MEC servers. The data mining also helps to reduce data size for CSs' EEATC computation.

Previously, the mobility of MEC servers are not influenced by traffic congestion, wherein MEC (R) is the case by bringing the mobility fluctuation of MEC servers. This degrades charging performance, primarily due to the inactive mobility-aware information dissemination and collection.

VI. Discussions And Open Issues

A. Compatibility to Advanced Energy System

The MEC based system is compatible to advanced renewable energy system (e.g., solar and wind powered) and advanced charging technologies (e.g., battery switch). Besides, the charging prices could be a metric introduced to shape charging behavior, such as to encourage more usage on those renewable energy sourced CSs.

B. Provisioning of MEC Servers

Although the concept of mobility-as-service benefits to improved charging performance, environmental condition like traffic congestion or work-off periods of MEC functioned entities, would affect their activities on information dissemination and collection. Therefore, a joint cooperation among heterogeneous MEC servers (in different locations) is desirable.

C. Security

Advanced secure communication is required to ensure confidentiality, integrity and availability of information exchange between GC/CSs and also between MEC servers and EVs. Moreover, peer-to-peer based trust and reputation management system could be further explored to detect and avoid various malicious attacks.

VII. Conclusion

In this paper, we propose a MEC based system, enabled by big data analytics for EV charging use case. Mobility-aware MEC servers scalably and ubiquitously disseminate CSs' EEATC and collect charging reservations from EVs. With data mining and aggregation primarily running on MEC servers, the communication costs for charging reservation making associate to CSs, while the computation complexity of GC are reduced. Such a decentralized system shows its comparable charging performance to the centralized cloud based system.

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