Smart electric vehicle charging management for smart cities

Binod Vaidya1, Hussein T. Mouftah1

1School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, Canada
E-mail: bvaidya@uottawa.ca

Abstract: In recent years, attraction to alternative urban mobility paradigms such as electric vehicles (EVs) is increasing since EVs can significantly minimise fossil fuel dependency and reduce carbon emission in urban areas. Nonetheless, there are several barriers toward widespread adoption of EVs. Moreover, as EV penetration increases in urban areas, uncoordinated charging may cause power outage. Deployment of EV charging network can allow EVs to communicate with the service provider to coordinate charging activities. Taking into account, increased growth of EVs, number of charging facilities will be inadequate in urban areas, so efficient EV charging management is required for managing and allocating scarce charging station (CS) resources. In this study, the authors have designed and implemented a smart EV charging management system utilizing charging strategy that includes effective reservation management and efficient slot allocation of CSs. Considering composite cost that includes waiting time, estimated charging time, estimated charging cost, user discontent factor and CS factor and average waiting time, they have evaluated performance of proposed strategy. The proposed charging strategy is effective than the existing one in terms of average waiting time.

Nomenclature

- $e_{req}$: requested energy of EV
- $\chi_{ini}$: initial SoC value of EV
- $\chi_{tar}$: targeted SoC value of EV
- $\Delta \chi$: difference SoC value between targeted and initial for EV
- $t_{arr}$: expected arrival time of EV i at the CS
- $t_{dep}$: expected departure time of EV i from the CS
- $t_{wa}$: waiting (queuing) time of EV i at the CS
- $t_{rs}$: reservation start time
- $t_{rf}$: reservation finish time of EV i
- $t_{rf}$: reservation duration for EV i
- $\delta$: time-slot interval

1 Introduction

Climate change has been a buzzing issue since the past few decades. Environmental problems caused due to traditional mobility using fossil fuels are well known. Since large majority of people in the world lives in an urban environment at present and is anticipated to grow by 80% by 2050, a large amount of greenhouse gas emissions caused from transportation is due to the urban mobility. Addressing environmental tribulations caused by the existing urban mobility is vital, and an electro-mobility is one of the foremost contenders for mitigating the impact of climate change and improving quality of life in an urban area.

Since a traditional electric power grid infrastructure might result in unpredictable and substantial loads on the power grid, which might, in turn, trigger imbalances, leading to blackouts, modernisation in the existing electric grid, which is known as smart grid, is taking place in many countries. Moreover, the tendency toward electrification of transportation is also growing since electrified transportation can offer considerable benefits in terms of reducing CO2 emissions and minimising fossil-fuel dependence.

In recent years, attraction to alternative urban mobility paradigms such as electric vehicles (EVs) is increasing since EVs can significantly contribute to minimise dependence on fossil fuel and reduce carbon emission in urban areas [1]. Furthermore, because of the use of patterns of EVs in urban environments, they can supplement as dynamic electric storages to support the operation of electric power systems. Thus, EVs can not only provide a cleaner environment but also reduce operational costs of the electric power systems.

Nonetheless, widespread adoption of EVs encounters several challenges including technological constraints (e.g. long charging time and inadequate public EV charging network), limited driving range, limited efficiency and high initial investment. Only overcoming impediments of EV technologies can boost user acceptance for the use of EVs in urban areas [2].

Moreover, as EV penetration increases in the urban areas, uncoordinated charging could yield power losses and undesirable voltage variation that may overload the electric power grid. Appropriate deployment of smart grid technology and EV–grid integration can allow EVs to communicate with the energy service provider (ESP) that, in turn, coordinates the charging activities [3].

A large number of public charging station (CS) networks may not come shortly in some urban areas due to many constraints such as financial, technological limitations etc. [4]. For instance, investing in fast-charging infrastructure may be improbable in the places with lower EV adoption rates because it is not economically viable.

In the coming years, EVs and autonomous vehicles will be imperative for the infrastructure and layout of the cityscape in smart cities. Constructing public EV charging infrastructure in smart cities would substantially encourage EV users to use EVs as well as promote commercial electric fleets, for instance, electric taxi and ridesharing. Thus, a higher EV adoption rate can be achieved if adequate such infrastructures are accessible [5, 6].

With the increased growth of EVs in urban areas, the extensive EV charging network would be in place to meet the anticipated EV demand shortly. Nonetheless, the number of available charging facilities could be inadequate, so an efficient smart EV charging management would be required for managing and allocating the limited EV charging facilities [7–9].

In this paper, we have presented a reservation-based charging strategy that deploys a novel multi-objective slot allocation (MOSAL) technique as well as designed and implemented an inclusive system with consideration of the urban environment such as...
that it can provide effective reservation management and efficient slot allocation for CSs.

The proposed MOSAL approach is based on simulated annealing (SA) [10], specifically on multi-objective SA (MOSA) [11]. Such MOSA can find a set of solutions called the Pareto set, as all the Pareto solutions are equivalently important since they are the global optimal. Considering composite cost that includes waiting time, estimated charging time, estimated charging cost, user discontent factor and CS congestion impact in such a method, our scheduling scheme shall furnish a set of optimal solutions.

Thus, a SecCharge system aims to provide a comprehensive solution for efficient, coordinated smart management for EV charging. Using its web/mobile application, the system can not only alleviate challenges related to the allocation of scarce CS resources in busy urban area [12] but also assure convenience of coordinated charging strategies viewing user’s perspective and e-mobility patterns [13].

The remainder of this paper is organised as follows. Section 2 provides motivation, whereas Section 3 introduces system architecture. Reservation mechanism is described in Section 4, while EV charging slot allocation problem is depicted in Section 5. Moreover, the MOSAL approach is introduced in Section 6, whereas the implementation aspect is provided in Section 7. Finally, conclusion is drawn in Section 8.

2 Motivation

This section highlights motivation for our proposed approach and also depicts related works on it.

In the real-world scenarios, the EV charging network or the public EV infrastructure is still immature. Still, most of the existing charging facilities in the urban areas provide ‘best-effort’ services, that means, EV supply equipment (EVSEs) in public places such as parking lots, shopping malls may not provide the actual status of EVSEs, i.e. availability status or allow reservation of EVSEs. Thus, when an EV user needs to recharge, he has to drive to the charging facility and can recharge his EV only if the EVSE is available. If the EVSE is not free, he may have to wait for the service until the charging port becomes vacant.

The extensive efforts for seeking available EVSEs in the urban areas and queuing for the recharging at CSs would yield exhausting experience for EV drivers. Thus, searching for appropriate EVSE in the urban area might be a concern for EV drivers.

Even though several EV mobile apps have been popped up these days for getting various information on CSs that will provide user convenience [14, 15], only a few of them furnish real-time information on EVSEs such as availability status and allow to reserve EVSEs before going to the charging points.

In several occasions, EV drivers might get frustrated due to not able to charge their EVs. For instance, they might not have sufficient time to be in a queue or might be impatient to wait for a long time. Particularly, during peak hours, when charging points might not be sufficient to handle all the EV charging demand.

Thus, provisioning reservation services in the EV charging portal would help to improve the charging quality of experience (QoE). Offering reservation services could minimise the anxiety of waiting time [16] and alleviate congestion at the CSs (i.e. recharging congestion) [4]. Reservation mechanisms could allow EV users to book the EVSE before they even reach the charging facilities [17–19].

Indubitably, the charging QoE might be degraded if the improper reservation is made for recharging [20]. For instance, having two AC level 2 chargers with different power ratings, let us consider an AC level 2 charger with higher-output power is assigned to an EV with lower acceptance rate, whereas an AC Level 2 charger with lower is assigned to an EV with higher acceptance rate during the reservation process. Owing to longer charging time in both cases, it might not solve CS congestion problems in urban areas.

Furthermore, selection of the charger type may depend not only various factors such as estimated waiting time, estimated charging time and estimated charging cost but also on the dwell time at the CS; as these factors shall be counted on while determining the user discontent factor. For instance, if the dwell time is sufficiently long (i.e. during shopping at the mall), AC Level 2 charger with lower-output power may be acceptable since the longer charging time may not have a significant impact on the user discontent factor if it is within the dwell time.

Viewing the above problems, we have designed and implemented a system called SecCharge, which furnishes a reservation service that permits an EV driver to reserve CS. Moreover, the system utilises charging strategies that include effective reservation management and efficient slot allocation of CSs. Using the MOSAL approach is on MOSA [11] that shall find a set of solutions called the Pareto set, as all the Pareto solutions are equivalently important since they are the global optimal. The main objective of the charging schedule is to minimise composite cost function of estimated waiting time, estimated charging time, estimated charging cost and CS congestion impact with the consideration of user discontent factor, such that it can furnish a set of optimal solutions.

2.1 Recent works

Research in EV technologies, primarily related to the use of EVs in urban areas, has been paying a lot of attention in the past few years [1, 2, 4]. In recent years, there have been many studies undertaken to design charging strategies for charging EVs [7, 21–23]. Timper and Wolf [7] presented CS scheduling strategies that provide efficient parking management and assignment of CSs to connected EVs, where Moghaddam et al. [21] present a smart charging strategy for plug-in EV (PEV) network that offers multiple charging options, including AC level 2 charging, DC fast charging and battery swapping facilities at CSs.

Similarly, in [22], Kuran et al. proposed a parking lot recharge scheduling system that takes EV information such as arrival time, departure time, state of charge (SoC) of battery and travel distance to generate a daily recharging schedule for EVs. Moreover, in [23], Wei et al. presented an intelligent multi-charging system for the parking garage to efficiently provide charging service and manage the charging process as well as design an efficient scheduling algorithm for maximising total utility for the charging operator and customer satisfaction.

Primarily, these works focus on charging scheduling for already arrived EVs at CSs; however, not on charging assistance for EVs on the road [24].

Several prior works have addressed reservation or recommendation services in order to improve QoE in the charging process [13, 16, 17, 25–27]. In [13], Cao et al. proposed a CS-selection scheme in a charging management system to minimise the EVs’ trip duration, taking into consideration of EV parking duration and charging reservation information, whereas, in [16], a distributed charging scheduling scheme was proposed to minimise charging waiting time of EVs at the CSs.

Similarly, Cao et al. [17] proposed not only a centralised reservation enabling service, considering EVs’ reservations for optimal battery switch plans but also a decentralised system by facilitating vehicle-to-vehicle anycasting to deliver EV’s reservation. Moreover, in [25], the authors present a real-time recommendation system for EV taxi drivers in order to minimise the cost time for recharging at the CS.

Moreover, Cassandras and Geng [26] proposed an optimal allocation and reservation system for EVs at CSs distributed in an urban environment that can assign and reserve an optimal space at a CS based on proximity to the current location and charging cost. While, in [27], Cao et al. proposed a mobile edge computing supporting architecture along with an intelligent EV charging recommendation strategy.

Zhang et al. [28] formulated the operation of a dual-mode CS and analyse the relationship between the service dropping rate of the CS and the selections of EVs. While in [29], Rezgui and Cherkauhi have highlighted multi-objective charging slots assignment (CSA) optimisation model that shall balance energy usage between EVSEs, as well as minimise the latency time of
EVs. For this purpose, they have proposed a greedy search heuristic to search for feasible CSA solution, called CSA heuristic (CSAH).

In most of the above research works, they have discussed several smart charging strategies as well as reservation mechanisms for EVs; however, none has presented an integrated solution that considers multiple charging options, waiting time, charging time and CS congestion impact.

In this paper, we introduce a smart charging management system, focusing on effective reservation management and efficient slot allocation of CSs. Furthermore, just a few works have real-world implementations but not considered prevailing EV standards such as open charge point protocol (Ocpp). The implemented system furnishes advanced charging management strategies that include CS information, reservation and navigation, aiming to help EV drivers find CSs quickly.

3 System architecture

In this section, we illustrate a basic building block of the system architecture. The building block of the system architecture consists of four key components: SecCharge backend, CS operators (CSOs), ESPs and distributed energy resources (DERs). Fig. 1 shows an overview of the basic building block of the system architecture.

ESP are autonomous entities producing and distributing energy to the consumers, whereas DERs are supplementary renewable energy sources such as photovoltaic, the wind that can be aggregated to provide the required power. With the advent of smart grid, DERs are getting prevalent since they are cleaner and renewable.

CSOs are fundamentally accountable for the operation and maintenance of CSs. They can typically manage multiple EVCSs or simply CSs at various charging sites/locations. A particular EV charging network can have several CSOs.

A SecCharge, which acts as a coordinated smart management centre (CSMC) for EV charging, is a central component of the system architecture. It is meant for facilitating charging services to EV drivers ensuring user's satisfaction as well as providing effectual coordination with various CSOs in EV charging networks.

On the one hand, the SecCharge acts as e-mobility service provider, which provides charging-related services to EV drivers including searching CS location, assigning reservation and managing customer information and financial transactions.

On the other hand, the SecCharge is responsible for interacting with CSOs for efficient, coordinated smart charging. The SecCharge shall establish agreements with different CSOs in the EV network such that the EV drivers can charge their EVs in the entire EV charging infrastructure.

The SecCharge system is based on a centralised server that smartly manages charging-related activities. This system primarily consists of the following functional entities: application server, database server and mobile application. Major functionalities in application server of the SecCharge system are data collection, route/trip planning and scheduling and reservation services.

Data collection service: EV users can obtain information on CSs (location, technical characteristics and current status). The system also obtains information (i.e. current SoC and current location) from the EV and EV users.

Scheduling and reservation services: EV users can reserve the CSs operated by various CSOs. The system collects all the information about the reservation. Reservation allocation information including occupied time slot and available time slots can be retrieved. Reservation can be modified or deleted by the EV driver. EV driver can also view the historical data of his previous reservations.

The mobile app is one of the vital components of the SecCharge system for providing ubiquitous services. Within urban area, EV drivers can use the mobile app to check for EVSE availability status, nearest charging facility as well as make a reservation for desired EVSE. Similarly, an EV driver can initiate a charging session by sending a charging request through his mobile app.

4 Reservation mechanism

In this section, a reservation mechanism is presented that is one of the main components of the SecCharge EV charging management system. Basically, managing EV charging activities primarily depends on choosing the proper charging strategy. Thus, we present a reservation-based charging strategy that encompasses effective slot allocation and scheduling of the charging points.

It can be observed that range anxiety is one of the major issues in EV recharging. To minimise such anxiety, charging EV in a timely fashion is imperative to guarantee a certain degree of its mobility.

For the charging operations (sessions), the waiting time and charging time at a charging point are the most important indicators.

EV users are concerned with charging operations since charging time periods are still significantly longer, especially for AC level 2 chargers. Possibly, long charging times may cause considerable delays, owing to not only the EV charging process but also the waiting times due to busy charging points.

Furthermore, the charging time of the EV depends on the charge rate, which can be either an EVSE power-output rate or an...
EV acceptance rate. For instance, if Nissan Leaf with 6.6 kWh onboard charger is being charged at the AC level 2 charging point with 7.3 kWh power-output rate, its charging time depends on the onboard charger rate, not on the power-output rate of the level 2 charger.

In the future, number of EVs will increase significantly in the urban areas, and then they may experience significant congestion at several CSs. Since waiting in a queue at the CSs may not be convenient for EVs, the system should be able to provide current waiting time for the CSs such that the EVs would recharge accordingly. This would help to curtail queuing time at the CSs.

In this paper, we have proposed a reservation mechanism for charging EVs that includes efficient slot allocation technique and scheduling. By deploying such a reservation mechanism, the EV users can reserve recharging schedule ahead of time, so such a strategy can not only minimise waiting time and charging time but also alleviate congestion at the CSs (i.e. recharging congestion).

The proposed slot allocation approach, which is a strategic constituent of the charging strategies in the reservation mechanism, shall be discussed in Section 6.

The ‘Nomenclature’ section shows the notations used in the scheme.

Some of the basic terminologies are as follows. Time-slot interval is a time interval of each slot. An expected charging session is a charging operation that is supposed to occur during reserved time slots, while an actual charging session is charging process that occurs when an EV is plugged into EVSE until it is unplugged. Similarly, reservation start time and reservation finish time are time when expected charging session starts and final deadline before which expected charging session must be finished, respectively, whereas reservation duration is number of consecutive time slots for which CS is reserved in the [t_r, t_f] interval. Moreover, charging start time and charging finish time are time when actual charging session starts and terminates respectively, while charging time is charging time of an EV at an EVSE is the time taken for the actual charging session at that EVSE.

By offering reservation service, the EV users can book recharging schedule ahead of time, so such a strategy can not only minimise waiting time but also alleviate congestion at the CSs (i.e. recharging congestion). Primarily, SecCharge system embraces charging strategies based on the slotted reservation, so they depend on information in the reservation (i.e. r, t_r, t_f, r).

In the proposed reservation scheme, the EV user sends a charging request to the SecCharge EV system indicating that the EV needs to be recharged. On receiving such a request, the system shall deploy the scheduling algorithm to obtain appropriate scheduling so that it can send reservation response to the corresponding EV user. Fig. 2 depicts message flows for reservation-based EV charging. In our reservation system, the time horizon is discretised into 7 time intervals, each having 6 time units. Each time interval i starts at time t = 1 and ends at time t, i.e. we consider the time periods {1, 2, ..., T}. Primarily, SecCharge EV system implies such that a 24 h period is divided into time-slot intervals δ, for instance, δ is set at 15 min.

EV user starts the reservation process by sending a charging request for reserving the desired CS site. An EV charging request \( h = (t_r^i, t_f^i, \epsilon) \) is represented by a triple specified by the expected arrival time, the expected departure time and the requested energy [30].

The requested energy \( \epsilon^\text{req} \) for EV i is basically a difference between the targeted SoC value of EV i and the initial SoC value of EV i. This difference in SoC value, which is represented by \( \Delta \chi^i \), can be computed as follows:

\[
\Delta \chi^i = \chi^\text{ini} - \chi^\text{ini}^\text{req}
\]  

On receiving the reservation request, the SecCharge server shall check availability of the slots for all the charging points. Depending on the slot availability, all available slots on the charging points specified within the dwelling time interval are extracted. Taking into account the user preference, the SecCharge server shall compute all possible optimal solutions.

After processing at the SecCharge server, the system shall send two optimal solutions that may be suitable for the EV i to the EV user.

The EV user shall select one appropriate solution for EV charging.

The SecCharge shall then confirm the reservation and also send reservation information to the designated charge point.

Reservation response shall include at least reservation information such as \( t_r^i, t_f^i \) and output power. The selection of charger type is quite vital as the output power shall define the charging rate. Furthermore, the price/kWh may increase with higher recharge power.

Termination of an actual charging session may occur either if the EV user wishes to stop charging or the reservation finish time ticks; whichever first prevails. So, the actual charging session would be different than \( \tau_l \).

5 EV charging slot allocation problem

In this section, we depict the EV charging slot allocation problem that includes system model, system description and the problem formulation in such a system.

Recharging the EVs timely is a key factor to guarantee a certain degree of mobility of the EV users. Nevertheless, unlike gas filling at a gas station (which takes a shorter time), most EV users are concerned with the charging process as the charging time periods are still significantly long. Possibly, long charging times can cause considerable delays, owing to not only the EV charging process but also the waiting times due to busy CSs. If not appropriately addressed these issues, widespread adoption of EVs would likely be hindered.

With the increasing number of EVs in the urban areas, EV users may experience congestion at several CSs. Waiting (queuing) time is one of the major aspects of influencing EV users' satisfaction. Since waiting in a queue at the CSs may not be convenient for EV drivers, the system should be able to provide current waiting time for the CSs such that the EV drivers would plan their EV recharging accordingly. This would help to curtail queuing time at the CSs.

It can be observed that during peak hours, charging activities are extremely influenced by e-mobility traffic and congestion at CSs. Customarily, the estimated waiting time varies directly proportional to the number of EVs charging during peak hours.

In some cases, the charging time of the EV may not matter on the charger type used. For instance, the charging time of Nissan Leaf would not be much affected whether being charged with AC level 2 with 7.3 kW or with AC level 2 with 11 kW.
Fig. 3  Time horizon during the slot allocation process

5.1 System model

We consider an urban area (i.e. downtown) having several CSs and several EVs. The main objective is to coordinate the charging operations in such an area by optimally assigning each EV to a charging point and identifying the optimal charging period for the EV.

The SoC is a measure of the remaining charge in the battery of the EV. So, understanding the SoC of the battery is indispensable, as it is one of the important parameters and reflects EV’s performance. If the SoC reaches below minimum SoC, there may not be enough power to run the EV, so it has to be recharged to be operational. In case, if the EV driver could not find the nearby charge point, he may be in trouble. Thus, one of the foremost concerns is that the EV driver may have range anxiety while driving his EV.

5.2 System description

We consider the EV charging reservation system composed of CSMC, EVs, EV drivers and EV CSs. One of the prime objectives of the system is to coordinate the charging operations by optimally assigning each EV to an EV CS.

Considering an urban area served by several EV CSs and having several EVs that want to recharge. It can be assumed that $I > J$ since the number of EVs is usually higher than the number of CSs.

- EV driver/user has a corresponding EV. When EV user needs to recharge his EV, each vehicle communicates its position, its residual battery SoC, when it desires to start the recharge (i.e. EV release time) and the time within which it wants to leave the charging infrastructure (i.e. EV deadline). Let $\mathcal{U} = \{1, 2, \ldots, K\}$ and $\mathcal{V} = \{1, 2, \ldots, I\}$ be a set of EV users or drivers and a set of EVs, respectively. Every EV user $k \in \mathcal{U}$ can make a charging request for his/her EV $i_k$. Each EV $j$ desires to have a charging spot in the EV CS.

- EVCS or charging points or EVSE is an element in an EV charging infrastructure that supplies electric energy for the recharging of battery EVs (BEVs) or PEVs. Let $\mathcal{S} = \{1, 2, \ldots, J\}$ be a set of charging points or CSs. Each charge station $j \in \mathcal{S}$ may have one or more than one charging ports or outlets $r_j$; i.e. $r_j \geq 1$.

- Charging sessions/operations: It is assumed that charging session of an EV is non-pre-emptive that means it cannot be interrupted and restarted later. We consider a time-slotted system model, in which the time horizon is divided to $T$ equal length time slots, denoted by $\mathcal{T} = \{1, 2, \ldots, T\}$ A set of time periods. Moreover, the charging cannot start before the stated start time, and it must be interrupted within the specified deadline.

It should be noted that during the charging operations, $t^w_i$ may be later than $t^d_i$ and/or $t^d_i$ may be earlier than $t^w_i$. As $t^w_i$ and $t^d_i$ may be flexible, charging session may have a flexible loosely bound interval:

- Requested energy and received energy ($e^{req}_i$ and $e^{rec}_i$): As mentioned above, the requested energy $e^{req}_i$ for EV $i$ is the amount of energy expected to reach the targeted SoC value; that means it is basically a difference between the targeted SoC value of EV $i$ and initial SoC value of EV $i$. However, due to the busy operation hour, the EV user may not be provided with the amount of energy requested. Thus, the received energy $e^{rec}_i$ is the actual amount of the energy to be received during the charging operation, so $e^{rec}_i \leq e^{req}_i$.

- Estimated dwell time $t^d_i$: It is the estimated amount of time elapsed at the CS from the arrival time to the estimated departure time. That means $t^d_i$ indicates how much time the EV user may be willing to spend at the CS. For instance, the EV user might be engaged in various activities such as eating and shopping, while the EV is being charged. Here, $t^d_i$ includes waiting time at the CS and charging time.

- Estimated mean time $t^m_i$: Typically, it is the time difference between $t^{dep}_i$ and $t^d_i$. While estimating the expected arrival time $t^{dep}_i$ and expected departure time $t^{dep}_i$, the waiting time at the CS could be accounted, such that the reservation duration $\tau_i$ would be within the dwell time $t^d_i$. It is expected that $\tau_i$ is less than the time difference between $t^{dep}_i$ and $t^d_i$, i.e. $\tau_i \leq t^{dep}_i - t^d_i$. Hence, $t^m_i$ would be less or equal to $t^{dep}_i$, so the EV user could be able to depart before or on $t^{dep}_i$; in this case, $t^m_i$ would be negative or zero, respectively. However, in real-world scenarios, due to insufficient time slots during the dwell time, the system may suggest a reservation duration such that the $t^m_i$ may exceed the $t^{dep}_i$. In those cases, the EV user may have to wait beyond the dwell time for the completion of the specified reservation period. In this case, $t^m_i$ would be positive.

In Fig. 3, it shows the time horizon during the typical slot allocation process. For instance, EV user wants to charge his BMW i3. In reservation request, $e^{req}_i$, $t^r_i$, $t^d_i$ and $t^{dep}_i$ are indicated as 21 kW, 14:00 and 17:00; thus, $t^m_i$ would be 3 h. During the slot allocation process, for delivering the same amount of energy (i.e. 21 kW), the system may identify the following options.

Reservation option 1 ($r^1$) is obtained while assigning level 2 charger with 7.3 kW, such that $t^{dep}_i$ and $t^{d}_i$ would be 14:15 and 17:15, whereas reservation option 2 ($r^2$) is obtained while assigning level 2 charger with 11 kW, such that $t^{dep}_i$ and $t^{d}_i$ would be 14:20 and 16:20. It can be observed that $r^1$ has $t^{ AUX }_i$ of 15 min, which is less than $r^2$; however, $r^2$ has added $t^{ AUX }_i$ of 15 min.

5.3 Problem formulation

In this section, we have formulated an optimal charging assignment problem as an integer linear programming (ILP). The inputs of the ILP solution are as follows:

- $i \in \mathcal{V}$.
- $j \in \mathcal{S}$.
- A matrix $F$ of costs denoted as $F = [F_{ij}]_{1 \times 1}$

In the problem formulation, $F_{ij}$ represents the composite cost function of the EV $i$ in case a corresponding EV is assigned a charging point $j$. It should be noted that the following crucial costs shall be included in the cost computation of $F_{ij}$:

(i) Estimated waiting time: We denote the waiting time by $t^w_i$, where $t^w_i$ is the starting time of the EV charging and $t^{d}_i$ is the arrival time of the EV.

$$t^{wa}_i = t^w_i - t^{d}_i$$

This criteria is used to prioritise the selection of charging spot for EV charging such that queuing time is minimised.

(ii) Estimated charging time: The estimated charging time $t^{rec}_i$ at the selected CS is given by
\begin{equation}
\epsilon_{\text{ct}} = (\beta \times \Delta \epsilon_{i}) \times \frac{\Theta_t}{\zeta_{i} \times \mu}
\end{equation}

where \( \Theta_t \) is the battery capacity of EV \( i \) (kWh); \( \zeta_{i} \) is the charge rate (either EV acceptance rate or CS power-output rate); \( \beta \) is a coefficient for recharging and \( \mu \) is the EV charging efficiency.

On computing \( \epsilon_{\text{ct}} \), \( \zeta_{i} \) should be considered with a lower value of either the EV acceptance rate or the CS power-output rate. It should be noted that \( \beta \in [0, 1) \) and \( \mu \in [0, 1) \); typically \( \mu \) is considered as 0.9.

In our case, the estimated charging time would be the same as the reservation duration \( t \). However, the actual charging time \( \epsilon_{\text{ct}} \) may not be the same as \( t \).

It is used to allow the selection of power level at the CS depending on the onboard charger on the EV. In this regards, the high-powered onboard charger will yield a short charging time.

(iii) \textbf{User discontent factor:} In this scheme, the user discontent factor depends on various aspects such as the received energy, the waiting time, reservation duration (i.e. estimated charging time), the mean time and the dwell time in the CS. The user discontent factor can be defined considering the above-mentioned parameters as follows:

\begin{equation}
\Psi_{i,j} = \gamma_{(1 - \frac{\epsilon_{\text{ct}}}{\epsilon_i})} + \gamma_{\frac{\epsilon_{\text{ct}}}{\epsilon_i}} + \gamma_{\frac{\epsilon_{\text{ct}}}{\epsilon_i}} + \gamma_{\frac{\epsilon_{\text{ct}}}{\epsilon_i}}
\end{equation}

where the variables \( \gamma_{1}, \gamma_{2}, \gamma_{3} \) and \( \gamma_{4} \) represent weights for different factors considered.

(iv) \textbf{Estimated charging cost:} Estimated total charging cost \( \kappa_{i} \) is the product of the amount of the received energy (in kWh) \( \epsilon_{\text{ct}} \) and unit price/kWh \( \nu \). It can be computed as

\begin{equation}
\kappa_{i} = \epsilon_{\text{ct}} \times \nu
\end{equation}

It can be noted that unit price may be increased with higher recharge power.

(v) \textbf{Estimated impact of the CS congestion:} In fact, current and future charging demands of one EV will also influence the waiting and charging time of other EVs due to the limited number of charging ports at the CS. This criterion is denoted as \( \Psi_{i,j} \) and represents the CS congestion impact if the charging request sent for the EV will be assigned a charging spot within the charging point \( j \). It can be computed as follows:

\begin{equation}
\Psi_{i,j} = \frac{M_i}{N_i}
\end{equation}

where \( M_i \) represents the number of EVs that have charging requests for the CS at a certain time frame and \( N_i \) represents the number of available charging spots. This ratio denotes the capacity of the CS to fulfil the charging request of EV \( i \). The lower the value of \( \Psi_{i,j} \) is, the higher is the probability of fulfilment of the EV charging request by the CS.

Let \( x_{ij} \in \{0, 1\} \) be a binary decision variable, which indicates whether \( i \in i' \) has been assigned a charging slot belonging to the charging point \( j \).

Let \( F_{ij} \) be the cost function of EV \( i \) in case it got a charging slot at the charging point \( j \). \( F_{ij} \) is defined as the weighted sum of the above-mentioned costs, can be computed as follows:

\begin{equation}
F_{ij} = \eta_{i} \epsilon_{\text{ct}} + \eta_{j} \epsilon_{\text{ct}} + \eta_{j} \Psi_{i,j} + \eta_{j} \kappa_{i} + \eta_{j} \Psi_{i,j}
\end{equation}

where \( \epsilon_{\text{ct}} \) and \( \epsilon_{\text{ct}} \) represent, respectively, the normalised values of \( \epsilon_{\text{ct}} \) and \( \epsilon_{\text{ct}} \) by all eligible charging facilities; the variables \( \eta_{i}, \eta_{j}, \eta_{i}, \eta_{j} \) and \( \eta_{j} \) represent weights to be given to each EV in the optimisation problem such that \( \eta_{i} + \eta_{j} + \eta_{i} + \eta_{j} + \eta_{i} = 1 \).

The objective of the optimisation problem is to minimise the charging assignment cost function, denoted as \( \Omega_{i,j} \), defined as follows:

\begin{equation}
\Omega_{i,j} = \sum_{i} \sum_{j} \sum_{k} x_{ij} F_{ij}
\end{equation}

\begin{equation}
\text{minimise} \quad \Omega_{i,j}
\end{equation}

subject to

\begin{equation}
\tau_{i,j} = \left( \epsilon_{\text{ct}} - \epsilon_{\text{ct}} + \epsilon_{\text{ct}} \right), \quad \forall i \in i'
\end{equation}

\begin{equation}
\epsilon_{\text{ct}} \leq \epsilon_{\text{ct}}, \quad \forall i \in i'
\end{equation}

\begin{equation}
\sum_{i \in j} x_{ij} = 1, \quad \forall j \in j
\end{equation}

\begin{equation}
\sum_{j \in j} x_{ij} \leq 1, \quad \forall i \in i', \quad \forall j \in j
\end{equation}

Constraints (12) and (13) indicate that each EV can only be charged by one charging port at a time, and each charging port can be assigned to only one EV at a time.

6 MOSAL approach

In this section, we introduce a novel slot allocation technique called MOSAL approach, which is based on the SA algorithm. Furthermore, we provide the performance evaluation of the MOSAL approach.

6.1 SA algorithm

SA [31] is a well known probabilistic approach for optimisation with provable global convergence. In this regard, SA is a local search-based algorithm that has a mechanism to avoid the local optima for seeking a global optimum. Park-and-charge problems [32], parking spot problems [33], congestion avoidance in e-mobility [10] and other problems [34] have been solved effectively by using SA.

In the MOSAL approach, MOSA is adopted as the algorithm to optimise the charging slot allocation in the charging points.

6.1.1 Preliminaries:

• A weighting function \( s(x, \lambda) \) is chosen; the effect of this choice on the procedure is small due to the stochastic character of the method. It can be computed as [35]

\begin{equation}
s(x, \lambda) = \sum_{i=1}^{s} \lambda_{i} \Psi_{i}
\end{equation}

• The basic parameters of an SA procedure are initialised: \( T_{0} \) — initial temperature; \( \alpha < 1 \) — the cooling factor; and \( N_{\text{max}} \) — the length of temperature step in the cooling schedule.

• A stopping criterion is set: \( N_{\text{max}} \) is the maximum number of iterations without improvement.

• A neighbourhood \( N(X) \) of feasible solutions in the vicinity of an existing solution \( X \) is defined.

Algorithm 1 depicts MOSA algorithm that is used in the MOSAL approach (Fig. 4).

The basic steps of the MOSA are as follows:

Step 1: Initialise with an initial solution \( X_{0} \), and let a starting set PE as the initial Pareto set. Moreover, let the current temperature \( T_{0} \) be an initial temperature \( T_{\text{max}} \).
Step 2: Generate randomly new candidate solution Y within the
neighbourhood of the current solution X(n).
Step 3: Calculate the difference of weighting functions between
the candidate solution and the current solution; i.e. 
\[ \Delta s = s(z(Y), \lambda) - s(z(X_n), \lambda) \]. If \( \Delta s < 0 \), then accept the new
solution; otherwise, accept the new solution with a certain
probability p.
Step 4: If necessary, update Pareto set PE with current solution Y.
Step 5: Repeat the progress unless the maximum number of
iterations is reached, and the temperature is significantly low, i.e.
\( T_n \) using the cooling schedule \( T_n = \alpha \times T_{n-1} \).

6.2 Performance evaluation

In this section, we evaluate the efficiency of our proposed MOSAL
mechanism based on MOSA by conducting extensive simulation
experiments on several real-world scenarios. To observe the
effectiveness of the MOSAL approach, we have compared its
performance with some existing algorithm.

To evaluate the performance of the MOSAL approach, we
considered in experiments a realistic scenario using simulation of
urban mobility simulation tool. Moreover, to evaluate the
performance of the MOSAL approach, we have considered the
following performance metrics:

- **Average waiting time**: The average period between the time and
  EV need to arrive at the specified CS and the time to start the
  reservation process.
- **Average user discontent factor**: It quantifies the average quality
  of service measure of charging assignment to the user. That
  means it shows how much the user is discontent with the
  recharging target.

6.2.1 Preliminaries: Typically, the charging time for BEV may
depend on the following parameters:

- Current SoC level or energy stored in its battery pack.
- Size of the battery pack or battery capacity.
- Onboard charger capacity or vehicle acceptance rate.
- Output of a CS.

We have considered different types of BEVs with various battery
capacities and vehicle acceptance rates. Table 1 shows the technical
specification of BEVs.

Environmental Protection Agency (EPA) has specified a total
range (EPA rating) covered by a BEV with a full charge, shown in
Table 1.

In the experiments, we have considered only AC level 2
chargers as they are currently the most widely spread. For instance,
The electric circuit [36], which is the largest public charging
network for EVs in Quebec and Eastern Ontario, has 2354 CSs that
include 290 fast-charge stations. Hence, for the real-world
scenario, we have considered three types of AC Level 2 chargers,
namely (a) charger with 3.6 kW and 240 V, 16A; (b) Charger with
7.3 kW and 240 V, 32A; and (c) charger with 11 kW and 400 V,
16A.

6.2.2 Case I: In the case I, let us assume that the charging site
consists of 15 different charging points – 3 points with 3.7 kW
maximum charging power, 5 with 7.4 kW and 7 with 11 kW. It is
obvious that using the level 2 charger, an EV may require more
than one time slot to recharge the requested energy. We consider
that the EV user makes a charging reservation request at least 10
min before reaching its designated charging point.

It is assumed that EV request arrivals are based on Poisson
distributed.

During this period, the system shall receive incoming charging
requests and process using the MOSAL approach to generate a set
of optimal solutions; thus, the system can send responses
accordingly.

Fig. 5 shows average waiting time for different number of EVs.

\[ e^{-(\frac{\Delta s}{\Delta k})} \]

\[ Y \left\{ \begin{array}{ll}
X_n \quad N_{count} = 0, \\
Y \quad N_{count} = N_{count} + 1.
\end{array} \right. \]

**Fig. 4 Algorithm 1: Pseudocode for MOSA algorithm [11]**

**Table 1 Technical specifications of BEVs**

| Make, model, year | Battery capacity, kWh | Onboard charger, kW | Total range (EPA rating), km | Average fuel consumption rating, kWh/100 km |
|-------------------|-----------------------|---------------------|------------------------------|---------------------------------------------|
| Nissan, Leaf, 2019 | 40                    | 6.6                 | 243                          | 18.7                                        |
| BMW, i3, 120Ah, 2019 | 42.2                 | 11                  | 246                          | 18.5                                        |
| Chevrolet, Bolt, 2019 | 60                   | 7.2                 | 383                          | 17.6                                        |

**Fig. 5 Average waiting time with varying the number of EVs**

\[ \text{Average waiting time} = \frac{1}{n} \sum_{i=1}^{n} w_i(t_i) \]

\[ N_{steps} = N_{max} \]

\[ T \left\{ \begin{array}{ll}
X_0 \quad N_{count} = 0, \\
Y \quad N_{count} = N_{count} + 1.
\end{array} \right. \]
6.2.3 Case II: In the case II, we have considered two scenarios – first one having ten CSs with two points with 3.7 kW maximum charging power, four with 7.4 kW and 4 with 11 kW; and second one having 20 CSs with four points with 3.7 kW maximum charging power, 6 with 7.4 kW and 10 with 11 kW.

User satisfaction is one of the key goals of the MOSAL approach such that EV user can choose the most appropriate one for the possible solutions. Moreover, it is one of the means to evaluate the efficiency of smart charging reservation mechanisms. Fig. 5 shows that by varying number of EV charging requests, in both scenarios, the average user discontent factor increases. With a large number of requests (i.e. 120 EVs), the reservation options may not be satisfying such that the user discontent factor shall be relatively high. It can be seen that Scenario 2 is much better than Scenario 1 since the system can provide more high-power chargers.

6.2.4 Case III: In case III, we have considered five CSs of same type and ten same types of EV models shall request in each scenario. Furthermore, we have evaluated the average user discontent factor with respect to $\tau/t_d$ neglecting other factors.

It can be noted that the selection of appropriate charger type is critical since the charging time depends on the charge rate. For instance, let us consider both Nissan Leaf and BMW i3 need the same amount of increment in SoC value (i.e. let us say $\Delta x = 50\%$). From Table 1, it can be observed that the vehicle acceptance rate of Nissan Leaf is 6.6 kWh, whereas that of BMW i3 is 11 kWh. Then, for Nissan Leaf, using either the charger with 7.3 kW or the charger with 11 kW, the charging time will be about 3 h 22 min. However, for BMW i3, using the charger with 7.3 kW, the charging time will be about 3h 11 min, whereas, using the charger with 11 kW, the charging time will be about 2 h 8 min:

(a) for output power 11 kW
(b) for output power 7.3 kW
(c) for output power 3.6 kW

Fig. 7 shows average user discontent factor with respect to $\tau/t_d$ for various EV models, namely Chevrolet Bolt, Nissan Leaf and BMW i3. In Fig. 7a, average user discontent factors for BMW i3 are significantly lower than the other two EV models. This is due to the fact that BMW i3 has higher vehicle acceptance rate. In Fig. 7b, average user discontent factors for Chevrolet Bolt are relatively higher than other two EV models. Moreover, in Fig. 7c, average user discontent factors for all three EV models are unacceptably high. This may be due to using chargers with 3.7 kW maximum charging power.

7 Implementation aspect

In this section, we present the design and implementation aspect of SecCharge EV charging system. The basic architecture of the EV charging system consists of SecCharge Server, Control centre, CS or EVSE and EV. Fig. 8 depicts the implementation of SecCharge EV charging system.

SecCharge software utilises a combination of client–server, mobile and web-based architectures. The web-based aspect of SecCharge software is hosted on SecCharge web server. The clients initiate a request to the server, and the web server provides an appropriate response to the browser. The client–server aspect of the software involves mobile devices initiating request(s) to the server. Hypertext transfer protocol is used for communication between clients and server.

Technical details of the SecCharge system are discussed as follows. Linux Ubuntu is deployed as a basic operating system in the servers. Moreover, application server is based on Apache Tomcat, which provides lightweight web container, whereas Oracle Database is functioned as an underlying database of the system. Model view controller (MVC) and hibernate object-relational mapping are utilised as core frameworks. Spring MVC framework, which provides MVC architecture, facilitates in constructing flexible and loosely coupled web applications. Hibernate provides a framework for mapping object-oriented domain model to the relational database.
Representational state transfer (REST) being lightweight, maintainable and scalable, RESTful services are implemented as SecCharge web services. Moreover, JavaScript Object Notation, which is a lightweight data-interchange format, is employed.

For our deployment, the EV charging emulator system is used, which is comprised of EV emulator and EVSE emulator. The EV emulator is built on Raspberry Pi and I2C-bus pulse-width modulation controller, namely PCA9685, whereas the EVSE emulator is built on Raspberry Pi 3.

The ISO 15118-3 protocol has been deployed for wired data transfer from the EVSE emulator to the EV emulator and vice versa using RS-232 interfaces.

OCPP, which is an open protocol between CSs and a central managing system, would allow CSs and central systems from different vendors to easily communicate with each other. Thus, the OCPP is used as communication protocols between the EVSE and the control centre.

One of the key features in SecCharge system is reservation services. Using Google Map services, EV user can view all the CSs in the vicinity (as shown in Fig. 9). He can choose the appropriate CS among them and send a reserve request to the SecCharge server for recharging at the desired CS. The system shall provide reservation information including reservation start time and finish time. Reservation summary information is depicted in Fig. 10.

8 Conclusion
In this paper, we have designed and implemented a smart EV charging management system utilising charging strategies that include effective reservation management and efficient allocation of time slots of CSs. Such a system is developed in consideration of the urban environment. In this regard, we have presented a reservation-based charging strategy that deploys a novel MOSAL technique. The proposed MOSAL approach is based on MOSA. Considering composite cost that includes waiting time, estimated
charging time, estimated charging cost, user discontent factor and CS congestion impact in such a method, our scheduling scheme shall furnish a set of optimal solutions. Viewing user discontent factor and average waiting time, we have evaluated the performance of the proposed strategy. Proposed charging strategy is effective than the existing charging strategy in terms of average waiting time.

9 Acknowledgment

This research work was supported by the Smart Grid Fund (SGF), Ministry of Energy, The Ontario Government and Canada Research Chair (CRC) Fund, Canada.

10 References

[1] Huang, S., He, L., Gu, Y., et al.: ‘Design of a mobile charging service for electric vehicles in an urban environment’, IEEE Trans. Intell. Transp. Syst., 2015, 16, (2), pp. 787–798

[2] Zhang, H., Hu, Z., Xu, Z., et al.: ‘An integrated planning framework for different types of PEV charging facilities in urban area’, IEEE Trans. Smart Grid, 2016, 7, (5), pp. 2273–2284

[3] Mehta, R., Srinivasan, D., Khambadkone, A.M., et al.: ‘Smart charging strategies for optimal integration of plug-in electric vehicles within existing distribution system infrastructure’, IEEE Trans. Smart Grid, 2018, 9, (1), pp. 299–312

[4] Rigan, E.S., Ramchum, S.D., Bassilades, N., et al.: ‘Congestion management for urban EV charging systems’. Proc. SmartGridComm, Vancouver, BC, Canada, 2013, pp. 121–126

[5] Wang, Y., Su, Z., Xu, Q., et al.: ‘A novel charging scheme for electric vehicles with smart communities in vehicular networks’, IEEE Trans. Veh. Technol., 2019, 68, (9), pp. 8487–8501

[6] Moghaddam, R., Mohammed, G.A., Skordilis, E., et al.: ‘Smart control of fleets of electric vehicles in smart and connected communities’, IEEE Trans. Smart Grid, 2019, 10, (6), pp. 6883–6897

[7] Timper, J., Wolf, L.: ‘Design and evaluation of station charging scheduling strategies for electric vehicles’, IEEE Trans. Intell. Transp. Syst., 2014, 15, (2), pp. 3122–3127

[8] Zhu, X., Han, H., Gao, S., et al.: ‘A multi-stage optimization approach for active distribution network scheduling considering coordinated electrical vehicle charging strategy’, IEEE Access, 2016, 6, pp. 50117–50130

[9] Wei, Z., Li, Y., Cai, L.: ‘Electric vehicle charging scheme for a park-and-charge system considering battery degradation costs’, IEEE Trans. Intell. Veh., 2018, 3, (3), pp. 361–373

[10] Amer, H., Salman, N., Hawes, M., et al.: ‘An improved simulated annealing technique for enhanced mobility in smart cities’, Sensors, 2016, 53, pp. 119–132

[11] Ullengu, E.L., Teghem, J., Fortemps, P.H., et al.: ‘MOSA method: a tool for solving multi-objective combinatorial optimization problems’, J. Multi-Criteria Decis. Anal., 1999, 8, (4), pp. 221–236

[12] Zhang, L., Li, Y.: ‘A game-theoretic approach to optimal scheduling of parking-lot electric vehicle charging’, IEEE Trans. Veh. Technol., 2016, 65, (6), pp. 4068–4078

[13] Cao, Y., Wang, T., Kawaiwarty, O., et al.: ‘An EV charging management system considering drivers’ trip duration and mobility uncertainty’, IEEE Trans. Syst. Man Cybern., 2018, 48, (4), pp. 596–607

[14] Argade, S.G., Aravinth, V., Buyukatkin, E., et al.: ‘Performance and consumer satisfaction based electricity charging scheme for EV charging as a VPP’, IET Gener. Transm. Distrib., 2019, 13, (11), pp. 2112–2122

[15] Chung, H.M., Li, W.T., Yuan, C., et al.: ‘Electric vehicle charging scheduling mechanism to maximize cost efficiency and user convenience’, IEEE Trans. Smart Grid, 2019, 10, (3), pp. 3020–3030

[16] Qin, H., Zhang, W.: ‘Charging scheduling with minimal waiting in a network of electric vehicles and charging stations’. Proc. VANET, Las Vegas, NV, USA, 2011, pp. 51–60

[17] Cao, Y., Wang, T., Cao, X., et al.: ‘Toward anycasting-driven reservation system for electric vehicle battery switch service’, IEEE J. Syst., 2019, 13, (1), pp. 2806–2816

[18] Alamia, B., Hajesmauli, M.H., Crespi, N.: ‘Online EV charging scheduling with on-arrival commitment’, IEEE Trans. Intell. Transp. Syst., 2019, 20, (12), pp. 4524–4537

[19] Tucker, N., Alizadeh, M.: ‘An online admission control mechanism for electric vehicles at public parking infrastructures’, IEEE Trans. Smart Grid, 2020, 11, (1), pp. 161–170

[20] Cao, Y., Lin, S., He, Z., et al.: ‘Electric vehicle charging reservation under pre-emptive service’. Proc. 2019 First Int. Conf. Artificial Intelligence (IAI), Shenzhen, China, 2019, pp. 1–6

[21] Moghaddam, Z., Ahmad, I., Habibi, D., et al.: ‘Smart charging strategy for electric vehicle charging stations’, IEEE Trans. Electr. Electrification, 2018, 4, (1), pp. 76–88

[22] Kurian, M.S., Viana, A.C., Iannone, L., et al.: ‘A smart parking lot management system for scheduling the recharging of electric vehicles’, IEEE Trans. Smart Grid, 2015, 6, (6), pp. 2942–2953

[23] Wei, Z., Li, Y., Zhang, Y., et al.: ‘Intelligent parking garage EV charging scheduling considering battery charging characteristic’, IEEE Trans. Ind. Electron., 2018, 65, (3), pp. 2806–2816

[24] Cao, Y., Kawaiwarty, O., Wang, R., et al.: ‘Towards efficient, scalable and coordinated EV charging management’, IEEE Wirel. Commun., 2017, 24, (2), pp. 66–73

[25] Tian, Z., Jung, T., Wang, Y., et al.: ‘Real-time charging station recommendation system for electric-vehicle taxis’, IEEE Trans. Intell. Transp. Syst., 2016, 17, (11), pp. 3098–3109

[26] Casandras, C.G., Geng, Y.: ‘Optimal dynamic allocation and space reservation for electric vehicles at charging stations’, IFAC Proc. Vol., 2014, 47, (3), pp. 4056–4061

[27] Cao, Y., Kawaiwarty, O., Zhang, Y., et al.: ‘A decentralized deadline-driven electric vehicle charging recommendation’, IEEE J. Syst., 2019, 13, (3), pp. 3410–3421

[28] Zhang, Y., You, P., Cai, L.: ‘Optimal charging scheduling by pricing for EV charging station with dual charging modes’, IEEE Trans. Intell. Transp. Syst., 2019, 20, (9), pp. 3386–3390

[29] Rezgui, J., Cherkoui, S.: ‘Smart charging schedule for EVs based on two-way communication’. Proc. 2017 IEEE Int. Conf. Communications (ICC), Paris, France, 2017, pp. 1–6

[30] Intelligent Transport Systems (ITS): ‘Infrastructure to vehicle communications part 3: communications system for the planning and reservation of EV energy supply using wireless networks’, ETSI TS 101 341–3421

[31] Cho, J.H., Wang, Y., Chen, L.R., et al.: ‘A survey on modeling and optimizing multi-objective systems’, IEEE Commun. Surv. Tutor., 2017, 19, (3), pp. 1867–1901

[32] Rahmani-Anderibi, M., Shen, H., Fotuli-Firuzabad, M.: ‘Planning and operation of parking lots considering system, traffic, and drivers behavioral model’, IEEE Trans. Syst. Man Cybern. Syst., 2019, 49, (9), pp. 1879–1892

[33] Zhao, C., Li, S., Wang, W., et al.: ‘Advanced parking space management strategy design: an agent-based simulation optimization approach’, Transp. Res. Rec., 2018, 2672, (8), pp. 901–910

[34] Yua, V.F., Redia, A.A.N.P., Hidayatb, Y.A.: et al.: ‘A simulated annealing heuristic for the hybrid vehicle routing problem’, Appl. Soft Comput., 2017, 53, pp. 119–132

[35] Loukil, T., Teghem, J., Tuyttens, D.: ‘Solving multi-objective production scheduling problems using metaheuristics’, Eur. J. Oper. Res., 2005, 161, pp. 42–61

[36] The Electric Circuit. Available at url: http://creativecommons.org/licenses/by-nc/3.0/