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

The authors propose a MEC-based system, in line with a big-data-driven planning strategy, for CS charging. The 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.

Abstract

As one of the key drivers of smart grid, EVs are environment-friendly to alleviate CO2 pollution. Big data analytics could enable the move from Internet of EVs, to optimized EV charging in smart transportation. In this article, we propose a MEC-based system, in line with a big data-driven planning strategy, for CS charging. The 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 the benefits of the MEC-based system in terms of communication efficiency (with repeated monitoring of a traffic jam) concerning the long-term popularity of EVs.

Introduction

The application of electric vehicles (EVs) [1] has been recognized as a significant means to reduce CO_2 emissions, and has attracted much attention from both academia and industry. In November 2016, the U.S. 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 commercial charging stations (CSs), but also in public service areas such as shopping malls and parking lots. EVs will converge in those places, and they must be served according to a well defined reservation and scheduling strategy [2], without unpleasant experiences of long waiting times to decrease drivers' comfort.

Different from previous works [3] addressing "when" EVs should be charged while they are parked at CSs (namely charging scheduling), we focus on "at which CS" 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 the CS selection problem has become a critical issue. First, how to optimally plan charging at a CS based on an EV's charging demand will have a 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. Second, 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 networks 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 charging, it sends a request to the GC seeking the best CS recommendation, and further reports 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 requesting charging and those with charging reservations) with the number of EVs. Moreover, the cellular network is costly and sometimes over-congested, which degrades the communication quality. Therefore, a decentralized EV 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 article, we propose a mobile edge computing (MEC)-based system [6] that integrates big data analytics to opportunistically disseminate the outcome from the 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.

Related Works

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

[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).

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that the GC can calculate the optimal solution and make a decision on where to charge EVs. While these mechanisms both use the conventional cellular network as the communications infrastructure, the infrastructure-based mobile networks are becoming increasingly overloaded due to the growing number of EVs, and other communication devices associated with their computing and communications demands. Previous work [1] has attempted to utilize additional infrastructures in cities, via roadside units (RSUs), to enable the publish/subscribe (P/S) communication paradigm.

The cost of maintaining and extending these infrastructures is high due to the increased geographical density of users (and also 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, and thus could finally harm the environment.

Urban Data in Smart Transportation

Smart transportation can fundamentally change urban lives at many levels, such as less pollution, garbage, and parking problems, and more energy savings. Exploring big data analytics via a 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.

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 toward the edge of the 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 functioning infrastructure.

The major difference between cloud computing and MEC lies in the location awareness to support application services. This is because the cloud server is located at a centralized place and 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 collaboration among different operators, they can form a collaborative and decentralized computing system in a wide region.

Provisioning of a MEC-Based System

Centralized vs. Distributed Charging Management

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

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

Charging Planning

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

CS's Location Condition refers to the 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 a 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 where EVs end up at the end of their 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 the CS and energy consumed from that CS. An EV within a certain range of traffic congestion will slow down its speed, while it will accelerate the speed once leaving that range.

Communication Technologies

As shown in Fig. 1, the communication technology adopted between the GC and CSs can be simply based on reliable Internet access or a 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' conditions fluctuate after certain periods (e.g., minutes). Besides, EVs' charging reservations are generated only when they intend to charge. Motivated by the above, an opportunistic communication paradigm, for example, delay/disruption-tolerant networking (DTN) [10], between EVs and MEC servers is desirable, alleviating the burden of relying on a cellular network. Table 1 summarizes communication technologies applicable in MEC and cloud-based systems.

Network Entities

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): When it is below the state of charge (SOC) threshold (a value under which the EV should seek charging) needs to travel toward a CS for charging. As long as the EV has

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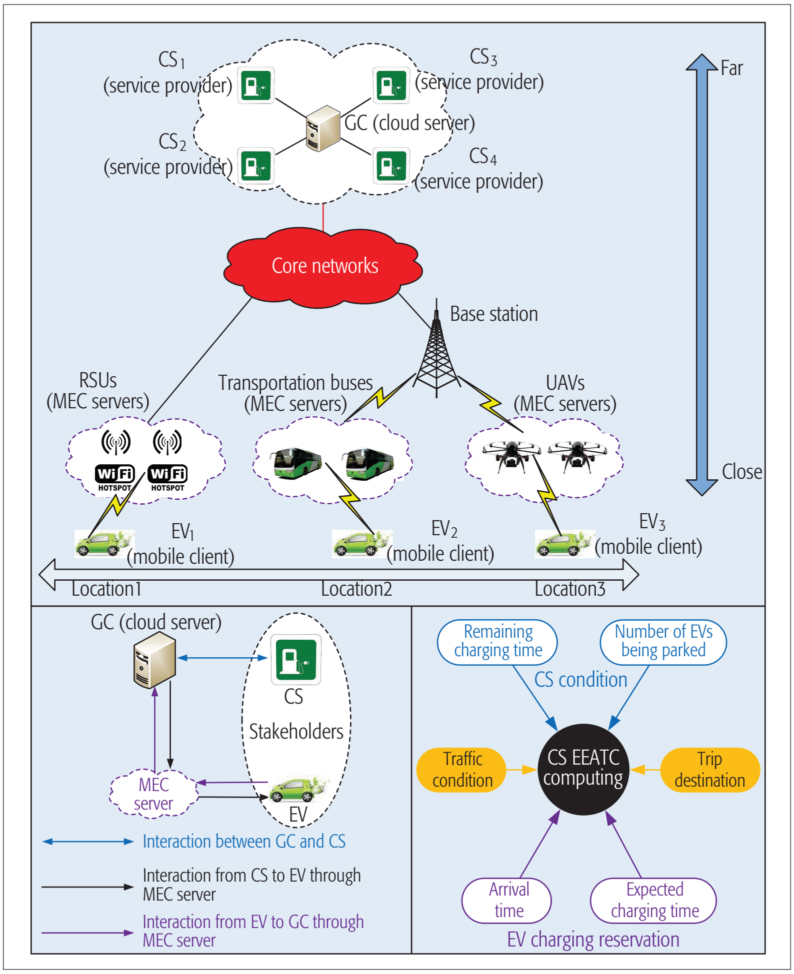

Figure 1. Big picture of the MEC-based system for EV charging.

an intention on where to charge, it further makes a charging reservation associated with that CS.

Charging Station (CS): It is located at a certain location (normally with high EV penetration) and equipped with 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) [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 GC[3] manages the CSs' EEATC dissemination based on the monitored CSs' local conditions and EVs' charging reservations collected by MEC servers.

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

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

Envisioning the smart transportation use case, we provision three types of MEC servers.

Roadside Units [1]: These 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]: These provide typical public transport services based on regular operation along a route calling at agreed bus stops (according to a timetable on when and how long to stop).

Unmanned Aerial Vehicles [13]: These are flying aircraft that can be controlled either remotely or autonomously. Despite the fact that relatively large UAV platforms are playing increasingly prominent roles in strategic and defense programs, technological advances in recent years have led to the emergence of significantly smaller and cheaper UAVs.

Proposed MEC-Based System

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 plans, and further report charging reservations (through MEC servers to the GC). The GC analyzes the EVs' charging reservations together with CSs' local conditions to compute CSs' EEATC. Note that the provisioning of MEC servers would influence how fast the CSs' EEATC can be accessed by EVs, as well as how possible EVs' charging reservations can be collected. Figure 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 gets cached there. Note that the information received at the previous time interval is replaced with that associated with the 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 it has a charging demand, the EV plans where to charge based on the accessed information.

Step 3: The EV, which is on the planned trip toward 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 does computation and notifies CSs regarding their EEATC to be published at ($T + L$).

Analysis of the MEC-Based System

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

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

Step 2: The GC makes a 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 sent from the GC to a pending EV.

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

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

[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.

[4] The charging reservation of an 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, once parking before ($T + L$).

MEC-Based System: The GC experiences a communication cost of $O(N_{mec}/T)$. 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.

Computation Cost: The computation complexity of the 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 a cloud-based system is given by $O(N_{cs} + N_{ev})$.

Discussion

The cloud-based system suffers from privacy concerns, 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 the long term). As such, we claim communication and computation efficiency of the MEC-based system.

Even though RSUs have been widely applied in vehicular ad hoc networks (VANETs), the deployment introduces additional economic cost. In addition to deployment cost, the effectiveness and utilization of RSUs may also depend on the number of EVs that are present in a given area. Although applying transportation buses envisions a more flexible way than RSUs, bus mobility, limited by regulated routes (only covers major 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 a UAV's energy (thus its average lifetime) [14]. Inevitably, frequently recharging UAVs degrades the network connectivity.

	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

Table 1. Summary of feasible communication technologies applied in MEC and cloud-based systems.

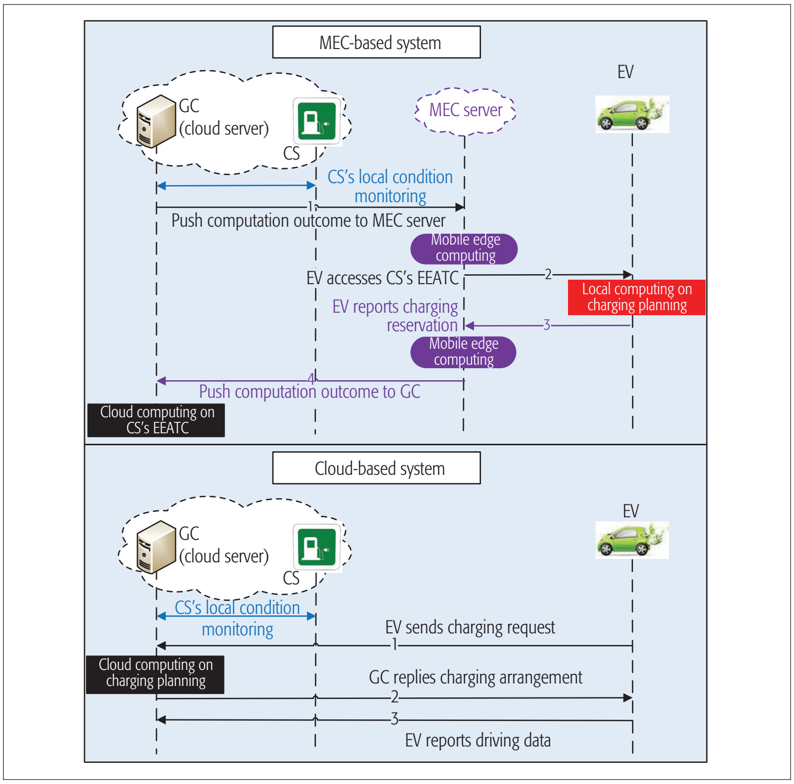

Figure 2. Signaling process for charging management.

Proposal of Big-Data-Driven EV Charging

System Cycle

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

Driving: The EV is traveling toward its trip destination and opportunistically accesses CSs' EEATC from MEC servers.

Charging Planning: The EV, reaching its SOC threshold, needs to plan where to charge. Based on its recorded CSs' EEATC information, the EV locally selects a CS as its 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 the EV is determined by the CS. First come first served (FCFS) is applied, so 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 the CS. Once the EV has been fully charged, it resumes its movement and enter the *driving phase*.

Charging Planning Logic

With charging demand, the EV moving during a journey is required to first travel toward a recommended CS for charging, after which it heads toward its trip destination. Intuitively, the charging planning logic aims to select one of Θ CSs, through which the EV will experience the minimum total trip duration:

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

This includes:
- Traveling time from the location of an EV to a CS, denoted by $T_{ev,cs}^{tra}$.
- Time to stay at a CS, given by ST_{cs}. Specifically, this value consists of the EV's expected charging time $T_{ev,cs}^{cha}$ and how long it needs to

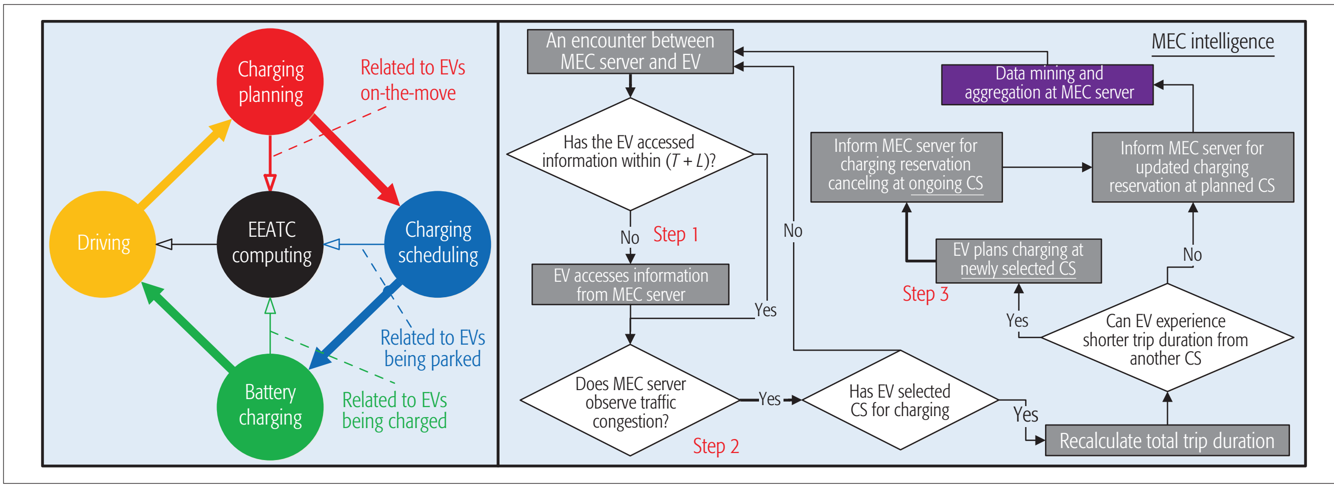

Figure 3. System cycle of EV charging management.

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

wait for charging. In the equation, the first subcase implies that the EV will be immediately scheduled for charging upon its arrival; as such, ST_{cs} equals to $T_{ev,cs}^{cha}$. This happens when there is still an unoccupied charging slot at the 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, $\mathrm{EEATC}_{cs} - (T_{ev,cs}^{tra} + T_{cur})$ refers to the additional time to wait for charging, where T_{cur} is the current time in the network.

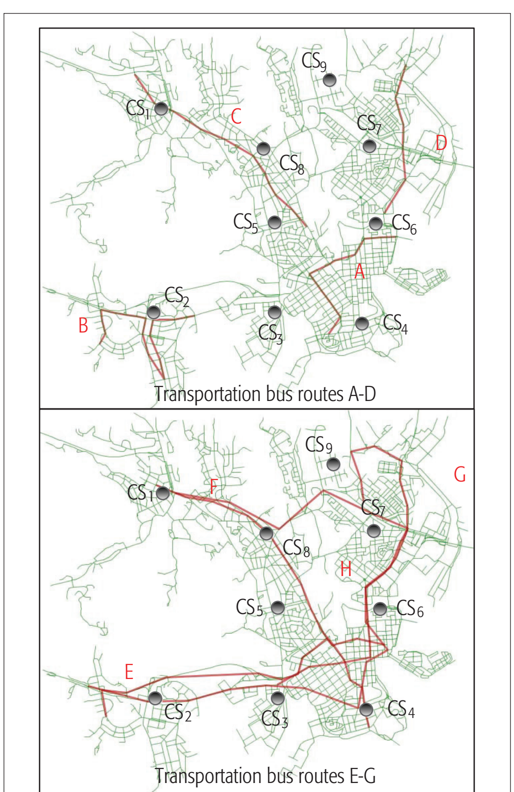

Figure 4. The Helsinki scenario.

- The estimated minimum traveling time from the selected CS to the trip destination of the EV, given by $T_{cs,d}^{min}$. We assume that upon being fully recharged at the selected CS, the EV will start to travel toward its destination at the maximum moving speed (e.g., speed acceleration).

MEC Intelligence

Figure 3 shows the intelligence running at the MEC server.

Step 1: A service discovery protocol is implemented between the EV and the MEC server. The EV, which has already accessed the 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 the GC has not been updated.

Step 2: Due to traffic congestion, components in Eq. 2 fluctuate. 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 the ongoing charging plan (by re-running CS selection).

Step 3: If the newly selected CS gives a shorter trip duration than that of the 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 and aggregation (possible with authentication) operations on the collected EV's charging reservations.

Case Study

Scenario Configuration

In the opportunistic network environment (ONE) [15], the underlying city scenario is based on Helsinki, Finland, with an 8300 × 7400 m^2 area, containing eight main districts, A–G. Every district is assigned 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 ~ 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

here), max traveling distance (MTD), and SOC. Here, the electricity consumption for the traveled distance (TD) is calculated based on MEC × TD/MTD. We configure the following EVs with 100 for each type:

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

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

Both MEC and cloud-based systems (discussed above) are implemented. Note that for fair comparison, the cloud-based system enables a periodic (set to be consistent with a GC dissemination interval in case of the MEC-based system) charging reservation updating mechanism. The simulation time is 43,200 s = 12 h. For charging performance at the EV side, 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.

Performance Results

In Fig. 5, we observe that the MEC and cloud-based systems achieve close charging performance. This implies the the decentralized MEC based system, with T = 300 s to disseminate CSs' EEATC and collect EVs' charging reservations, is able to achieve a comparable charging performance to that of the cloud-based system (requiring real-time and ubiquitous communication). Besides, a longer T from 300 s to 900 s degrades charging performance in both systems. Due to the same reason, with 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. Data mining also helps to reduce data size for CSs' EEATC computation.

Previously, the mobility of MEC servers has not been 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.

Discussions and Open Issues

Compatibility with an Advanced Energy System: The MEC based system is compatible with an advanced renewable energy system (e.g., solar and wind powered) and advanced charging technologies (e.g., battery switch). Also, the charging prices could be a metric introduced to shape charging behavior, such as to encourage more usage of renewable energy sourced CSs.

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

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

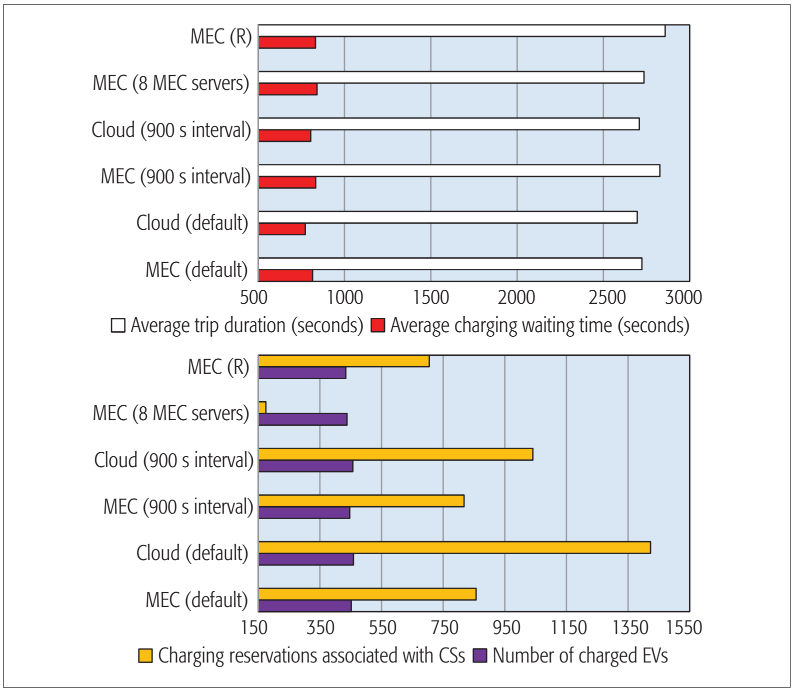

Figure 5. Performance results.

Conclusion

In this article, we propose a MEC-based system enabled by big data analytics for the 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 is associated with CSs, while the computation complexity of GCs is reduced. Such a decentralized system shows comparable charging performance to a centralized cloud-based system.

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Biographies

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