A Simulation-based Heuristic for City-scale Electric Vehicle Charging Station Placement

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Abstract—**Electric Vehicles (EVs) play an important role towards a more sustainable transportation system. Sufficient charging infrastructure is, however, needed in order to accommodate their power demand and increase EV adoption. In this paper, we propose a simulation-based approach for charging station (CS) placement using an agent-based traffic simulation. The heuristic's objective is to achieve sufficient network coverage to keep charging related inconvenience within an acceptable range while minimising the overall number of CSs. For this purpose, the algorithm identifies locations at which the charging procedure seamlessly integrates into the drivers' itineraries, thus minimising detours and waiting times. At the same time, the algorithm attempts to maximise the utilisation of each CS throughout the day in order to minimise the number of CSs. The methodology is demonstrated at the example of Singapore. The investigation shows that the charging demand of 20,000 EVs can be covered with approximately 2,500 CSs by accepting average detours no greater than 410 metres and average waiting time below 10 minutes. This number can be further reduced by relaxing the inconvenience criterion.**

I. Introduction

Electric vehicles (EVs) are considered an important measure towards mitigating local traffic emissions and reducing the dependency on fossil fuels [1]. In order to promote the deployment of EVs, battery range related anxiety needs to be prevented. While significant research has been conducted in advancement of battery technology for increasing range and lowering costs [2], a growing number of recent studies also point out that an effective and efficient charging infrastructure is crucial [3], [4]. In the last years, an increasing amount of research has focused on the *charging station* (CS) placement problem which is shown to be *NP*-hard [5]. Finding an optimal solution at the scale of an entire city thus requires heuristic approaches. This problem is further complicated by the fact that charging times and required energy depend on a large variety of different factors including traffic patterns and charging behaviour which are difficult to assess from a macroscopic perspective.

The CS placement problem faces a trade-off between network coverage and infrastructure costs. Since charging a battery is generally more time consuming than refuelling an internal combustion engine vehicle, CSs should be placed at locations where vehicles are naturally parked long enough to sufficiently cover their charging needs. Such broad coverage, however, leads to a large number of CSs which may only be rarely used. As this is prohibitive from a cost perspective, it is necessary to identify hotspots where the charging demand is sufficiently high to justify placing a CS while ensuring that it is close enough to the drivers' preferred parking locations.

Recent work has approached the CS placement problem with different optimisation objectives. Apart from investment costs, aspects taken into consideration include operation costs, maintenance, and network loss costs [6], network coverage, driver convenience [5], as well as energy costs for detours [7]. Time costs for drivers are considered in terms of delays for charging [8], driving time spent for reaching a CS [9], and queuing time [10].

Real world data is an important aspect for planning purposes attempting to identify optimal CS locations. In [11], household travel survey data is used to identify vehicles for which a fully charged battery is not sufficient to cover their drivers' daily commute and require intermediate charging. This knowledge is taken into account for charging cost optimisation. Similar data is also used in [12] to select CS locations minimising total walking distances from the CS to the driver's destination. Finally, charging event data from EV users can be analysed and the charging behaviours can be modelled according to user category and vehicle models [13], [14].

This work presents a heuristic using an agent-based traffic simulation including behavioural aspects with regard to charging decisions. The simulation framework allows simulating the traffic of an entire city as well as a variety of vehicle parameters such as energy consumption or the battery's *state-of-charge* (SOC) [15]. By further including charging behaviour models and CS distributions, the emergence of charging patterns can be investigated. This allows identifying CS locations which satisfy charging needs under various convenience constraints while minimising the number of required CSs. Benefits offered by this high resolution simulation-based approach are demonstrated in [16]–[18].

The remainder of the paper is organised as follows: Section II introduces the charging behaviour model and the CS placement algorithm. In Section III the proposed methodology is applied to the case of Singapore. Section IV discusses the results and an outlook on future work is given in Section V.

II. METHODOLOGY

The main components of the proposed methodology are a charging behaviour model and a CS placement algorithm. The first one determines under what conditions a driver decides to recharge the vehicle's battery, the latter aims for placing CSs in a way which best suits the drivers' charging needs.

A. Charging Behaviour Model

The charging behaviour model is based on our previously published work in [19]. In the current paper, we additionally distinguish between two aspects of charging which are i) *mandatory charging* and ii) *convenience charging*. Mandatory charging is invoked if an energy consumption estimate reveals that a planned trip cannot be completed with the current SOC. In contrast, convenience charging already takes place while the battery's SOC is still sufficiently high but a CS can be reached without a considerable detour. The authors in [20] suggest that users have different tendencies to charge when coping with limited battery capacity for mobility purposes. Some users might favour to take every charging opportunity while others only charge when the need arises. We introduce a convenience criterion that allows the agents to choose an appropriate CS depending on their remaining SOC and distance to the CS as in Equation (3).

Mandatory charging applies the concept of a range safety margin as in [20], where the authors define a comfortable range as the lowest remaining battery SOC which is not allowed to fall below. This range safety margin is reserved to buffer variations of energy consumption. The authors in [20] also show that whenever users interact with limited energy resources, they continuously monitor and manage the relation between their mobility needs (e.g. distance of next trip) and their mobility resources (e.g. remaining range). It considers the length of the next trip and estimates the resulting energy consumption which is compared to the remaining energy in the battery. The total estimated energy consumption E_{PQ} on a route from P to Q consists of the expected specific energy consumption λ, given in kWh/km, and distance d_{PQ} of the next trip so that

$$E_{\mathrm{PQ}} = \lambda \cdot d_{\mathrm{PQ}} \tag{1}$$

The mandatory charging model can be formalized in the way that for a trip starting from location P to destination Q charging is invoked at or near a location if

$$SOC < \frac{E_{\mathrm{PQ}}}{C} + \beta \tag{2}$$

Here, C denotes the battery capacity and β a safety margin parameter. In this case, the agent seeks the nearest CS from location P. Assuming *non-myopic* agents, the decision for charging at or near P is already made at the end of a trip

preceding P so that the entire stop duration at P is available for charging. Depending on the charging event start time $t_{\mathrm{startCharge}}$ and charging duration $t_{\mathrm{durationCharge}}$, the trip start time $t_{\mathrm{startTrip}}$ at P may be delayed until Condition 2 does not apply anymore. If the time period from $t_{\mathrm{startCharge}}$ until $t_{\mathrm{startTrip}}$ is sufficient to increase the SOC such that Condition 2 does not apply anymore, then the charging event ends at a predefined SOC_{stop} or at $t_{\mathrm{startTrip}}$ whichever is reached first.

The convenience charging accounts for the fact that agents will tend to charge when reaching a certain SOC level in any case, given a CS can be conveniently reached. Charging is therefore initiated at a CS P' near location P if

$$d_{\mathrm{PP'}} \cdot (SOC \cdot C)^a < \gamma \tag{3}$$

Including the distance $d_{\mathrm{PP'}}$ accounts for the fact that an agent is more likely to accept a higher inconvenience if the SOC is lower and vice versa. The exponent a allows taking into account a possible non-linearity in the trade-off between distance and SOC. In contrast to mandatory charging, the trip start time $t_{\mathrm{startTrip}}$ is never delayed in the case of convenience charging. The charging event ends at a predefined SOC_{stop} or until $t_{\mathrm{startTrip}}$ whichever comes first.

The charging behaviour model including mandatory and convenience charging is summarised in Algorithm 1. When an agent arrives at a location, the agent checks if the remaining SOC is sufficient to provide the energy required for the next trip plus a safety margin for mandatory charging. Should Condition (2) not apply anymore, the agent charges at the nearest CS and postpones the scheduled trip if necessary. Otherwise, the agent decides for convenience charging depending on the remaining SOC and the distance to the nearest CS. Should the agent decide for convenience charging, then the trip start schedule has priority over the charging need.

Algorithm 1: Charging Behaviour Model.

For each agent at each trip end
if $SOC < E_{\mathrm{PQ}}/C + \beta$ **then**
  charge at nearest CS P'
  if $t_{\mathrm{startCharge}} + t_{\mathrm{durationCharge}} > t_{\mathrm{startTrip}}$ **then**
   | postpone trip start time until $SOC > E_{\mathrm{PQ}}/C + \beta$
  else
   | charge until SOC_{stop} or $t_{\mathrm{startTrip}}$ whichever first
   | start trip as scheduled
  end
else
  if $d_{\mathrm{PP'}} \cdot (SOC \cdot C)^a < \gamma$ **then**
   | charge at CS P' if available
   | charge until SOC_{stop} or $t_{\mathrm{startTrip}}$ whichever first
   | start trip as scheduled
  else
   | stay at P until scheduled trip start time
  end
end

B. Charging Station Placement

Our CS placement approach uses an iterative approach in which each iteration simulates a predefined time period T of traffic for the area of interest, e.g., a whole day for an entire city. Initially, CSs are located at each available parking location. In every iteration, CSs are then subsequently removed according to the rules described in this section. The simulation is initialised with an *origin-destination* (O-D) matrix, an SOC_{init} distribution. A first simulation run then reveals a tempo-spatial pattern of charging demand which would result from the specific charging behaviour as described in Section II-A. Subsequently, the infrastructure is consolidated by clustering CSs in the same area which have complementary temporal usage patterns. This results in a reduced number of CSs with higher utilisation rates. In a next iteration, the system is simulated using the new CS distribution. The sparser network coverage will cause agents to adapt to the new conditions with some taking a small detour to recharge their batteries and others to delay their charging to the next stop, resulting in a variation of the charging pattern. This procedure is repeated by incrementally removing low-utilised CSs as long as the agents' total energy demand can be satisfied without violating the convenience criterion of acceptable detours.

An overview is illustrated in Algorithm 2. In detail, this algorithm operates as follows. For each CS i, a function $\vartheta_i(t) \in \{0, 1, 2, ...\}$ describes the occupancy of the CS at time t. For example, a value of $\vartheta_i(t = 8) = 2$ means that a lot is occupied by one vehicle which is charging plus another one waiting in the queue at 8 o'clock. The algorithm performs a pairwise comparison of these functions for any combination of CSs i and j of which the distance $d_{ij} \leq \delta$. The parameter δ is a threshold determining how large the distance between two, possibly combinable CSs may be. The pairwise comparison computes an *overlap indicator* $\tilde{\sigma}_{ij}$ which determines the degree to which two CSs exhibit conflicting occupancies. It is computed according to

$$\tilde{\sigma}_{ij} = \int_0^T \vartheta_i(t) \cdot \vartheta_j(t) \mathrm{dt} \tag{4}$$

with T as the time period for one simulation iteration. $\tilde{\sigma}_{ij}$ thus equals 0 if no overlap exists and T if both lots are occupied by one vehicle each throughout the entire day. In case additional vehicles are queuing at one of the lots, it may also assume values greater than T. Two lots may be combined if this overlap is sufficiently small while a large overlap indicates that both CSs are often needed at the same time. Apart from the temporal overlap, the decision whether to cluster two CSs further depends on their distance d_{ij} meaning that neighbouring lots should have a higher chance of being combined than those which are farther apart. This results in the definition of the *weighted overlap-distance indicator* σ_{ij} that includes

$$\sigma_{ij} = \alpha \cdot \frac{\tilde{\sigma}_{ij}}{T} + (1 - \alpha) \cdot \frac{d_{ij}}{d_0} \tag{5}$$

with the weight $\alpha \in [0, 1]$ and the characteristic distance d_0. Two CSs can be combined if they fulfil the condition

$$\sigma_{ij} < \theta \tag{6}$$

with the threshold θ. Depending on the weight assigned to the overlap and the distance, α and d_0 need to be adapted accordingly.

Algorithmically, the consolidation process is performed in the following way. Initially, for all possible pairs of lots σ_{ij} is computed. The pairwise computation can be limited to lots with a distance $d_{ij} \leq \delta$ with

$$\delta = \theta \cdot d_0 \cdot (1 - \alpha)^{-1} \qquad \alpha \neq 1 \tag{7}$$

since all other combinations are invalid due to Condition (6). The two lots with the smallest σ are then removed if Condition (6) is fulfilled. They are replaced by a new CS. Adopting the definition of the centre of mass, the new lot's position is located at the removed pair's load centre

$$\vec{R} = \frac{1}{E} (\vec{r}_i \cdot E_i + \vec{r}_j \cdot E_j) \tag{8}$$

$E = E + E_j$ denotes the total daily energy supply of both lots $E = \int_0^T (p_i(t) + p_j(t)) \mathrm{dt}$. As there is not necessarily a parking lot at the exact position $\vec{R}$, the parking lot closest to this position is chosen.

The entire consolidation procedure is repeated by choosing pairs with the next smallest σ value for consolidation until either a predefined share r of the initial CSs has been removed or until no further consolidation is possible without violating Condition (6).

Subsequently, the resulting CS network is used as an input parameter for the next iteration. As agents will adapt to the new charging infrastructure distribution as a result of the described charging behaviour in II-A, the new emerging tempo-spatial charging demand distribution will be different from the initial one. This simulation-consolidation process is repeated until no further consolidation is possible without violating the consolidation criteria.

Algorithm 2: Charging Station Consolidation.

while $\exists \sigma_{ij} < \theta$ *with distinct* $i, j \in \{1, \ldots, n_{cs}\}$ **do**
    forall the $d_{ij} \leq \delta$ *with distinct* $i, j \in \{1, \ldots, n_{cs}\}$ **do**
        compute σ_{ij}
        append σ_{ij} to list σ
    end
    while $min(\sigma) < \theta$ **do**
        get CS pair i and j with $min(\sigma)$
        remove CS i and j
        add new CS closest to $\vec{R}$
        remove σ_{ij} from list σ
    end
end

III. CASE STUDY

As an illustration of the functionality of the proposed methodology, the framework is applied to input data from Singapore. For the case study, the *City Mobility Simulator* (CityMoS), formerly known as SEMSim [15] is used. CityMoS is an agent-based traffic simulation. Agents in CityMoS consist of *driver-vehicle unit* (DVU) which contain both driver behaviour and vehicle models. The driver component includes acceleration and lane changing behaviour through car-following and lane-changing models [21], as well as charging behaviour models which determine a driver's decision to recharge the vehicle's battery *[19]*. The vehicle models allow simulating components such as engine, auxiliary power consumers, as well as the battery. This provides detailed information on power consumption at any point in time. Traffic is generated by creating an itinerary for each agent in a given road network. An itinerary may consist of multiple trips, each of which is characterised by an O-D tuple specifying starting time and location as well as the agent's destination. Based on this O-D matrix, routes are then calculated using *Dijkstra's* algorithm. Each agent is further assigned an initial SOC value.

A. Input Data

In this case study, we utilise the Singapore road network derived from Navteq data from the year 2009 which provides information regarding the number of lanes on roads as well as their coordinates and lengths. The *Household Interview Travel Survey* (HITS) data from the year 2012 is used to initialise the traffic demand by assigning each agent an itinerary extrapolated from this dataset. The dataset consists of information on daily commuters containing O-D pairs and journey time information for a typical working day in Singapore. A seed can be specified at the beginning of the simulation that influences the extrapolated traffic demand generation. Each iteration in the CS consolidation process is assigned with a different seed in order to avoid the exact same traffic demand that causes an overfitting of the CS distribution.

We simulate $54\,\text{h}$ for each simulation instance in total and each agent starts with full initial SOC. The first $24\,\text{h}$ are used as a warm-up period to derive an initial SOC distribution for the second day, in which the CS utilisation is accounted for the consolidation. The last $6\,\text{h}$ are a cool down phase, such that the agents can finish their trip or charging event after the end of the second day. In Singapore, each building is assigned a unique postal code. For the first simulation iteration, each of $131,549$ available postal codes is assigned 10 CSs.

B. Scenarios

Different scenarios are investigated by varying the CS consolidation parameters α and θ. The consolidation is influenced by the temporal overlap and spacial distance between the CSs. We determine α and θ according to the maximum allowable overlap $\tilde{\sigma}_{\max}$ when the distance is zero and the maximum allowable distance $d_{\text{PP'max}}$ when the overlap is zero. With Equation (5) and the characteristic distance d_0 set to

TABLE I: Consolidation Parameters.

$d_{\text{PP'max}}$ [m]	$\tilde{\sigma}_{\max}$ [h]	$=¿$	α	θ
250	2		0.75	0.063
	4		0.6	0.1
	6		0.5	0.125
500	2		0.857	0.071
	4		0.75	0.125
	6		0.667	0.167
750	2		0.9	0.075
	4		0.818	0.136
	6		0.75	0.188

TABLE II: Simulation Parameters.

Parameter	Description	Value	Unit
n_{agents}	number of agents	$20,000$	#
C	battery capacity	20	kWh
P_{Charge}	charging power	19.2	kW

$1,000$ metres, we derive values for α and θ from different levels of the maximum allowable distance and overlap at $250\,\text{m}$, $500\,\text{m}$, and $750\,\text{m}$ as well as $2\,\text{h}$, $4\,\text{h}$, and $6\,\text{h}$, respectively, as shown in Table I.

Other parameters are assumed to be constant. Values of parameters related to the simulation can be found in Table II. The $20,000$ agents are the total number of agents in the simulation distributed over the simulation period. The actual number of agents on the street at the same time is therefore less than this number. Each agent has a maximum battery capacity of $20\,\text{kWh}$. This value represents a realistic battery capacity of the affordable EVs ranging from $16\,\text{kWh}$ of the i-MiEV to $24\,\text{kWh}$ of the Nissan Leaf. The charging power of the charging infrastructure is assumed to be $19.2\,\text{kW}$ with level 2 AC chargers.

Table III lists the parameters described in Section II-A. The parameter λ is the specific energy consumption which is used for the energy estimation of the next trip by the agent. The actual energy consumption is determined by the acceleration model under the respective traffic conditions. Charging is assumed to be conducted at constant power.

C. Results

This section shows the results from applying the CS placement algorithm to the case of Singapore.

1) Sustainable Scenarios with Regard to Energy Consumption: The SOC distribution at the simulation end is generally different from the beginning of the simulation. This is illustrated in Figure 1 which shows the distribution of the

TABLE III: Charging Behaviour Parameters.

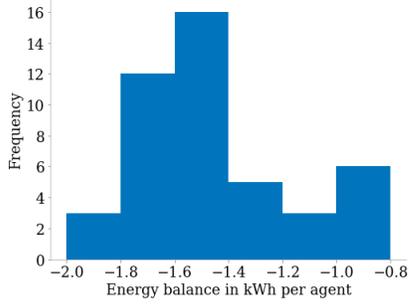| Parameter	Description	Value	Unit
λ	specific energy consumption	0.2	kWh / km
β	safety margin	20	%
SOC_{stop}	SOC to stop charging	100	%
a	non-linearity factor	1	
γ	convenience threshold	16	kWh · km

Fig. 1: Histogram of energy balance. The energy balance is the difference between the charged and consumed energy of all agents in one scenario in Wh per agent.
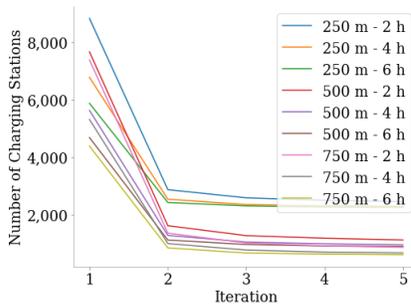

Fig. 2: Number of CSs over iteration for different consolidation parameters $d_{\text{PP'max}}$ and $\tilde{\sigma}_{\max}$.

difference between the charged and consumed energy of the second simulation day in each scenario. In this case, a negative value indicates that more energy is consumed than charged. All of the scenarios are, however, negatively balanced in terms of energy consumption and charging.

2) Number of Charging Stations : With each iteration, CSs are removed according to the algorithm described in Section II. The largest decrease in the number of CSs occurs at the first iteration as shown in Figure 2. In this case study, the result suggests that the maximum allowable distance $d_{\text{PP'max}}$ has a larger influence on the number of CSs than the maximum allowable overlap $\tilde{\sigma}_{\max}$.

3) Influence of Consolidation Parameter $d_{PP'\max}$ and $\tilde{\sigma}_{max}$: The maximum allowable distance $d_{\text{PP'max}}$ and the maximum allowable overlap $\tilde{\sigma}_{\max}$ are important parameters in the CS consolidation algorithm that affects the final number and distribution of CSs. Figure 3 shows the number of CSs, detour, and waiting time over different $d_{\text{PP'max}}$ and $\tilde{\sigma}_{\max}$ values in the last iteration.

The number of CSs is clearly affected by the $d_{\text{PP'max}}$ value with larger $d_{\text{PP'max}}$ allowing more distant CSs to be consolidated. The $\tilde{\sigma}_{\max}$ also influences the number of CSs as longer $\tilde{\sigma}_{\max}$ increases the chance of CSs to be combined. The difference between $4\,\text{h}$ and $6\,\text{h}$, however, is small indicating that only little CSs overlap more than $4\,\text{h}$ in usage.

When the agent decides to charge, it needs to deviate from the original route to reach the desired CS. The extra distance is the detour the agent has to take. The detour increases with larger $d_{\text{PP'max}}$ and $\tilde{\sigma}_{\max}$ due to the reduction in number of CSs.

Each CS location has a specified number of CSs. If all lots are occupied, an agent has to queue at the CS until a lot becomes available. The waiting time is averaged over those agents that recorded a charging event. The waiting time increases with larger $d_{\text{PP'max}}$ and $\tilde{\sigma}_{\max}$ due to less CSs remaining. The result suggests that the effect of $\tilde{\sigma}_{\max}$ is larger with increasing $d_{\text{PP'max}}$.

Figure 3 illustrates the relationship between the required number of CSs and the inconvenience to satisfy the charging demand of $20,000$ EVs. Under the investigated conditions, results show that the charging demand can be covered with $2,445$ CSs by accepting average detours of 410 metres and an average waiting time of 9 minutes. This number can further be reduced to 603 CSs at the cost of 198 metres longer average detours and 56 minutes longer average waiting time.

The results also suggest that $\tilde{\sigma}_{\max}$ might not be a good parameter to reduce the number of CSs as the increase in waiting time at high $d_{\text{PP'max}}$ level is significant compared to the reduction in CSs.

4) Charging Station Distribution: The CS distribution at the last iteration of the proposed algorithm is illustrated in Figure 4. It shows the CS distribution scenario with different $d_{\text{PP'max}}$ values. Figure 4 clearly shows that a higher value of $d_{\text{PP'max}}$ results in a lower density of CSs and vice versa. The scenario with $250\,\text{m}$ $d_{\text{PP'max}}$ presents a much higher density than the other two scenarios as seen in Figure 3

IV. DISCUSSION

According to the presented outcome, a CS can serve between approximately 8 and 33 EVs under the given inconvenience criteria. While the results indicate that the algorithm converges to a reasonable outcome in terms of network coverage and temporal CS utilisation, a few aspects have to be considered which may limit the practical applicability of the quantitative results which are elaborated in the following.

The quality of the simulation results highly depends on the simulation input data. The mobility demand represents such a critical input. Although the travel survey data is collected from tens of thousands of households, it still only reflects around one percent of the Singapore population. The mobility demand generated from the travel survey data might be biased towards certain areas and periods of time and thus cause different inconvenience values.

Currently, the model does not implement any waiting behaviour as agents simply queue until a CS becomes available. In the real world, this will not be entirely true since, depending on the expected waiting time and the distance to the next CS, agents may choose alternative charging locations. More sophisticated navigation and recommendation systems may therefore lead to a more even distribution of CS utilisation and further minimisation of detours and waiting times, thus further reducing the number of required CSs.
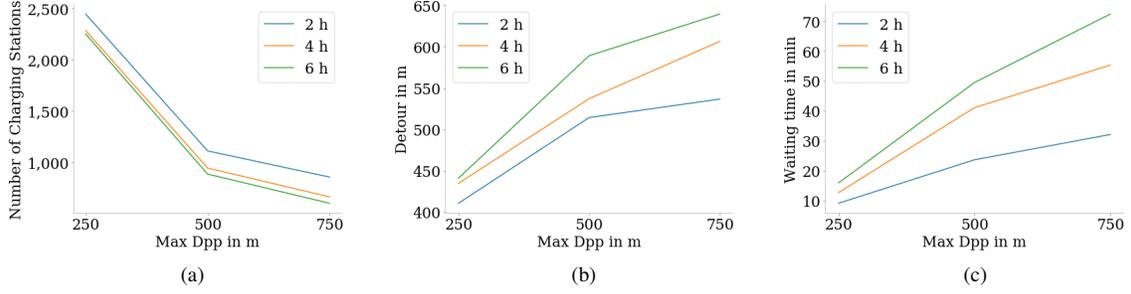
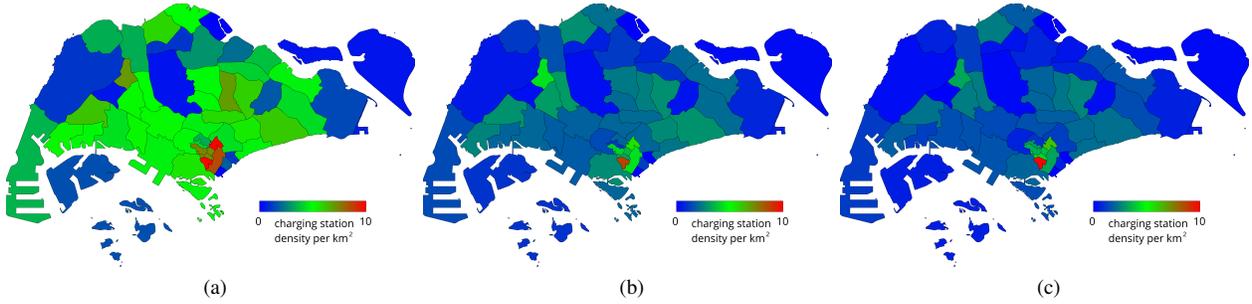Fig. 3: (a) Number of CSs, (b) detour, and (c) waiting time for different $d_{\text{PP'max}}$ and $\tilde{\sigma}_{\text{max}}$ scenarios.

Fig. 4: CS distribution with (a) $250\,\text{m}$, (b) $500\,\text{m}$, (c) $750\,\text{m}$ $d_{\text{PP'max}}$ and $2\,\text{h}$ $\tilde{\sigma}_{\text{max}}$ at the last iteration.

The ratio between charging time and connection time at a CS is assumed to be one in our study. That means the EV user immediately frees the CS when the charging process ends. Data analysis in [22], however, shows that the connection time can be much longer than the actual charging time. This behaviour blocks resources which could lead to less CSs being consolidated. The longer connection to charging time ratio can be utilised to test more intelligent distribution of the charging demand from the charging infrastructure perspective with load shifting. The study in [23] reveals that EV users prefer to charge at home in the evening at peak demand times. Considering the load profile of a city, the price sensitivity of the user can be an important factor to shift the charging demand tempo-spatially by providing incentives to EV users.

In the considered case, the energy balance turns out to be slightly negative which means more energy is consumed than charged. This leads to a small underestimation of the number of required CSs. This is a drawback of a warm-up period of one day only for deriving an initial SOC distribution. The majority of the negative energy balance is, however, less than $10\,\%$ of the battery capacity. At the considered connection power, this amount of energy requires only several minutes of charging time so that this influence on the CS consolidation is small. Given limited computing resources, the slight underestimation of energy demand is therefore neglected.

The number of required CSs depends on the number of EVs and at the same time on the CS occupancy duration which

is determined by the charging power. These aspects depend on political, economic, and technical framework conditions including EV market penetration targets, CS costs, and the capacity of the power network to accommodate additional loads. For optimising charging infrastructures not only with regard to the transportation system but also with respect to the power network, the implementation of CityMoS traffic simulation coupled with CityMoS power system simulation as decribed in [24]. A study serving for planning purposes would therefore need to take these factors into account in a more differentiated way.

In the present study, inconvenience parameters have been set to intuitively reasonable values. These values might, however, turn out to be different in real-world behaviour. The parameters need to be calibrated by conducting user studies.

While the case study results show the effectiveness of the presented approach, the quantitative results derived from the simulation study cannot be directly translated into infrastructure planning decisions. In this regard, more sophisticated assumptions regarding waiting behaviour, charge connection power, and traffic data need to be made to obtain a sufficiently accurate representation of real-world conditions. Building on these more realistic assumptions, it is believed that the presented framework could serve as an effective decision support system to explore a large variety of different infrastructure scenarios and to help infrastructure developers in making appropriate planning decisions.

V. Conclusion and Outlook

In this paper, we presented a simulation-based heuristic for optimal placement of EV CSs and demonstrated its effectiveness on the example of Singapore. In particular, we applied an agent-based traffic simulation together with a CS consolidation algorithm to identify optimal CS locations. The heuristic's objective is to achieve sufficient network coverage to keep charging related inconvenience within an acceptable range while minimising the overall number and thereby the costs of CSs.

Under the investigated conditions, results show that the charging demand of $20,000$ EVs can be covered with approximately $2,500$ CSs by accepting average detours no greater than 410 metres and average waiting time below 10 minutes. This number can be further reduced by relaxing the inconvenience criterion. The results of the case study show that the algorithm converges towards a CS distribution which effectively satisfies charging demand under the given inconvenience constraints.

In accordance with the limitations discussed in Section IV, future work will comprise simulations considering longer warm-up periods as well as more detailed sensitivity considerations with regard to different charging powers and EV numbers as well as empirically derived inconvenience acceptance parameters. Our CS consolidation algorithm represents a top-down approach where we remove CSs from an dense initial distribution. It remains to be seen how a bottom-up approach performs in which CSs are iteratively added to the network.

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