

Influence of Charging Behaviour given Charging Infrastructure Specification: A Case Study of Singapore*

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Abstract

Electric Vehicles (EVs) are set to play a crucial role in making transportation systems more sustainable. However, charging infrastructure needs to be built up before EV adoption can increase. A crucial factor that is ignored in most existing studies of optimal charging station (CS) deployment applying agent-based nanoscopic traffic simulation is the role played by the charging behaviour of drivers. In this study, through an agent-based traffic simulation, we analyse the impact of different driver charging behaviour under the assumption that CSs are placed at existing petrol stations and residential car park locations in Singapore. Three models are implemented: a simple model with a charging threshold and two more sophisticated models where the driver takes the current trip distance and existing CS locations into account. We analyse the effect of these three charging behaviour models on the performance of the charging infrastructure with respect to a number of different measures. Results suggest that charging behaviours do indeed have a significant impact on the simulation outcome. We also discover that the sensitivity of model parameters in each charging behaviour and initialisation parameters of the agents are an important factor to consider. Variations in model and initialisation parameters can lead to significant different results. In addition, we investigate into a different charging infrastructure distribution using a grid-based approach for Singapore. Results propose that a more evenly distributed charging infrastructure with the grid-based approach is less effective than the one with charging station placement at existing petrol stations and residential car park locations.

Keywords: Charging Station, Charging Infrastructure, Charging Behaviour, Traffic Simulation, Agent Based Simulation, Electric Mobility

1. Introduction

A wide adoption of Electric Vehicles (EVs) is important in moving towards a sustainable transportation system. An EV offers the advantage of zero local emissions; this is especially useful in mega-cities where dense vehicle population can cause significant health concerns [1]. The World Health Organization shows that tens of thousands of deaths per year are caused by transport-related air pollution [2].

According to the Paris Agreement [3], the global temperature rise this century should be kept well below 2 degrees Celsius above pre-industrial levels and efforts should be pursued to limit the temperature increase even further to 1.5 degrees Celsius. In order to achieve this ambitious goal, massive reduction in greenhouse gas emissions is unavoidable. The World Bank and International Energy Agency report that transportation accounts for nearly one-quarter of global energy-related CO2 emissions [4] [5]. More critically, transportation is the fastest growing source of CO2 emissions. A shift to EVs is one way to reduce CO2 emissions. While public incentives and vehicles' usability affects the adoption of EVs in the short run, factors like battery range and suitable charging infrastructure have a profound impact on the paradigm shift to EVs [6]. In order to promote the deployment of EVs, bat-

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tery range related anxiety needs to be prevented. On the one hand, there is significant research being done in advancement of battery technology for increased range and decreasing battery cost [7]; on the other hand, many studies point out that an effective and efficient charging infrastructure is also crucial [8] [9].

In the last few years, much research has focused on the charging station (CS) placement problem. Different optimisation objectives are chosen to address the problem, such as cost, travel time and waiting time at CS. These mathematical approaches are contrasted with a simulation-based approach, in this case an agent-based nanoscopic traffic simulation. However, most of these charging infrastructure optimisation studies that apply an agent-based nanoscopic traffic simulation either neglect the charging behaviour of the EV driver, or at best, consider very simple charging behaviours. A fixed threshold of the battery state-of-charge (SOC) is defined at which the EV driver decides to go charging [10].

In this paper, we analyse the impact that different charging behaviours can have on the effectiveness of CS placement using an agent-based nanoscopic traffic simulation. In particular, we consider three charging behaviours with different levels of complexity. The least complex one makes charging decisions based on a battery SOC threshold as in [10]. The next charging behaviour makes estimations on the trip energy consumption. The most complex one takes the CS locations at the trip destination into account, additionally to the energy consumption estimation in the previous behaviour. For our analysis, we investigate a Singapore based scenario. In this study, we extend the previous study [11] by a sensitivity analysis for initial SOC and considering (direct current) DC fast CSs to be placed at existing petrol stations and (alternating current) AC slower CSs at residential car park locations in Singapore. Furthermore, we also investigate into a grid-based CS distribution scenario.

The major contribution of this paper is the analysis of the effect that different charging behaviours can have on a realistic electric mobility scenario in the case study of Singapore. We discuss our findings with respect to real world traffic data and a realistic vehicle energy consumption model. Results show that different charging behaviours do have an influence on the electric mobility system as a whole. Performance differences are also observed

within one charging behaviour but using different model parameters. These results suggest that the charging behaviour plays an important role when optimising for CS locations. In addition, initialisation parameters of the agent and charging infrastructure specifications also impact the result of the simulation.

The remainder of the paper is organised as follows: Section 2 describes related work regarding the CS placement problem using analytical and simulation-based approaches. This section also highlights work addressing charging behaviour modelling from a psychological perspective. Section 3 explains the three charging behaviours in more detail. Section 4 provides an overview of the simulation set-up. Section 5 presents the experimental results. Section 6 discusses the work and Section 7 gives an outlook for future work.

2. Related Work

Different optimisation objectives are used to solve the CS placement problem. Operation costs, maintenance and network loss costs of the CSs [12], CS coverage and convenience for EV drivers to reach CSs [13] as well as energy cost for vehicles to travel to CSs [14] are objectives for minimization in addition to investment costs. The study in [15] estimated the optimal density of EV CSs accounting for the delay time cost of charging and access cost to the CS besides the investment and operation costs. The cost for EV drivers to go charging is modelled as the travel time to [16] and queuing time at the CS [17]. The authors of [18] and [19] maximises the CS coverage. The study in [20] has the objective to optimise the amount of energy recharged with a focus on different type of chargers.

Real world data can support the work towards CS placement optimisation. Household travel survey data is used to generate traffic pattern and breakdown vehicles are used as an input for the optimisation [21]. The objective is to minimise the total travelled distance to access CSs. Similarly, those vehicles where a full charge of battery is not sufficient to cover their daily commute and require intermediate charging are taken into account for charging cost optimisation in [22]. Household travel survey data is also used in [23] to select CS locations with an objective function that minimises the total walking distances from the CS to the destination. As an alternative to household travel survey, the

130 work in [24] describes the usage of pervasive cell-
phone data to model the mobility demand in the
city of Boston. The total travelled distance from
trip destination to the nearest CS is minimised. 185
Drivers' discomfort is considered in terms of maxi-
mum hops in a grid partitioned road network.

135 Another way to derive mobility demand is to use
large-scale trajectory data of taxi fleet [25]. Public
EV CS locations are identified in Beijing based on 190
these data. EV taxi trajectory data is used in [26] to
optimally locate CSs and assign optimised number
of charging plugs with the objective of minimizing
the average time to find a CS and waiting time be-
fore charging. Many studies apply large-scale anal- 195
ysis of real-world driving data with GPS devices in-
stalled on conventional fuel vehicles [27] [28]. The
data in these driving pattern databases are pro-
cessed to derive whether different types of charging
strategies and infrastructure can meet the mobility 200
needs. Finally, charging event data from EV users
can be analysed and the charging behaviours can
be modelled according to user category and vehi-
cle models in [29]. The study in [30] reveals that
EV users prefer to charge at home in the evening 205
peak hours in Ireland. Incentives are necessary to
encourage home charging at other times.

155 The CS placement problem can also be addressed
from the power grid perspective. A simulation-
based approach for investigating the impact of 210
transport electrification on power grids is presented
in [31]. A case study of Singapore shows that grid
congestion and voltage drops are observed on the
low voltage level while the high and medium volt-
age grid remain unaffected. 215

165 In contrast to those mathematical approaches, we
apply a nanoscopic city-scale traffic simulation to
study the influence of different charging behaviour
on CS placement at existing petrol stations and res-
idential car park locations in Singapore [32]. Re- 220
garding the charging infrastructure location and
charging speed, there are two paradigms in the liter-
ature [30] where DC fast CSs are placed at strategic
network locations as in [33] and AC slower CSs are
positioned at residential or commercial car park lo- 225
cations in [34]. In this study, we consider DC fast
CSs to be placed at existing petrol stations and AC
slower CSs at residential car park locations in Sin-
gapore. 230

180 In this agent-based nanoscopic traffic simulation,
a driver-vehicle-unit (DVU) consists of driver model
and vehicle model [35]. Advantages are that vehi- 235
cles and drivers can be modelled in greater de-

tail. Realistic vehicle energy consumption can be
simulated with individual driving and charging be-
haviour of the EV driver. Advantages that this
higher resolution nanoscopic simulation based ap-
proach offers is demonstrated in [32]. The emer-
gence of collective dynamic from individual inter-
actions between DVU agents can be captured [36].

Application of an agent-based simulation to anal-
yse how EV adoption could be affected by different
spatial deployment of CSs can be found in [37]. An
agent-based traffic simulation is used to provide in-
put to a power simulation which determines the op-
timal charging profile for EVs [38]. Another work
in [39] applies agent-based simulation to maximise
availability and profitability of CSs. The load curve
generated by EV power demand is studied in [40]
where the agent can only charge at the origin or
destination of a trip.

The major disadvantage of existing CS loca-
tion optimisation work using agent-based simula-
tion approach neglects the charging behaviour of
EV drivers or apply simple charging behaviour
model. The work in [15] assumes that a charging
event occurs when the SOC is below a threshold.
Similarly, vehicles route to the nearest CS when be-
ing low on energy before they continue their journey
to the final destination in [10].

Looking from the charging behaviour perspec-
tive, the authors in [41] analyses the psychologi-
cal dynamics underlying charging behaviour of EV
users assessing data in a EV field study. The au-
thors attempt to understand how users cope with
limited mobility resources and define a comfort-
able range as the lowest remaining battery SOC
which is not allowed to fall below. This preferred
range safety margin is reserved against variations
of energy consumption. They also find that "user-
battery interaction style" plays a role in the deci-
sion when to start a charging event [42]. The "user
battery interaction style" is a qualitative classifica-
tion based on their tendency to charge. The work
in [43] applies expected utility theory to model the
charging behaviour of EV drivers considering cost,
charging duration, range, trip distance to be impor-
tant when making charging decisions.

3. Charging Behaviour Models

In this section, we describe the three charging be-
haviours in greater detail [11]. Their difference is
the amount of information they consider for mak-
ing the charging decisions. The first and simplest

model, *Zero Estimation Model (ZEM)*, considers only a SOC threshold for routing to CSs like in other studies [15] and [10].

The next model, *Semi Estimation Model (SEM)*, applies the concept of a range safety margin as in [42], where the authors define a comfortable range as the lowest remaining battery SOC which is not allowed to fall below. This preferred range safety margin is reserved against variations of energy consumption. The authors in [42] 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). This model considers the trip length of the next trip and estimates the resulting energy consumption, which is compared to the remaining energy in the EV.

The last model, *Full Estimation Model (FEM)*, not only incorporates the comparison of mobility needs and resources, it goes one step further assuming that the agents also know the locations of the CSs near the destination. This information allows the agents to abandon the preferred range safety margin because they are guaranteed to be able to charge near the destination when they account this information into their estimation.

We define the following preliminaries for all three models: 1) A charging event stops when the battery SOC reaches 80% of its maximum capacity. This is the level at which a battery can be charged without reducing charging power. 2) When the agent actively searches for a CS, either because the SOC drops below a preferred threshold or the energy estimation for the next trip exceeds the current energy resource, the agent only takes DC fast CSs into account for their choice to charge. 3) The agent takes every charging opportunity at trip destination to charge if there is a CS available. However, DC fast CSs are excluded from this opportunistic convenience charging and only AC residential CSs are utilised. It is also to mention that this kind of convenience charging does not delay the schedule of the next itinerary. 4) Estimation of energy consumption for the next trip is made based on 150 Wh per kilometre times a variable factor k that models a conservative energy consumption estimation from the driver’s perspective. This value is the average energy consumption generated from our agent-based traffic simulation. 5) When an EV breaks down on the road network, it stays on the current road for 10 minutes and continues to the intended

destination with a full charge. This is to simulate a realistic break down scenario which might cause traffic congestion due to the depleted EV.

The authors in [42] also find that “user-battery interaction style” plays a role in the decision when to start a charging event. The “user battery interaction style” is a qualitative classification based on their tendency to charge and is represented by the opportunistic convenience charging in our charging behaviour models.

Price for charging is another potentially important factor; however, as it is not the subject of this study, we assume a flat rate for charging service. This is a fair assumption as it was used in the EV test-bed in Singapore [44].

Algorithm 1: Zero Estimation Model

```

For each agent at any time
if currentSOC < SOCThreshold then
  | goToNearestCS
else
  | continueCurrentTrip
end

```

Zero Estimation Model (ZEM). No energy consumption estimation is considered before or during trips. The driver seeks the nearest DC fast CS (*goToNearestCS*) when its current SOC (*currentSOC*) is below certain SOC threshold (*SOCThreshold*). Otherwise, the driver continues the current trip (*continueCurrentTrip*).

Algorithm 2: Semi Estimation Model

```

For each agent at each trip start
if currentSOC >
  estimateTripConsumption(k) +
  safetyMargin then
  | beginCurrentTrip
else
  | goToNearestCS
end

```

Semi Estimation Model (SEM). Energy consumption for the next trip is estimated before a trip starts. If the current SOC is enough to complete the trip based on estimation (*estimateTripConsumption(k)*) plus a safety margin (*safetyMargin*), the driver starts the trip to his intended destination (*beginCurrentTrip*).

Otherwise, the driver seeks the nearest DC fast CS from the origin of his trip.

Algorithm 3: Full Estimation Model

For each agent at each trip start
if $currentSOC >$
 $estimateTripConsumption(k) +$
 $energyToNearestCSAtD(k)$ **then**
| beginCurrentTrip
else
| goToNearestCS
end

315 *Full Estimation Model (FEM)*. Energy consumption for the next trip together with the energy to the nearest DC fast CS at destination ($energyToNearestCSAtD(k)$) is estimated before a trip starts. The driver seeks to find the nearest DC fast CS right after a trip starts when its current SOC is not enough to cover the estimated energy consumption. CS locations at destination is taken into account for this model.

4. Simulation Setup

325 For the analysis in this study, a simulation tool SEMSim Traffic [35] is used. It is a nanoscopic agent-based traffic simulation with driver-vehicle-units (DVUs) forming the basic units of computation, i.e. the agents. A DVU consists of a driver model and a vehicle model. In order to be able to move on the road network, the driver model contains a car-following model and a lane-changing model to simulate the movement of DVUs. The work in [32] provides a more detailed description of the SEMSim traffic models. In this paper, we describe the vehicle energy consumption model in greater detail. The energy consumption of components connected to the battery can be calculated. By extending the car park model to a CS model, it is possible to simulate the charging process of EVs. All of the above features make this platform well suited for our simulation setup. We run the simulation with 19,130 agents for a 24 hour working day period. The number of agents equals the number of charging lots.

4.1. Mobility Demand

In this experiment, we utilise the Singapore road network data derived from Navteq 2009 data which

Table 1: Mobility Demand Statistics

Variable	Average	Max
Trip distance	10.74 km	47.14 km
Daily distance per agent	24.04 km	178.85 km
Trip count per agent	2.25	10

provides information regarding number of lanes on roads, their coordinates and length. The HITS 2012 travel survey data is used to initialise the traffic demand. At the beginning of the simulation, each agent is assigned an itinerary from this itinerary dataset. This itinerary dataset is initialised from available data on daily commuters containing origin-destination pairs and journey time information for a typical whole working day period in Singapore. It is to be noted that this dataset is only collected from around 1% of total 1.1 million households in Singapore which might not represent the whole population. Thus, both a temporal and spatial extrapolation is imposed to simulate the realistic traffic scope of Singapore. Details of how the extrapolation is performed can be found in [32].

Each agent has at least two origin-destination pairs, which means the minimum number of trips is two. The origin of the first pair and destination of the last pair is always the same location, ensuring that the agent is returning to the starting point of the simulation day. Table 1 provides statistics on the mobility demand that is generated in our simulation after the extrapolation of the travel survey data.

4.2. Vehicle Energy Consumption Model

The vehicle battery of 20 kWh maximum capacity provides power to the motor, air-conditioner and auxiliary components in the EV. In this experiment, we take the parameters of an electric vehicle called EVA which is designed by TUM CREATE for tropical mega-cities [45].

The motor power P_{motor} is a function of velocity and force. The efficiency factor f_{loss} reflects losses in the drive train. Depending on the direction of the power flow, P_{motor} is either weighted with f_{loss} when the motor delivers power back to the battery due to regenerative braking, or with

Table 2: Vehicle Energy Consumption Parameters

Parameter	Description	Value
g	Acceleration of gravity	9.81 m/s ²
f_r	Rolling coefficient	0.01
C_d	Drag coefficient	0.4
ρ	Air density	1.13 kg/m ³
λ	Percentage of equivalent mass of rotating parts	0.13
m_{car}	Car weight	1,500 kg
f_{loss}	Losses in the drive train	0.9
A_f	Car frontal area	2.24 m ²

its inverse when the motor draws power from the battery as in Equation 1. F_{motor} is the force provided by the motor and is needed to overcome resistances forces, such as air- (F_{air}), rolling- (F_{roll}) and inertia- ($F_{inertia}$) resistance, as shown in Equation 2, 3, 4 and 5.

$$P_{motor} = \begin{cases} \frac{1}{f_{loss}} F_{motor} v & \text{when } F_{motor} > 0 \\ f_{loss} F_{motor} v & \text{when } F_{motor} \leq 0 \end{cases} \quad (1)$$

$$F_{motor} = F_{air} + F_{roll} + F_{inertia} \quad (2)$$

$$F_{air} = \frac{1}{2} \rho A_f C_d v^2; \quad (3)$$

$$F_{roll} = f_r m_{car} g; \quad (4)$$

$$F_{inertia} = (1 + \lambda) m_{car} a \quad (5)$$

where v is the velocity in m/s . The parameters in Equations 1, 3, 4 and 5 are shown in Table 2.

Air conditioning is necessary for vehicles in tropical cities like Singapore. Its power is set to 800 W as suggested by EVA specification. Other on-board auxiliary components consist of lights, engine control unit, infotainment system etc. We assume that a power of 750 W is required to operate these components.

4.3. Charging Station Model

There are two paradigms in the literature [30] regarding the charging infrastructure location and charging speed. High speed DC fast CSs are placed at strategic network locations as in [33] and AC slower CSs are positioned at residential or commercial car park locations in [34]. In this study, we consider DC fast CSs to be placed at existing petrol stations and AC slower CSs at residential car park locations in Singapore.

We retrieve petrol station locations from the website [46] for the DC charging infrastructure with 50 kW charging power. Residential car park locations are provided by Infocomm Development Authority [47] and are used for placement of the AC charging infrastructure with 7.2 kW charging power. In total, we identify 1,913 CS locations, from which 186 and 1,727 locations are allocated for DC and AC charging respectively. We assume 10 charging lots at each CS location. It is also assumed that each CS can have a queue of infinite length. In the event of a fully occupied CS location, the incoming agents can wait in the CS queue before the charging lots are available again.

The spatial distribution of these CSs is illustrated in Fig 1 for DC and AC charging infrastructure separately. The heat map shows the number of charging lots in each of the 28 postal districts in Singapore. Table 3 includes some statistics on how far the CSs are apart from each other for the DC and AC charging infrastructure respectively. The minimum distance between CSs is the distance of each CS to their nearest CS. This variable indicates how dense the charging infrastructure is in terms of driving distance and provides a measure of how far the agent need to drive in order to reach a CS.

Table 3: Charging Infrastructure Statistics for CSs at Existing Petrol Stations and Residential Car Park Locations

Variable	Average	Max
Minimum distance between 7.2 kW AC CSs	347 m	5,491 m
Minimum distance between 50 kW DC CSs	993 m	3,934 m

5. Results

In this section, we present the results from our simulation. Section 5.1 highlights the findings in a base scenario. In the base scenario, we analyse the influence of the three charging behaviours with fixed model parameters on the effectiveness of CS placement as described in Section 4.3. Section 5.2 explores the effect of a more uniformly distributed CS placement setting. A grid-based approach is used to determine the locations of the CSs. Section 5.3 discusses the sensitivity of different charging behaviour model parameters with the base scenario as reference. Section 5.4 estimates the effect of various initial SOC parameter settings at the start of the simulation. For all the simulated scenarios, there are no agent break down events.

5.1. Base Scenario

In the base scenario, we analyse the influence of the three charging behaviours on the effectiveness of CS placement at existing petrol stations and residential car park locations in Singapore. For the *SOCThreshold* in *ZEM* and *safetyMargin* in *SEM*, we implement that both parameters take 20% of the total battery capacity. Regarding the estimation of energy consumption, i.e. *energyToNear-estCSAtD* in *FEM* and *estimateTripConsumption* in *SEM* and *FEM*, we model a 20% increase in energy consumption estimation with $k = 1.2$ than the average 150 Wh per kilometre. This is to account for a conservative energy consumption estimation from the driver's perspective. We further assume that all EVs start with 50% SOC at the beginning of the simulation.

We compute the average SOC, charging event count, charging energy per agent and charging agent count for these three charging behaviours. The average SOC is the average remaining energy in the battery over the whole simulation period. This variable could be interesting for V2G applications where the EV battery acts like an energy storage. The charging event count and charging energy per agent is calculated over those agents that actually go for a charging event. The charging agent count shows the number of agents that record a charging event.

The average SOC are 46.70%, 46.33% and 45.05% for *ZEM*, *SEM* and *FEM* respectively, which does not show a big difference between the three charging behaviours. Fig 2 shows the charging energy per agent and charging agent count for the

three behaviours and divided by AC and DC charging infrastructure. The charging energy per agent illustrates a declining trend from *ZEM* over *SEM* to *FEM* when not differentiating between AC and DC charging infrastructure. However, looking only at the DC charging infrastructure, there are quite some difference in the amount of energy charged per agent for the three charging behaviours. *ZEM* still displays the highest energy charged per agent as in the combined figure, but the *FEM* presents a higher amount of energy charged per agent than the *SEM*. This shows that the *FEM* uses more of its battery capacity before going charging than the *SEM* when the agents seek for DC CSs. The lower value of the *FEM* in the combined figure is due to the fact that the actual number of agents that charge at DC CSs are very low compared to the other two charging behaviours.

The DC charging agent count of the *SEM* is higher than the *ZEM* and *FEM*. This can be explained by the *safetyMargin* that this behaviour model contains. This 20% *safetyMargin* of the *SEM* leads to earlier charging compared to *ZEM* with 20% *SOCThreshold* and *FEM* without *safetyMargin*, in the context of this CS placement scenario.

Looking at the CS performance, we compute the mean occupancy and number of unused CS locations for the three charging behaviours. The mean occupancy is calculated as the area under the occupied charging lots over time graph divided by the 24h simulation period. The unit in charging lots explains how many charging lots would be constantly occupied during the simulation period for each CS location. The number of unused CS locations shows how many CS locations are not visited by any agents.

Fig 2 also illustrates the mean occupancy and number of unused CS locations with respect to AC and DC charging infrastructure. The results suggest that the mean occupancy is very low for all three charging behaviour models. This may serve as an indicator that the current CS placement is not effective. Especially for the *FEM*, the mean occupancy is much lower compared to the other two charging behaviours due to the smaller charging agent count. The same is true for the much higher number of unused CS locations for the *FEM*. Looking only at the AC charging infrastructure, there is not much difference between these three charging behaviours. However, it is to mention that the number of unused AC CS locations are very high.

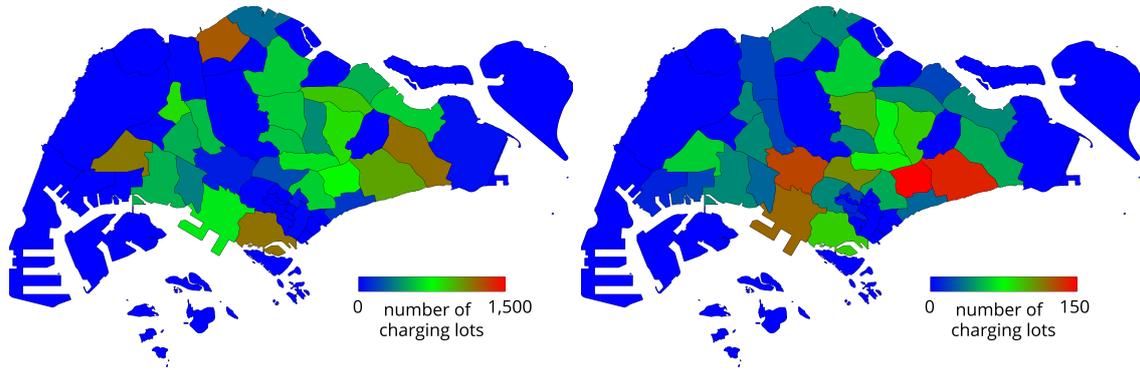


Figure 1: Distribution of CSs on the Singapore map. Singapore is partitioned into 54 planning areas. The heat maps show the number of charging lots in each planning area with 7.2kW AC (left) and 50kW DC (right) charging power. The DC charging lots are placed at existing petrol stations and the AC charging lots at residential car park locations in Singapore.

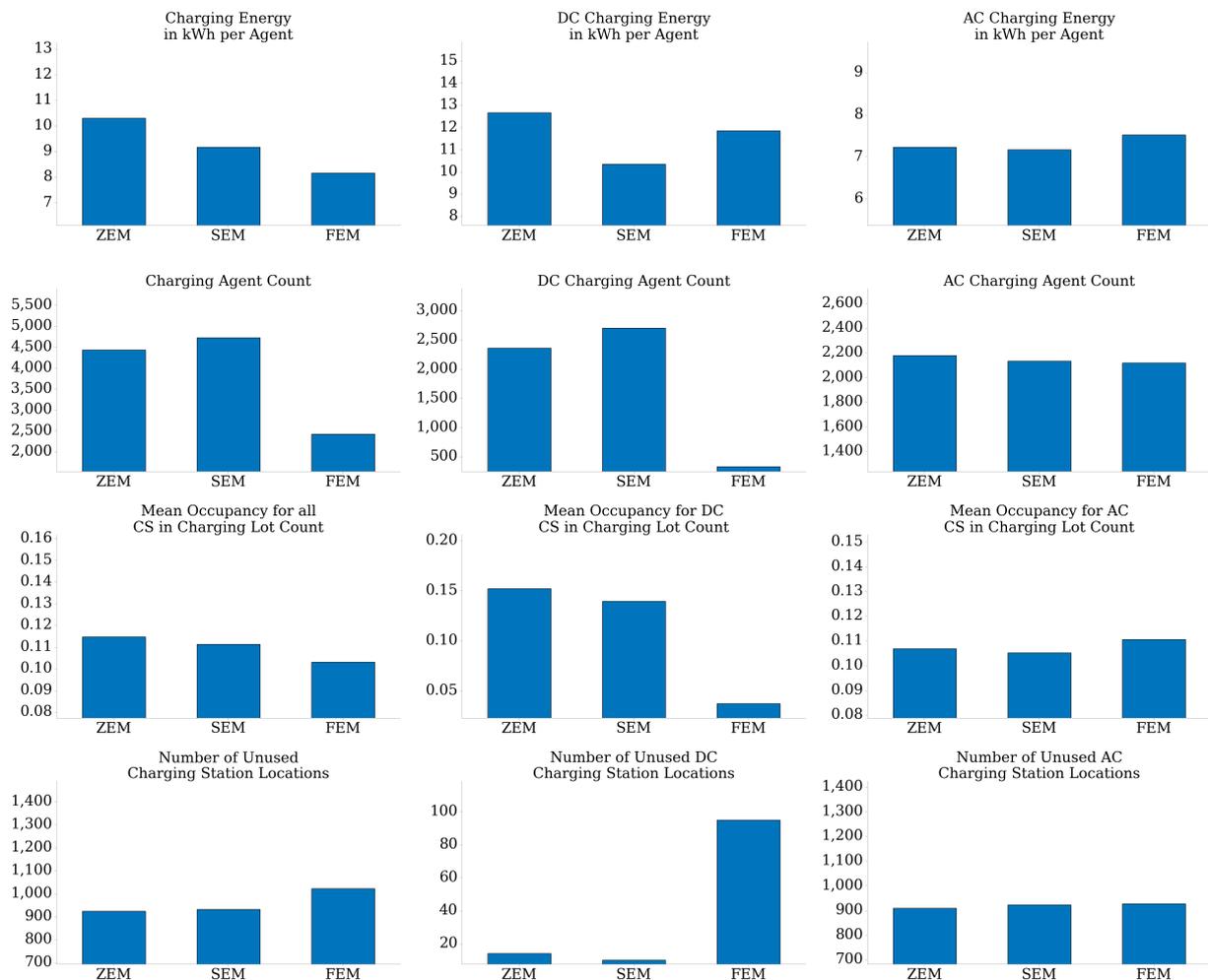


Figure 2: Charging energy per agent, charging agent count, mean occupancy and number of unused CS locations for the three charging behaviours with CS placement at existing petrol stations for DC charging infrastructure and residential car park locations for AC charging infrastructure. Each row shows the metric for AC and DC charging infrastructure combined, DC charging infrastructure only and AC charging infrastructure only respectively.

One possible reason for this high number might be the fact that the mobility demand is only generated from data that surveys a small percentage of the population while the data of the residential car park locations is rather complete. The travel survey data could be biased towards certain areas.

In general, the results suggest that the *FEM* differs from the *ZEM* and *SEM* due to the lack of a *SOCThreshold* or *safetyMargin*. This allows the *FEM* to better utilise the battery capacity which results in less charging events and less occupancy of the CSs.

5.2. Sensitivity of Charging Station Distribution

This section studies how the CS spatial distribution affects the simulation outcome. We generate an artificial CS distribution across Singapore using a grid-based approach and compare this distribution to the one described in Section 4.3. This grid-based approach of CS placement allows for a more uniformed distribution of CSs. The area of the bounding box of Singapore is calculated. Following the same number of AC and DC CSs as in CS placement at existing petrol stations and residential car park locations, 1,913 CS locations are identified using the grid-based approach, from which 1,727 and 186 are AC and DC CS locations. The area of the bounding box is divided by the number of respective AC and DC CS locations to obtain the area and length of each location square. The Singapore road network is partitioned into such location squares with the aim to put one CS in each location square. The ratio between the number of placed CSs and the total intended number of CSs is used for the next iteration to adjust the length of the location squares. This process terminates when the deviation of placed CSs is within 5%. The remaining CSs are placed randomly in the road network. The CS distribution of this grid-based CS placement approach is illustrated in Figure 3. Table 4 includes the minimum distance between CSs for AC and DC charging infrastructure using the grid-based approach. This variable indicates how dense the charging infrastructure is in terms of driving distance and provides a measure of how far the agent need to drive in order to reach a CS.

In this scenario with CS placement using grid-based approach, the charging agent count and charging energy per agent in Fig 4 show the same trend over the charging behaviours as those in the CS placement scenario at existing petrol stations and residential car park locations. However, the

Table 4: Charging Infrastructure Statistics using Grid-based Approach

Variable	Average	Max
Minimum distance between 7.2 kW AC CSs	710 m	4,434 m
Minimum distance between 50 kW DC CSs	2,216 m	5,118 m

charging agent count in the grid-based CS distribution decreases significantly for each behaviour. Separating the charging agent count into DC and AC charging agent count reveals that the decrease is caused by the AC charging agent count. These are the CS locations where the agents decide for convenience charging. In the grid-based scenario, the CS locations are uniformly distributed over the road network which means that the density of CSs at residential car park locations is less in the grid-based scenario, which causes less convenience AC charging agent count.

More interesting is the utilisation of the CSs illustrated in Fig 4. The number of unused CS locations is higher than that in the CS placement scenario at existing petrol stations and residential car park locations. The grid-based CS placement approach results in a more evenly distribution of CSs across the Singapore road network, which also means that areas with less charging demand are placed with more CSs and vice versa. This is the reason why the number of unused CS locations is actually higher in the grid-based approach. The mean occupancy for AC CSs is lower in the grid-based approach for the same reason.

5.3. Sensitivity of Charging Behaviour Model Parameters

In this section, we investigate how the different model parameters for each of the three behaviour models influence the outcome of the simulation. For the *ZEM*, we increase the *SOCThreshold* to 30% and 40% of battery capacity. Concerning energy consumption estimation as in *estimateTripConsumption* and *energyToNearestCSAtD*, we look at the factor *k* with 1.4 and 1.6 compared to the 1.2 in the base scenario. At the beginning of the simulation, all EVs start with 50% SOC, same as in the base scenario.

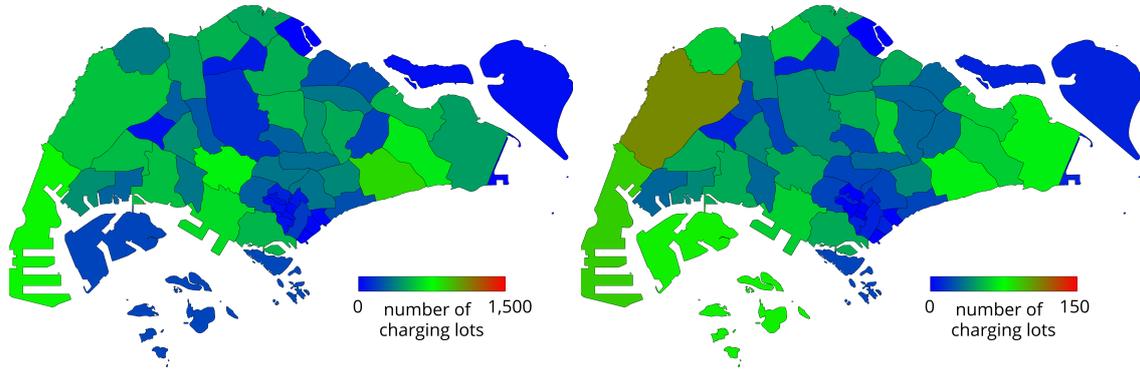


Figure 3: Distribution of CSs on the Singapore map using grid-based approach. Singapore is partitioned into 54 planning areas. The heat maps show the number of charging lots in each planning area with 7.2kW AC (left) and 50kW DC (right) charging power. The AC and DC charging lots are distributed evenly with 17,270 AC and 1,860 DC charging lots in Singapore.

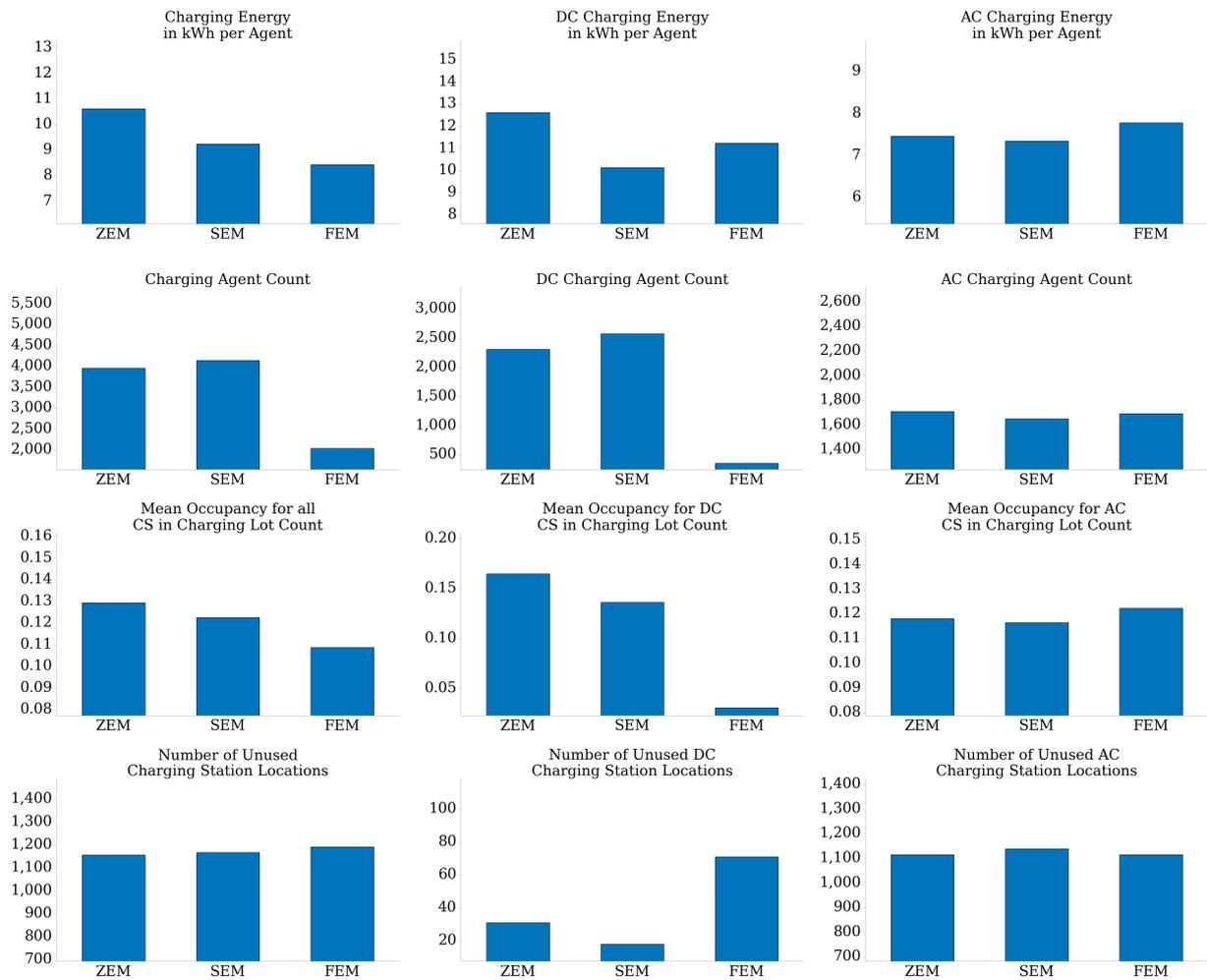


Figure 4: Charging energy per agent, charging agent count, mean occupancy and number of unused CS locations for the three charging behaviours with CS placement using grid-based approach. Each row shows the metric for AC and DC charging infrastructure combined, DC charging infrastructure only and AC charging infrastructure only respectively.

Table 5: Sensitivity of the three Charging Behaviour Model Parameters. The Numbers in the Model Parameters Column indicate the Parameter Value for the respective Model in %

Model Pa-rameters	Average SOC per Agent in %	Charging Event Count per Agent	Charging Agent Count	Charging Energy per Agent in kWh	CS Count with more than 100 % Occupancy	Mean Occu-pancy in Lots	Unused CS Location Count
ZEM 20	46.70	1.05	4, 431	10.29	3	0.11	923
ZEM 30	49.38	1.06	8, 107	9.96	17	0.13	915
ZEM 40	56.53	1.07	13, 429	8.88	19	0.16	962
SEM 20	46.33	1.06	4, 721	9.17	5	0.11	932
SEM 40	47.37	1.07	5, 653	9.20	7	0.12	923
SEM 60	47.94	1.09	6, 379	9.12	6	0.12	928
FEM 20	45.05	1.06	2, 426	8.16	1	0.10	1, 022
FEM 40	45.06	1.05	2, 529	8.31	1	0.10	1, 019
FEM 60	45.40	1.06	2, 749	8.55	1	0.11	987

The results are presented in Table 5. As the *SOCThreshold* in *ZEM* increases from 20 % to 40 %, there are significantly more charging agent counts while the charging event count per agent remains at the same level. The average SOC also shows the same trend of increasing with the *SOCThreshold* in *ZEM* whereas the charging energy per agent drops due to earlier charging with increasing *SOCThreshold* level. For *SEM* and *FEM*, although we increase the energy consumption estimation factor to 1.4 and 1.6 compared to the base 1.2, the increase in average SOC and charging agent count is moderate. As a result, the CS occupancy in *ZEM* grows faster than in *SEM* and *FEM*.

5.4. Sensitivity of Initial SOC at the Start of the Simulation

In this section, we vary the initial SOC parameter of the simulation. Compared to the 50 % initial SOC described in the base scenario 5.1, the simulation is also initialised with 75 % and 100 % of initial SOC for each of the three behaviour models. Other assumptions are identical with the base scenario.

The results presented in Table 6 show that the initial SOC plays a significant role in terms of simulation outcome. The average SOC per agent increases proportionally to the initial SOC value across all three behaviour models. Interestingly, the deviation of the average SOC from the initial SOC is within a 10 % range. This result suggests that the initial SOC distribution is an important factor when considering smart grid applications.

A higher average SOC can be interesting for smart grid operators because they can draw more energy when needed, but on the other hand, an average SOC closer to the maximum capacity prevents large amount of excess energy to be stored into the battery of the EVs. A scenario with 100 % initial SOC may reflect the real world case that every EV owner has a charging opportunity at home which allows them to charge the EV over night and start the day with a full charge.

The initial SOC parameter also influences the charging agent count. From the data in Table 6, the charging agent count decreases with increasing initial SOC. At 100 % initial SOC, there are less than 400 agents charging in the simulation across all three charging behaviours. This leads to the fact that more than 1,600 CS locations are unused in the 100 % initial SOC scenarios, whereas for the 50 % and 75 % initial SOC, the unused CS locations are only at around 1,000.

6. Discussion

The quality of the simulation result highly depends on the input data fed into the simulation. The mobility demand represents such a critical input. Although the travel survey data is collected from over ten thousand of households, it still only reflects around one percent of the whole Singapore population. The mobility demand generated from the travel survey data might be biased towards certain areas and periods of time. A strong indicator that this happens is the high number of unused CS

Table 6: Sensitivity of the Initial SOC for each Charging Behaviour. The Numbers in the Model Initial SOC Column indicate the Initial SOC for each Agent at Simulation Start in %

Model Initial SOC	Average SOC per Agent in %	Charging Event Count per Agent	Charging Agent Count	Charging Energy per Agent in kWh	CS Count with more than 100% Occupancy	Mean Occupancy in Lots	Unused CS Location Count
ZEM 50	46.70	1.05	4,431	10.29	3	0.11	923
ZEM 75	68.39	1.06	2,450	3.59	0	0.04	976
ZEM 100	92.62	1.01	378	2.67	0	0.02	1,649
SEM 50	46.33	1.06	4,721	9.17	5	0.11	932
SEM 75	68.38	1.06	2,434	3.25	1	0.04	1008
SEM 100	92.62	1.01	387	2.20	0	0.02	1,648
FEM 50	45.05	1.06	2,426	8.16	1	0.10	1022
FEM 75	67.88	1.06	2,220	2.75	0	0.04	1046
FEM 100	92.61	1.01	361	2.04	0	0.02	1,666

locations even in low initial SOC scenarios where the charging demand of the agents are the highest. This suggests that more than half of residential car park locations are not utilised meaning the agents don't start or end their trips at these locations.

Furthermore, the demand modelling is of stochastic nature as the O-D pairs are sampled from the data set. As we only perform one simulation run for each scenario in this case study, the sensitivity of this demand modelling on the simulation outcome needs to be looked at more closely.

The initial SOC is a parameter that also deserves attention as this parameter together with the maximum capacity determines the starting energy of the agent. We simulate a 24 hours weekday which does not allow us to estimate a realistic initial SOC distribution compared to a multi-day simulation. However, we discuss our results based on different initial SOC levels to partly compensate the lack of a multi-day simulation. Higher initial SOC means lower probability to go charging at the beginning, thus shifting the charging demand in time and space. This can lead to the fact that for high initial SOC scenarios, more agents don't even require to go to a CS. This unbalanced energy consumption and demand is another disadvantage of a 24 h only simulation time. A multi-day simulation could yield more accurate results as the charging behaviour is executed by all agents in the simulation.

We also have to bear in mind that the battery user interaction style is assumed that the agent charges at every destination if there is a CS available in this study. This behaviour can be valid for

CSs equipped with wireless charging lots, but might not hold true when a cable has to be plugged in manually. A different battery user interaction style could yield in different charging infrastructure utilisation.

We currently do not have any waiting behaviour of the agents when the DC fast CS is fully occupied. The agents simply wait at the CS until a charging lot becomes available. In the real world, this might not hold true. Depending on the distance to the next CS and the remaining waiting time at the occupied CS, the driver makes a decision whether to wait or not. This can influence the tempo-spatial charging demand as well as the charging infrastructure utilisation.

Instead of the EV driver searching for the CS to go charging, many advanced navigation and recommendation system can provide more sophisticated information to guide the EV driver with their charging decisions and provide en-route charging where the detour to the destination is minimised. Our current model only supports searching for the nearest CS, which creates the charging demand at the origin of the trip. These more intelligent recommendation system can also shift the tempo-spatial charging demand which affects the simulation outcome.

7. Conclusion and Outlook

In this paper, we show that charging behaviour is an important factor to consider besides others. In particular, we apply *ZEM*, *SEM* and *FEM* in

our simulation. Results suggest that especially the *FEM* differs from the other two behaviour models due to the lack of a *SOCThreshold* or *safetyMargin*. This allows the *FEM* to better utilise the battery capacity. Our findings also suggest that not only the different charging behaviour models impact the simulation outcome, but also variations in model parameter values, especially the *SOCThreshold* in the *ZEM* model. We conclude that a range safety buffer parameter has a crucial impact on the charging infrastructure utilisation as shown in the model parameter variation of the *ZEM*. Accurate information on the charging infrastructure can reduce the need for a large range safety buffer.

The initial SOC distribution might be an important information for smart grid operators. In our simulated results with the implemented charging behaviours, the average SOC of all agents during the simulation period is within a 10% range of the initial SOC value. The initial SOC could serve as an indicator of how much energy can be drawn from or charged to the system.

Despite our charging behaviour modelling effort, there are still many input variables that can be considered to further improve the models. Information about categories of locations can be integrated to account for the purpose of the trip being for work, leisure or simply returning home. Based on these intentions the agent can exhibit different charging behaviours. Although we already differentiate between strategic network locations like petrol stations and residential car park locations, more location categories can be used for CS placement, especially for deciding on the charging power of each CS to be installed.

While the cost of charging an EV is relatively low compared to fossil fuel, the price sensitivity of the user can be an important factor to shift the charging demand in order to avoid bottlenecks in the system. The study in [30] reveals that EV users prefer to charge at home in the evening at peak demand times. This energy demand could be shifted in time by providing incentives to EV users to change their tempo-spatial charging behaviour for the benefit of a more efficient system.

Weekend mobility demand and charging behaviour is not accounted in our simulation. Data analysis in [48] suggests that EV users tend to show different charging infrastructure usage intensity on weekdays and weekends. Furthermore, the benefits of a multi-day simulation is discussed before. Incorporation of weekend behaviour and a multi-day

simulation into our agent-based traffic simulation framework can be implemented in the future.

Another fact to be mentioned is that the ratio between charging time and connection time at a charging lot is assumed to be one in our study. That means the EV user immediately frees the charging lot when the charging process ends. However, data analysis in [49] shows that the connection time can be much longer than the actual charging time of the EV. This behaviour blocks resources and we are sure that intelligent technological solutions in the future are likely to address this problem and increase the efficiency of the charging infrastructure.

The advantage of applying this high resolution agent-based traffic simulation is illustrated in [32]. The CS placement problem is a very complex one [50] and we can only optimise with regard to specific objectives. One possible algorithm to address this problem could be to iteratively reduce or increase the CS number. It can be assumed that in the beginning, everywhere are CSs, and they are iteratively removed based on certain criteria. Such an algorithm could be implemented in the future with this agent-based simulation framework.

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