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Influence of Charging Behaviour given Charging Station Placement at Existing Petrol Stations and Residential Car Park Locations in 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 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 performance of these three charging behaviours 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 is an important factor to consider as variations in model parameter can lead to significant different results.

Keywords: Charging Station, Charging Behavior, Traffic 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. In order to prevent range related anxiety, two approaches exist. On the one hand, there is significant

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research being done in advancement of battery technology for increased range and decreasing battery cost [25]; on the other hand, there is a recognition that an efficient charging infrastructure is also crucial.

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. However, most of these charging infrastructure optimisation work either neglects the charging behaviour of the EV driver, or at best, considers 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 [19].

In this paper, we analyse the impact that different charging behaviours can have on the effectiveness of CS placement. In particular, we consider three charging behaviour with different level of complexity. The least complex one makes charging decision based on a battery SOC threshold as in [19]. The next charging behaviour makes estimation 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.

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.

The remainder of the paper is organized 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 setup. Section 5 presents the experimental results. Section 6 discusses the work and 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 [34], CS coverage and convenience for EV drivers to reach CSs [23] as well as energy cost for vehicles to travel to CSs [8] are objectives for minimization in addition to investment costs. [6] 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 [32] and queuing time at the CS [26]. [16] and [21] maximises the CS coverage. [31] 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 break down vehicles are used as an input for the optimisation [7]. 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 [17]. Household travel survey data is also used in [10] 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, [29] 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. Drivers' discomfort is considered in terms of maximum hops in a grid partitioned road network. Another way to derive mobility demand is to use large-scale trajectory data of taxi fleet [9]. Public EV CS locations are identified in Beijing based on these data. EV taxi trajectory data is used in [24] to optimally locate CSs and assign optimized number of charging plugs with the objective of minimizing the average time to find a CS and waiting time before charging.

The CS placement problem can also be addressed from the power grid perspective. A simulation-based approach for investigating the impact of transport electrification on power grids is presented in [11]. A case study of Singapore shows that grid congestion and voltage drops are observed on the low voltage level while the high and medium voltage grid remain unaffected.

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 residential car park locations in Singapore [30]. In this agent-based nanoscopic traffic simulation, a driver-vehicle-unit (DVU) consists of driver model and vehicle model [33]. Advantages are that vehicles and drivers can be modelled in greater detail. Realistic vehicle energy consumption can be simulated with individual driving and charging behaviour of the EV driver. The emergence of collective dynamic from individual interactions between DVU agents can be captured [22].

Application of an agent-based simulation to analyse how EV adoption could be affected by different spatial deployment of CSs can be found in [27]. An agent-based traffic simulation is used to provide input to a power simulation which determines the optimal charging profile for EVs [5]. Another work [18] applies agent-based simulation to maximize availability and profitability of CSs. The load curve generated by EV power demand is studied in [28] where the agent can only charge at the origin or destination of a trip.

The major disadvantage of existing CS location optimisation work neglects the charging behaviour of EV drivers or apply simple charging behaviour model. [6] assumes that a charging event occurs when the SOC is below a threshold. Similarly, vehicles route to the nearest CS when being low on energy before they continue their journey to the final destination in [19]. Data analysis of 15 EVs over a course of 230 days to predict the probability of an EV deciding for a charge event at a particular level of SOC is carried out in [20]. This simple stochastic model only considers SOC as an input.

Looking from the charging behaviour perspective, [14] analyses the psychological dynamics underlying charging behaviour of EV users assessing data in a EV field study. The authors attempt to understand how users cope with limited mobility resources and defines 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. They also find that user-battery interaction style plays a role in the decision when to start a charging event [15]. The user battery interaction style is a qualitative classification based on their tendency to charge. [13] applies expected utility theory to model the charging behaviour of EV drivers considering cost, charging duration, range, trip distance to be important when making charging decision.

3 Charging Behaviour Models

In this section, we describe the three charging behaviours in greater detail. Their difference is the amount of information they consider for making charging decisions. The first and simplest model considers only a SOC threshold for routing to CSs like in other studies [6] and [19], the other two models consider trip length and CS locations to base their charging decisions. We also apply the concept of a range safety margin as in [15]. 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 [1].

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) The driver takes every charging opportunity at trip destination to charge if there is a CS available. 3) Estimation of energy consumption for the next trip is made based on 150 Wh per kilometre. This value is the average energy consumption generated from our agent-based traffic simulation. 4) 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.

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

Algorithm 1: Zero Estimation Model

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

Algorithm 2: Semi Estimation Model

For each agent at each trip start
if $currentSOC > estimateTripConsumption + safetyMargin$ **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`) plus a safety margin (`safetyMargin`), the driver starts the trip to his intended destination (`beginCurrentTrip`). Otherwise, the driver seeks the nearest CS from the origin of his trip.

Full Estimation Model (FEM). Energy consumption for the next trip together with the energy to the nearest CS at destination (`energyToNearestCSAtD`) is estimated before a trip starts. The driver seeks to find the nearest 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.

Algorithm 3: Full Estimation Model

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

4 Simulation Setup

For the analysis in this study, a simulation tool SEMSim Traffic[33] is used. It is a nanoscopic agent-based traffic simulation with driver-vehicle units (DVUs) forming the basic unit 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 traffic patterns realistically. [30] 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.

In this experiment, we utilise the Singapore road network data derived from Navteq 2009. HITS 2012 travel survey data is used to initialise the traffic. This data is in the form of origin-destination pairs showing a portion of travelling demands in Singapore for a typical whole day period. Each agent has at least two origin-destination pairs. 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. Extrapolation is thus imposed to simulate the realistic traffic scope of Singapore [30]. We run the simulation with 21500 agents for a 24 hour period. The number of agents equals the number of charging lots.

4.1 Vehicle Energy Consumption Model

The vehicle battery of $20kWh$ maximum capacity provides power to the motor, air-conditioner and auxiliary components in the EV. In this experiment, we take vehicle parameters of an electric vehicle called EVA which is exclusively designed by TUM CREATE for tropical megacities [2].

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 its inverse when the motor requires 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 in Equation 2 and 3.

$$P_{motor} = \begin{cases} \dfrac{1}{f_{loss}} F_{motor} v & when\ F_{motor} > 0 \\ f_{loss} F_{motor} v & when\ F_{motor} \leq 0 \end{cases} \tag{1}$$

$$F_{motor} = F_{air} + F_{roll} + F_{inertia} \tag{2}$$

$$F_{air} = \frac{1}{2}\rho A_f C_d v^2; \qquad F_{roll} = f_r m_{car} g; \qquad F_{inertia} = (1+\lambda) m_{car} a \tag{3}$$

where v is the velocity in m/s. The parameters in Equation 1 and 3 are shown in Table 1.

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

4.2 Charging Station Model

We retrieve petrol station locations from the website [4]. Residential car park locations which are open to public are provided by Singapore Land Transport Authority [3]. In total, we identify

Parameter	Description	Value	Parameter	Description	Value
g	Acceleration of gravity	$9.81m/s^2$	λ	Percentage of equivalent mass of rotating parts	0.13
f_r	Rolling coefficient	0.01	m_{car}	Car weight	$1500kg$
C_d	Drag coefficient	0.4	f_{loss}	Losses in the drive train	0.9
ρ	Air density	$1.13kg/m^3$	A_f	Car frontal area	$2.24m^2$

Table 1: Vehicle energy consumption parameters

2150 CS locations. The spatial distribution of these CSs is illustrated in Fig 1. It is assumed that each CS can have a queue of infinite length. We assume 10 charging lots at each CS location. It is simulated that each charging lot is installed with 19.2 kW of charging power as per SAE J1722 Level 2 standard (240V/80A) [12].

Figure 1: Distribution of charging stations on Singapore road network. Charging stations are indicated in red dots.

5 Results

In this section, we present the results from our simulation. Section 5.1 highlights findings in a base scenario. In this 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 4.2. Section 5.2 discuss the sensitivity of different charging behaviour model parameters with the base scenario as reference.

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 estimation of energy consumption, either *energyToNearestCSAtD* in *FEM* or *estimateTripConsumption* in *SEM* and *FEM*, we model a 20% increase in energy consumption estimation 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% of their battery capacity at the beginning of the simulation.

We compute the average SOC, charging event count and charging energy per agent for these three charging behaviours as in Fig 2. The *SEM* scenario shows a higher value of average SOC, charging event count as well as charging energy per agent than the other two charging behaviour models. 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. In particular, the *FEM* shows a notably smaller number of charging event count and charging energy per agent. There is no agent break down event in the simulation.

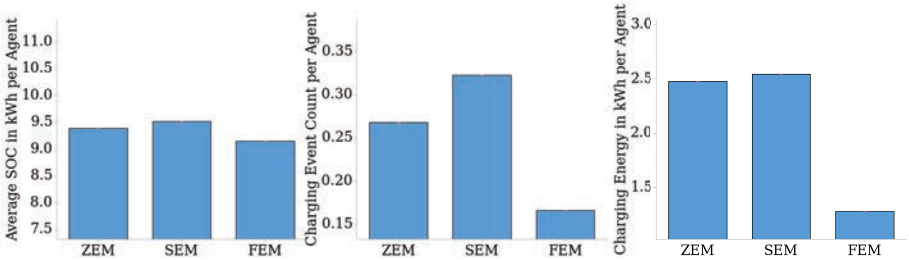

Figure 2: Average SOC, charging event count and charging energy per agent for the three charging behaviours

Looking at the CS occupancy, the results in Fig 3 suggest that although some CSs reach a 80% occupancy at some time in the simulation, the mean occupancy for all three charging behaviour models is very low. The mean occupancy is calculated as the area under the occupied charging lots over time figure divided by the 24*h* simulation period. The number of unused CS locations are high across all three behaviours. This may serve as an indicator that the current CS placement is not efficient.

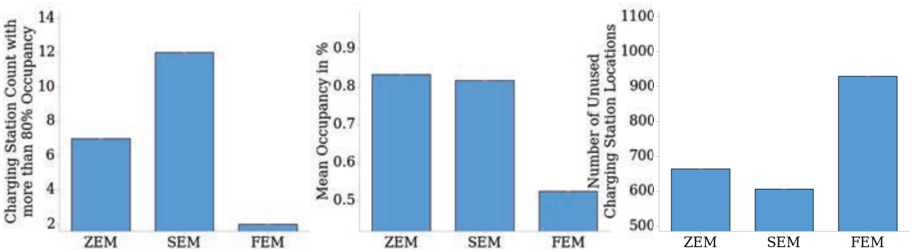

Figure 3: CS count with more than 80% occupancy, mean occupancy and number of unused CS locations for the three charging behaviours

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.

5.2 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 a 40% and 60% increase compared to the 20% in the base scenario. At the beginning of the simulation, all EVs start with 50% of their battery capacity.

The results are presented in Table 2. As the *SOCThreshold* in *ZEM* increases from 20% to 40%, there are significantly more charging events occurring. The average SOC and charging energy per agent also shows the same trend. For *SEM* and *FEM*, although we increase the energy consumption estimation by 40% and 60% compared to the base $150Wh$ per kilometre, the increase in average SOC, charging event count and charging energy is moderate. As a result, the CS occupancy in *ZEM* grows faster than in *SEM* and *FEM*.

Model Parameters	Average SOC per Agent in kWh	Charging Event Count per Agent	Charging Energy per Agent in kWh	CS Count with more than 80% occupancy	Mean Occupancy in %	Unused CS Location Count
ZEM 20	9.39	0.27	2.48	7	0.83	664
ZEM 30	9.9	0.49	4.42	35	1.37	537
ZEM 40	11.22	0.83	6.46	49	1.9	446
SEM 20	9.52	0.32	2.54	12	0.82	607
SEM 40	9.69	0.38	2.82	9	0.88	555
SEM 60	9.88	0.43	3.07	9	0.92	502
FEM 20	9.15	0.17	1.28	2	0.53	930
FEM 40	9.17	0.18	1.38	3	0.55	890
FEM 60	9.23	0.19	1.49	1	0.56	834

Table 2: Sensitivity of the three charging behaviour model parameters. The numbers in the model parameters column indicate the paramter value for the respective model in %

6 Discussion and Outlook

EVs are the key to a more sustainable transportation system. The charging infrastructure supporting the adoption of EVs are crucial and the locations of CS directly influence the effectiveness of the electrified system. 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 variations in model parameter values influence the simulation as well. The sensitivity of different model parameters is surely an important factor to consider. It is to note that a fixed initial SOC is assumed for all EVs in our experiments. A more realistic distribution of the initial SOC can be obtained by simulating for several days until the agents reach a steady state in terms of their SOC.

Despite our charging behaviour modelling effort, there are still many input variables that can be considered to further improve the model. 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.

In addition, these location categories can also be used for CS placement, especially deciding on the charging power of each CS to be installed. Although 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 bottle necks in the system. EV users can be incentivised to change their tempo-spacial charging behaviour for the benefit of a more efficient system. Another factor is the battery user interaction style which 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 manually a cable has to be plugged in. All these factors mentioned can have an influence on the efficiency of the system.

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