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Simulation-assisted exploration of charging infrastructure requirements for electric vehicles in urban environments☆

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ABSTRACT

High population densities in today's cities are leading to increasing congestion and air pollution. Sustainable cities of the future will require a large scale transition to electro-mobility. The development of electric vehicle charging infrastructure is necessary to enable this transition. Existing methods for determining charging infrastructure take an optimization approach that ignores existing traffic demands and infrastructure. Moreover, the dynamics of vehicle movement like stop-and-go traffic, congestion and the effect of traffic lights are not considered in determining energy consumption. In this paper, we propose a novel nanoscopic city-scale traffic simulation based method for determining charging infrastructure locations; subsequently, we demonstrate its usefulness in spatio-temporal planning through a case-study of Singapore. Through this method, existing traffic and road network data and the dynamics of individual vehicle movement can be taken into consideration in planning.

1. Introduction

Urbanisation is a trend which has been accelerating and is expected to continue doing so, ultimately leading to more densely populated cities across the world. Today, several mega-cities can be found in Asia, particularly in China. Due to high density, these cities are facing many problems like congestion and increasing air pollution. In most cities, traffic is a significant contributor to these problems. Future mobility will likely be characterized by a number of major transitions. One such transition will be the shift from fossil-fueled internal combustion engine vehicles to electric vehicles (EVs) which is already slowly taking place today and this trend is likely to accelerate. While EVs cannot be expected to solve the congestion problem, they can be a solution to the decreasing air quality in cities. EVs generate no local emissions. In addition, they also produce less noise since electric engines hardly generate any noise. Having an all-electric traffic system in densely populated cities is thus very attractive. However, a common problem in this vision coming to fruition for city planners is the installation of the required charging infrastructure. There seems to exist a type of chicken-and-egg problem here: vehicle users feel uncomfortable changing to EVs because sufficient charging infrastructure has not been developed; on the other hand, installing charging station infrastructure is costly and without a sizeable number of customers, the private sector may not see the business opportunity in even developing cars that would make use of this infrastructure.

However, despite the ostensible lack of business opportunities, the private sector has made significant progress in the development of EV technologies. For example, most major automobile companies do have vehicles with electric power-trains. Of these, the majority are hybrid solutions but more and more all-electric vehicles are entering the market (e.g., Tesla, BMW i-Series). However, as far as the required charging infrastructure is concerned, this generally has to be undertaken by the public sector. This is particularly true for large cities, such as Singapore, because most people live in high-rise buildings and do not have the luxury of their own garage for conveniently installing a charging station. Instead, large car parks would have to be equipped with a sufficient amount of charging stations.

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Therefore, for a city government to aim for a city-wide all-electric traffic system, various problems associated with the infrastructure for EVs need to be addressed first.

One issue concerning charging infrastructure is the issue of placement of charging stations. Ideally, charging stations would only have to be placed where there is sufficient demand. Depending on the assumed scenario (e.g., all vehicles in a city are electric, only certain fleets, etc.), the placement problem can become non-trivial [1]; in such cases, as traffic is not taken into consideration, existing methods [1–4] are likely to fall short. Traditionally, even when real world data is used, energy utilization is calculated based on the average speed on roads and this is used to predict ideal charging station placement. Studies have shown that taking into consideration the driving style of individual drivers or factors like congestion can have a significant effect on energy consumption [5,6]. Another problem that existing methods to not address is the issue of long term planning for development of charging infrastructure. Given the capital costs and time taken to build charging infrastructure, it is important to identify not only the locations where charging stations will have to be developed but also the order in which they will have to be built.

The major contribution of this paper is the description of a computational science approach, based on modelling and simulation, that allows us to evaluate both the spatial and temporal aspects of charging station placement based on available real world traffic data. We apply our method to the case of Singapore and discuss our findings with respect to the typical energy consumption of vehicles over the course of a typical day in Singapore; subsequently, we derive plans for charging station locations from this.

2. Related work

A primary issue regarding the placement of charging stations is the range of vehicles, i.e., the distance that the EV can travel in one full charge. In EVs, the vehicle range is one of the fundamental specifications that is considered. In transportation engineering, energy consumption of vehicles is estimated using driving cycles [7,8]. A driving cycle is a time-series of data points indicating the speed of a vehicle. For a given environment, based on a given driving cycle and a specific type of vehicle, it is possible to estimate the energy consumption. There are a number of standard driving cycles that are used world-wide by the automobile industry. Although driving cycles allow the estimation of energy consumption, they do not provide spatial information, i.e., they cannot be used to estimate the temporo-spatial energy consumption and demand for an entire city. In contrast to this, as per SAE J1634 Recommended Practice, EV range is generally calculated separately for cities and highways by fully charging the battery and driving the vehicle through the particular conditions [9]. While this method is ideal for the purpose of determining vehicle range, it is not practical for determining energy demand of a city.

Despite recent vehicles, like Tesla Model S, having much larger battery capacities, *range anxiety* is still observed in EV drivers. Range anxiety is the phenomenon where EV drivers are continually concerned about becoming stranded with a limited range vehicle [10]. While the exact causes of range anxiety are unknown, studies have shown that most drivers need a *range buffer* of around 20 miles and that their behaviour starts noticeably changing once the State of Charge (SoC) of the EV drops below 50% [10].

This suggests that larger availability of charging stations may address the range anxiety concerns of EV drivers. However, at least initially, charging stations will have to be placed strategically to address these concerns. There have been several ways in which the problem of optimal placement of charging stations in a city has been approached. Some have tried to optimize charging station placement in order maximize coverage [1,2]. Lam et al. [1] analysed the problem of optimal placement of charging stations to get maximum coverage at minimum cost. Their approach was to consider a graph of all possible locations of charging stations and to find the optimal sub-graph of this graph that has complete coverage of all areas in the network. After proving the NP-hardness, the authors proceeded to demonstrate how a greedy algorithm is sufficient to solve this problem while being faster than a mixed integer approach. A similar approach was taken by Ge et al. [2] where the area was partitioned into grids and the optimal layout of charging stations determined. Xiong et al. [11] take a game theory based approach to the optimization problem that considers the mutual impact between allocation of charging stations and charging activities of EV drivers.

There have also been approaches that made use of existing travel data to determine ideal locations for charging stations [3,4]. These approaches used mixed integer programs to select charging station spots with an objective function that seeks to minimize the total access costs (walking distances) from the charging station to the driver's ultimate destination zone in selected US cities like Chicago and Seattle. Others have approached the problem from the power grid perspective, i.e., place stations such that the load on the power network is minimized [12]. Other aspects of the problem like the construction and environment costs of the project have been studied as well [13].

These mathematical approaches, however, by their nature, cannot take into consideration the effect of traffic. Also, while it would be ideal to have complete coverage, from a practical standpoint, city planners will have to determine which areas of the city should have a charging infrastructure built first. These kinds of questions are most easily answered through a modelling and simulation based approach.

Modelling and simulation is an interesting alternative to the mostly mathematical methods discussed above. Traffic simulations allow us to analyse in more detail the impact of individual vehicles, their route choices and driving behaviour [14–17]. Based on the level of detail in which the traffic flow is modelled traffic simulations are generally classified as macroscopic, mesoscopic and microscopic simulations. Macroscopic simulations [18] are used when fast simulations are required; this is generally the case for traffic control policy evaluation on the basis of aggregate properties like speed, density and flow of the traffic. These simulations are heavily inspired by fluid dynamics. On the other hand, speed density relationships and queuing theory form the basis of mesoscopic approaches [19] which, unlike macroscopic models, have individual vehicles as the basic units of the system. Microscopic models have an even higher level of detail than mesoscopic models in that they model individual driver–vehicle-units (DVU) occupying streets [15,17]. The movement of these DVUs is a result of a combination of car-following models, lane-changing and gap acceptance behaviours which are discussed in more detail in Section 3.

Besides the aforementioned three approaches, traffic modelling and simulation has recently been extended into, what is termed, the nanoscopic level [20]. In nanoscopic simulations, the DVUs themselves are considered to be a combination of drivers and vehicles. This enables the modelling of the effect of driver behaviours and a more detailed model of the vehicle and, more importantly, the interaction of these two detailed models. For example, drivers who drive brashly will tend to pull more energy from their batteries and drain their batteries faster than calmer drivers. The effect of such repeated microscopic, heterogeneous behaviour on the macroscopic city level can be explored using nanoscopic simulation engines like SUMO [21] and SEMSim traffic, used in this paper. We use the term "nanoscopic simulation" in the sense used by [22,23] of having models with detailed vehicle and driver models and their interaction. Other models, like the Commuter model [24], use the term to describe those that contain computational models of pedestrians and their interaction with the traffic as well.

There have been instances where agent based modelling and simulation has been used for EV charging infrastructure assessment. Sweda and Klabjan [25] used an agent based macro-simulation to analyse how EV adoption could be affected by different spatial deployment of charging stations. However, rather than simulating traffic and battery usage, their model is based on the central idea of economic viability being used to determine the replacement of internal combustion engine vehicles by EVs over a period of years. In a similar vein, Acha et al. [26] used a very simple agent based mesoscopic traffic simulation to provide input to a power simulation; this was then used to determine the optimal charging profile for EVs. Another interesting simulation based approach to the problem of charging station placement is taken by Hess et al. [27] in their analysis of the city of Vienna. They use an agent based traffic simulation of vehicles whose origins and destinations are chosen randomly. Vehicles running low on charge go to the nearest charging station before continuing their journey to their destination. The optimal placement of charging stations from a set of candidate locations is determined in this scenario with the objective of minimizing average travel time. Our approach in this paper is different in three fundamental ways. Firstly, we do not make any assumptions about existing charging infrastructure placement because, in doing so, we would need to alter the daily routes taken by commuters to include trips to these charging stations based on some hypothetical charging behaviour; we rather consider the development of infrastructure in a way that least affects the status quo. Secondly, the routes of the vehicles in our simulation (as explained in Section 3) reflect the real world daily traffic patterns. Most importantly, rather than a simple linear charge depletion model, we use a nanoscopic simulation where the driver behaviour and vehicle properties determine the SoC of the vehicle.

3. Computational model

Evaluating planning scenarios for EV charging infrastructure requires information about the expected energy demand at different locations. If data about the actual energy demand is not available due to the lack of a sufficient number of EV users, energy consumption and the resulting energy demand can be estimated by means of simulation. The energy demand of a single vehicle depends on the amount of energy used throughout the day. This depends on many factors, including traffic conditions (e.g., time spent waiting at traffic lights and stop-and-go traffic during peak hours), terrain (e.g., energy consumption is higher when driving up an incline), driving behaviour (e.g., aggressiveness of acceleration and deceleration as well as speed limits), and ultimately also the vehicle itself whose aggregated energy consumption is determined by its components (e.g., drive train, air conditioning, etc.).

Agent based traffic simulations are well suited to track individual vehicles for a simulation run. Typically, traffic in these simulations is generated based on an origin-destination (O/D) matrix that describes (1) when an agent starts a trip, (2) from which location and (3) to what destination. The route can be pre-determined or computed dynamically in order to allow agents to react to emerging traffic conditions. The behaviour of individual agents is characterized by car-following behaviour models (for acceleration/deceleration) and lane-changing behaviour models that emulate human drivers. This in combination with realistic models of traffic lights, enables the realistic simulation of stop-and-go behaviour. The following sections explain each of these parts in more detail. A calibrated agent based traffic model is capable of producing traffic patterns very close to those observed in reality.

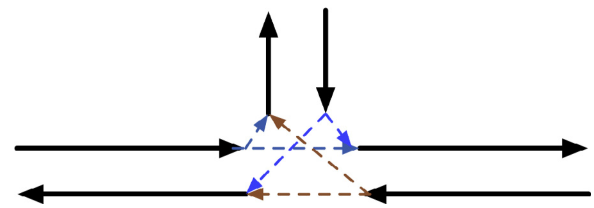


Fig. 1. This figure illustrates how traffic lights are modelled. Coloured links indicate links that are either accessible or inaccessible. At any point in time only one group of links is active. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

As discussed in Section 2, energy consumption of vehicles today is estimated using driving cycles. Driving cycles, however, cannot be used to estimate the temporo-spatial energy consumption and demand for an entire city as they do not contain any spatial information. In principle, every agent in an agent based traffic simulation generates a time-series of speed values. In addition, it is also possible to directly obtain data regarding the exact location of the agent at any time of the simulation as well as other data such as its acceleration/deceleration at that point in time. An agent based traffic simulation is thus a lot more versatile and provides more useful information as compared to using driving cycles.

In a broad sense, there are three parts to an agent based traffic simulation: a road network model that describes the structure of the road network on which traffic is simulated, a vehicle model that describes the behaviour and movement of the vehicle and a traffic model that links the road network model and the vehicle model by giving vehicles itineraries and routes based on real world information that is available.

3.1. Road network model

A journey of a vehicle is characterized by an origin-destination tuple that represents the origin postal code and the destination postal code. Areas in the map are defined through positions (latitude-longitude tuples) and more granularly, through postal codes. Locations on the road network which serve as origins and/or destinations of vehicle units are modelled through car parks[1] which occupy a single postal code. Each road in a road network is characterized by a starting and ending position and is itself divided into a number of lanes. Each car park may be associated with multiple lanes and vice versa. When an agent starts a journey it is placed on one of the lanes adjoining a car park located at its origin postal code. A bi-directional Dijkstra algorithm is used to determine the shortest route on the road network from this lane to one of the lanes adjoining the destination postal code. When the journey is complete and the vehicle reaches a lane adjoining the destination postal code, it enters into a car park at this location. Each road has a speed range that determines the preferred speed of vehicles driving on that road segment.

Traffic lights are located at certain intersections. Fig. 1 illustrates the structure of a typical traffic light intersection. Links are special roads that connect any two road segments in an intersection. Vehicles can traverse a link only if the link is in *active* state. Links are divided into groups such that at any given time, all the links in a group are active or *inactive*. Traffic lights are simulated by controlling the accessibility of these link groups. In the experiments in this paper, we simulate simple static traffic lights where the order and duration for which each link group is activated is pre-determined at the start of the simulation for each intersection.

[1] The term *car park* is used in the very general sense of an area where a vehicle parks.

Intersections are a critical part of road network models used for traffic simulation. The deceleration and acceleration of vehicles at intersections can have a significant impact on energy use. In the case of EVs, recuperative braking can result in lesser loss of energy during deceleration than in ICE vehicles [5,6]. Unlike traditional mathematical and simulation models, a nanoscopic traffic simulation of the kind presented in this paper is ideal for considering these situations. Crucial to this is the vehicle model that is described next.

3.2. Electric driver-vehicle unit model

The main entity in our computational model is the driver–vehicle unit (DVU) which consists of a *driver* component that determines driving behaviour like acceleration and lane-changing and a *vehicle* component that determines the energy consumption of the vehicle by simulating the various components of the vehicle.

Car-following models [28,29] determine the acceleration of a simulated vehicle at any given point in time. More specifically, given the position of a vehicle on a road segment, the car-following model determines the vehicle's movement and velocity at the next timestep of the simulation as a function of its preferred velocity, maximum possible acceleration (and deceleration), and the gap it prefers to maintain with the vehicle ahead. In the present paper, we make use of the Intelligent Driver Model (IDM) [28], which has two modes of operation. If there is enough space ahead of a vehicle, it moves at its preferred speed or tries to accelerate to this preferred speed; if such space is not available, a differential equation is used to determine a realistic acceleration for the vehicle.

On multi-lane roads, a model for lane-changing is also required for realistic vehicle movement simulation. The first kind of lane-changing occurs when the DVU needs to change lanes in order to take turns that are part of the path from origin to destination. The second type of lane-changing occurs when faster vehicles are behind slower vehicles and perform an overtaking manouevre by shifting to faster lanes if available.

The other component in the DVU is the vehicle unit itself. Since the purpose of the simulation is the study of electro-mobility, we simulate the battery and the various components of the car that pull energy from the battery. Currently, the energy consumption by the drive-train and the air conditioning are modelled. The energy used by the drive train is calculated as the total of the energy used to accelerate and move the car at the speed determined by IDM and the energy lost in the form of heat due to air resistance (which depends on the frontal surface area, the speed and drag coefficient of the car) and the friction on the road (which depends on the rolling friction coefficient, weight and speed of the car). Recuperative braking is also modelled; thus, when the vehicle decelerates (i.e., the brakes are applied), energy is fed back into the battery.[2] For simplicity, in this paper, we assume that the energy used up by air conditioning is a constant.

3.3. Traffic assignment

At the beginning of the simulation, each agent is assigned an itinerary from an itinerary dataset. This itinerary dataset is initialized from available data on daily commutes containing origin-destination and journey time information. However, typically, information is available only for a small subset of the population. Thus, both a temporal and a spatial extrapolation of the data need to be performed in order to realistically simulate the traffic for thousands or hundreds of thousands of vehicles.

Temporally, a Gaussian noise of up to 30 min is added to the starting times sampled from the available data. Similarly, the starting and destination postal codes are more evenly distributed over the road network by only considering the first two digits of a six-digit postal code and picking the remaining digits in a biased random manner from a list of valid postal codes.[3] The postal codes are weighted such that postal codes that actually occur in the data have a higher likelihood of being the origin (or destination). How this is done is most easily explained using the basic urn model. Assume an urn corresponding to the first two digits of a postal code, with coloured balls corresponding to each valid 6-digit postal code within that sector. If a specific postal code occurs n times in the data, then there would be $n+1$ instances of that ball in the urn. For each valid postal code that does not occur in the data, there would be one ball of that colour in the urn. Thus, in the simulation, the actual origin and destination of an agent is determined by first sampling an itinerary from the actual dataset. The first two digits of the location in the actual itinerary are then used to determine the urn from which the specific location is to be determined. A ball is drawn from this urn and the colour of the ball determines the exact location in which the agent starts (or ends) its trip.

Data on number of passengers in a vehicle, if available, can be added to the vehicle. This influences the weight of the car which, in turn, has an impact on the amount of energy used by the EV as explained in Section 3.2.

In the next section, we demonstrate through a case-study of Singapore the usefulness of the proposed computational model.

4. Case-study: Singapore

The purpose of the experiments in this paper are two-fold: to demonstrate the proposed computational model's usefulness in analysing the EV charging infrastructure requirements in Singapore; secondly, and more importantly, to demonstrate its capability and validity in simulating traffic and its effects.

The experiments are based on implementing the computational model described in Section 3 in a Singapore context. The road network was derived from Navteq 2009 data which provides information on the road network; it also provides information regarding number of lanes on roads and also the locations of about 250 traffic lights. However, due to the incomplete nature of this data, the network had to be extrapolated in places were information was missing. Data from the HITS 2008 survey was used for initializing traffic. This dataset provides origin-destination and trip time information of about 24,000 households in Singapore which, as explained in Section 3.3, was then used for generating traffic information about the 100,000 vehicles that were simulated. Typically, each vehicle has at least two trips associated with it for a given day, thus this corresponds to roughly 200,000 trips being generated. The number of passengers per vehicle was also extrapolated from the HITS data. The usage of HITS data also implies that only household vehicle (private vehicle) usage patterns are included in the experiments in this paper. This is sufficient for the purposes of this paper where the primary aim is to demonstrate the new approach. Also, an analysis on only household vehicles would more accurately reveal the infrastructure required to encourage large scale household adoption of EVs which would likely be different from the infrastructure required to support the public transport network.

[2] Recuperative braking is done in all modern EVs [30].

[3] In the Singapore context, the first two digits represent the sector code. More generally, this approach would still be valid for spatial extrapolation of any data where spatial data is available as postal codes.

Table 1
IDM parameters used for modelling aggressive as opposed to normal driving (Section 4.1).

	Normal	Aggressive
Max acceleration (m/s^2)	1.4	3.0
Max deceleration (m/s^2)	2.0	3.0
Minimum gap (m)	2.0	1.0
Time headway (s)	1.5	1.0

Table 2
Average energy consumption and velocity of vehicles of the experiment described in Section 4.1. Aggressive driving results in more battery usage.

	Normal [mean (SD)]	Aggressive [mean (SD)]
Energy (Wh/m)	0.2186 (0.0051)	0.2306 (0.0037)
Velocity (km/h)	79.971 (0.555)	86.713 (0.171)

4.1. Advantages of using a nanoscopic traffic simulation

As mentioned in Section 2, there have previously been studies that have used simpler agent based traffic simulations to study charging demand. In this section, we demonstrate through a simple experiment the advantages that a higher resolution nanoscopic simulation based approach offers. We simulate traffic on a shorter 13 km stretch of a four-lane expressway in Singapore and determine the effect that driving aggression can have on energy consumption. Hundred replications of the simulation of 500 agents is run and their average energy and velocity computed. Agent spawning rate is defined by a Poisson process with an average inter-arrival duration of 5 s.

The parameters of the car-following model, IDM in the present case, can be chosen to model different types of drivers. As described previously, the movement of vehicles in IDM is determined by four parameters: maximum acceleration, maximum deceleration, minimum gap to the vehicle in front and desired time headway to the vehicle in front. These four parameters can be adjusted to model different kinds of driver behaviour. Kesting et al. [31] have identified parameters for different behaviour classes. In the present experiments, we simulate aggressive drivers (using parameters shown in Table 1) and determine the difference in energy consumption. Being an expressway in Singapore, the speed range on the highway is between 72 and 100 kmph. The preferred speed of each agent is sampled randomly from this range when it is spawned in the environment. However, despite having the same preferred speed, aggressive drivers do not just have a higher average velocity, they also consume more energy per km as shown in Table 2. This indicates that taking driving behaviour into consideration can have an impact on energy usage. Please note that the average energy usage is higher than observed later because these are cars on an expressway that travel much faster and thus consume more energy/km.

4.2. Validation of the traffic extrapolation

A fundamental component of the simulation is the traffic assignment from the HITS data and the spatial and temporal extrapolation that is performed (explained in Section 3.3). The spatial distribution of the HITS data, is given by the trip length histogram in Fig. 2(a) and the temporal distribution in Fig. 2(b). The former figure shows that there are few trips that are shorter than 2 km; the majority of the trips are between 3.5 km and 18.3 km. The latter, with two peaks in travel start time distribution, is also typical of a city like Singapore with a 9-hour work day starting around 8 am.

It would be expected that similar patterns are observed in the simulation of 100,000 vehicles. Fig. 2(c) and (d) shows that this is indeed the case.

4.3. Electro-mobility feasibility analysis

The aim of the experiments described in this section is to determine how charging infrastructure will have to be developed in Singapore if a large scale conversion to EVs were made today while maintaining today's mobility patterns. Seventeen replications of a 24-hour day in Singapore were simulated with 100,000 vehicles[4]; logs of the vehicles' SoC and trajectories were kept and analysed. Since our objective is to find the typical energy consumption of an EV driver with the least disruption (in the form of visits to charging stations) of his/her current daily commute, we assume that each DVU does not run out of charge during the course of the simulation; this is done by giving each vehicle an infinite SoC initially. The main parameters used for the simulations are described in Table 3. Fig. 3, which shows the average energy used per vehicle per meter, indicates that the median energy consumption per meter is 0.1702 Wh/m. When compared against commercially available cars and values that manufacturers state, the energy use is just above the BMW i3 consumption of 0.169 Wh/m and below the Fiat 500e with 0.181 Wh/m.[5]

4.4. Energy usage statistics for a typical Singapore day

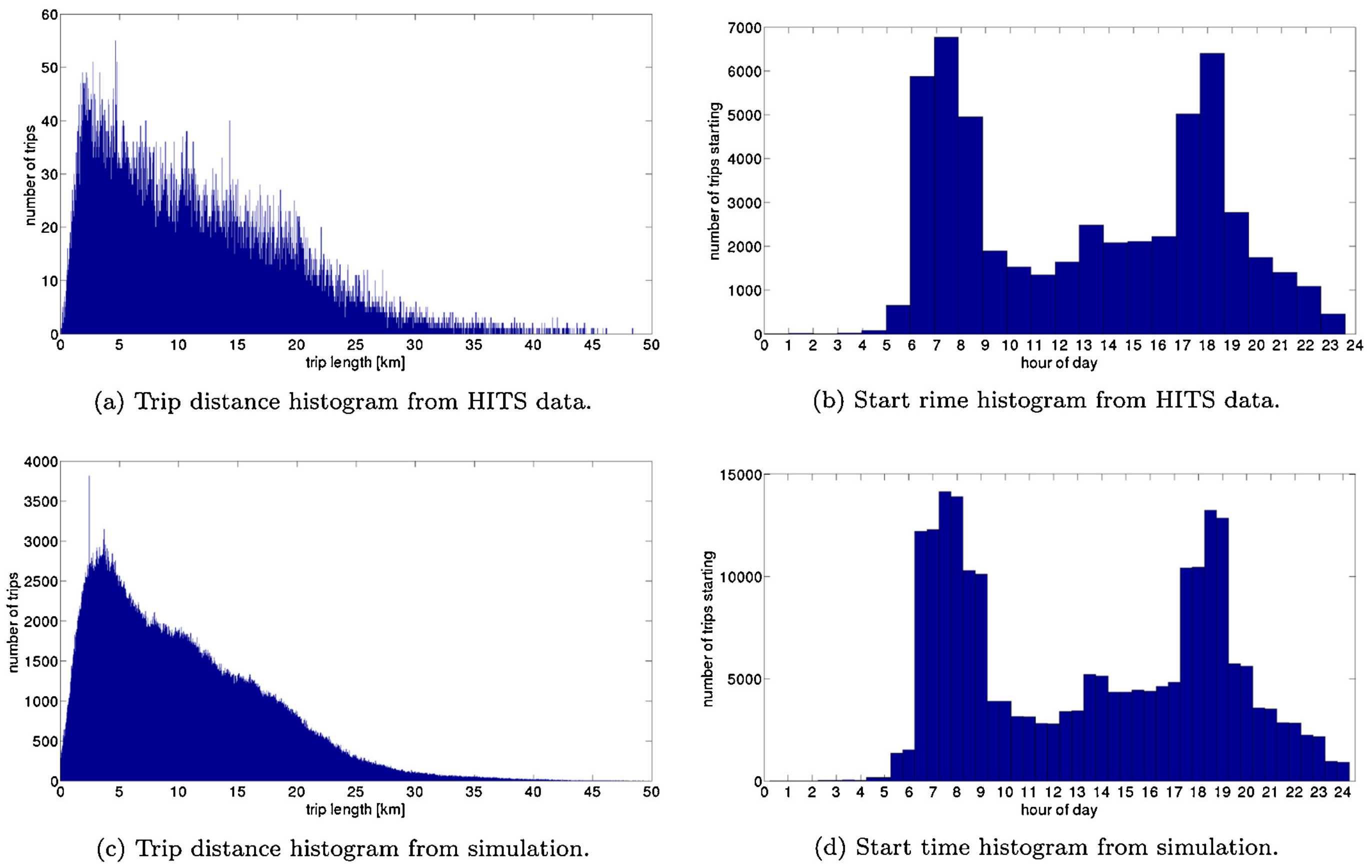
As described earlier, one of the advantages of using the nanoscopic simulation of the kind that is used, is that it allows us to estimate the energy used by a vehicle during a typical commute while taking into account the traffic and driver behaviour. This information is obtained for each of the 100,000 agents in the simulation and their SoC at the end of the day is plotted in Fig. 4.

The graph suggests that less than 10% of the driving population uses more than 7.2 kWh of energy; and less than 1% use more than 12.32 kWh. Even accounting for more battery usage in case of unexpected traffic jams or similar cases, most modern EVs will easily be able to satisfy this demand with just one long charge a day. This is likely because, unlike major cities in the United States and Europe, long distance trips are much rarer in a city as small and densely populated as Singapore.

These results suggest that a large scale conversion to electromobility should be possible in Singapore without existing drivers having to change their behaviour. Nevertheless, an important pre-condition for this to happen, as discussed earlier, is the development of the requisite infrastructure, i.e., charging stations, to handle this demand. A primary difficulty in EV adoption is the time taken to charge vehicles. In the work discussed in Section 2, it is generally argued that to address the difficulty of vehicles that actually use 10 kWh or more energy during the day or to address the general range anxiety of drivers, charging stations should be uniformly distributed [1,2]; at least along the most common routes taken by daily commuters. This is the approach taken by most of the studies discussed in Section 2. However, considering that even fast charging today takes more than 10 min, the availability of a fast charging station is unlikely to solve this issue in a satisfactory manner. It is also assumed that all EV drivers will have charging facilities at their homes. This, however, is a difficult assumption to make in Singapore where most people live in public housing estates where installation of private charging points is more difficult. Thus, the question still remains as to where these expensive charging stations are to be placed. In the next section we explain how the proposed agent based simulation provides a novel method for solving this problem.

[4] The performance of the simulation is dependent on the amount of traffic on the road. In the worst case, when there are 10,000 active vehicles on the road, the multithreaded simulation with 16 cores achieves a minimum speed-up of 5.5 times, i.e., 5.5 s are simulated in 1 s.

[5] http://www.fueleconomy.gov.



(a) Trip distance histogram from HITS data.

(b) Start rime histogram from HITS data.

(c) Trip distance histogram from simulation.

(d) Start time histogram from simulation.

Fig. 2. These figures show the trip distance and the start time histograms for the HITS data and the simulation for the purpose of validation. The data generated from the simulation is seen to be equivalent to the real world HITS data from which it was generated.

Table 3
List of parameters and values used for the simulation.

	Value
Vehicle weight	$\mathcal{N}(1{,}500{,}200^2)$ kg
Max acceleration	$1.4 \pm 0.2\,\mathrm{m/s^2}$
Max deceleration	$2.0 \pm 0.2\,\mathrm{m/s^2}$
Minimum gap	2.0 m
Time headway	1.4 s
Vehicle length	$\mathcal{N}(400, 10^2)\,cm$
Car-following model	Intelligent Driver Model
Road network characteristics	
Number of road segments	244, 971
Number of nodes	168, 684
Some results	
Energy consumption per meter (median)	0.1702 Wh/m
Average trip length – HITS	10.87 km
Average trip length – simulation	10.31 km

4.5. Determining charging station locations

One possible method, in which the interpolated HITS data could be used to determine charging structure placement is by simply plotting a histogram of the trip origins of vehicles and placing charging stations at the most frequent starting points. Fig. 5 shows this histogram in the form of a heatmap. However, this does not give an estimate of which locations have a more crucial need for charging stations. In order to do this, it is important to first identify the commuters whose needs have to be satisfied first. We hypothesize that the commuters with the lowest SoC at the end of the day have to be serviced first. This is based on two assumptions: (1) These commuters will neither have the time nor the battery capacity to go to charging locations that are farther away; (2) other commuters that use less of their capacity can go to these locations to satisfy their charging needs as required without fear of running out of charge.

Using the simulation, it is possible to determine the origins (and destinations) of the trips that end with the vehicle having the lowest SoC. From the experiments in the previous section, we assume that each vehicle has a battery capacity of 10 kWh and plot the number of vehicles that have below 15% SoC at the end of the day. The drivers of these vehicles are most likely to feel range anxiety and it is their needs that will need to be addressed first. Another factor that needs to be taken into consideration is the time taken to charge the vehicle. This can be taken into consideration in the histogram by filtering out those trips in which the vehicle had been at its origin for less than 2 h. The resulting histogram is shown in the form of a heatmap in Fig. 6.

Fig. 6 gives some locations that are likely to be best locations for placement of charging infrastructure. With the three most beneficial areas being near the central business district where a large proportion of Singapore residents are employed, towards the west and north-east ends of Singapore where commuters are likely to have to travel large distances to either get to or back from work. In order to determine whether these distances are traveled during a commute to work or from work, the temporal distribution of checkouts of these vehicles at these three locations were plotted as a histogram in the same figure. We can see that in the north-east the long distances are travelled by morning commutes indicating that this is probably occurring during a trip to work; while, for the other two locations this seems to be happening on a trip back from work. The temporal histogram is also useful in determining the rough demand of the charging station at any given time. However,

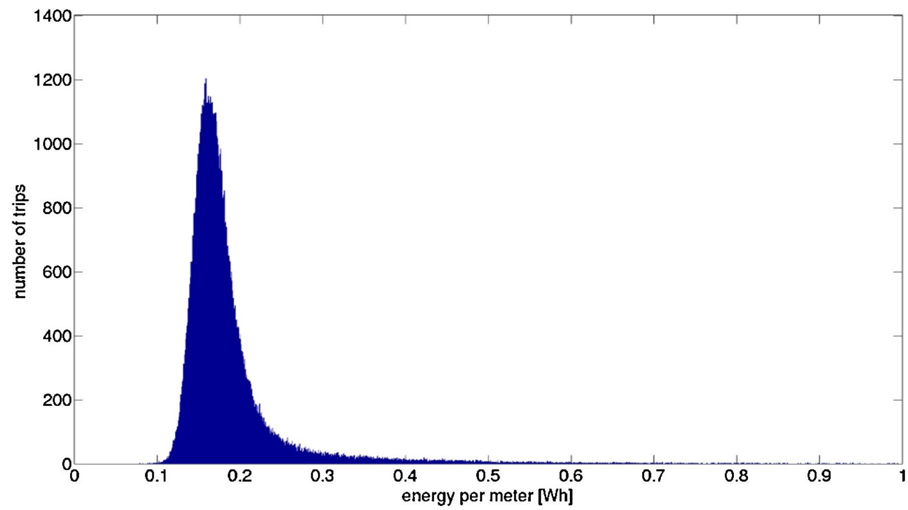


Fig. 3. Histogram of the average energy use per meter on a trip.

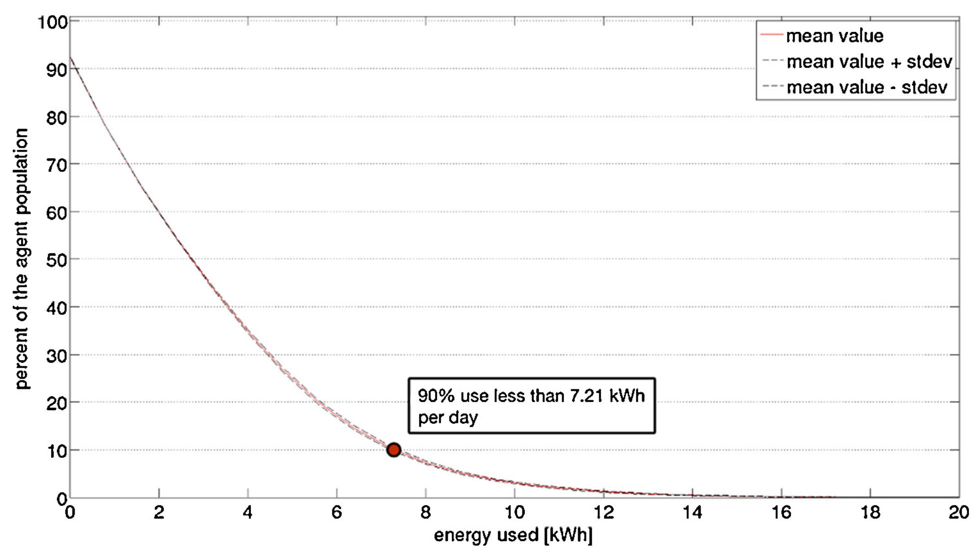


Fig. 4. This figure shows the amount of energy used for day driving in Singapore without charging. Less than 10% of the population use more than 7.2 kWh.

it is difficult to determine an exact number without making some approximations of charging time and vehicle types.

5. Discussion

The experiments in Section 4 demonstrated how existing data on road networks and daily traffic patterns could be used to plan and prepare for future electro-mobility through a city-scale nanoscopic traffic simulation. Locations for charging stations were proposed so that vehicles that currently consume the most energy daily will have access to charging stations without additional travel. We hypothesize that, at least initially, the remaining drivers will have enough battery capacity remaining to travel to one of these locations to satisfy their charging requirements. Unlike existing methodologies, the proposed modelling and simulation based method takes into consideration the effect of driving patterns, traffic and the existing real world road network. In a real world scenario, it would be necessary to run multiple iterations of the proposed process with a realistic, calibrated charging behaviour model to determine the locations of subsequent charging stations.

The number of vehicles originating at each location and over time as shown in Fig. 6 gives an approximate idea of the number of charging points that are required at each of the charging stations; i.e., we know that a little more than twice as many charging points are probably required in the central location than in the west and north-east. However, exactly how many charging points should be built is a policy decision that needs to take into consideration various other factors like finances, the speed of charging infrastructure development, the different charging requirements of the vehicles, the impact on the power grid, etc. Some of these factors can be studied with extensions to the basic method presented here. Heterogeneous charging requirements and vehicle types can be added to the model without affecting any other component; the impact on the power grid could be studied by coupling the proposed simulation with a power network simulation [32].

It is important to note that the quality of the results produced by the proposed method depends on the quality of the input data i.e., the road network and traffic data available. For the Singapore case study, we used available data about the road network and origin/destination distributions which covers roughly 1% of the population. This amount of data may not be enough to come to any definite conclusions regarding charging infrastructure development for Singapore.

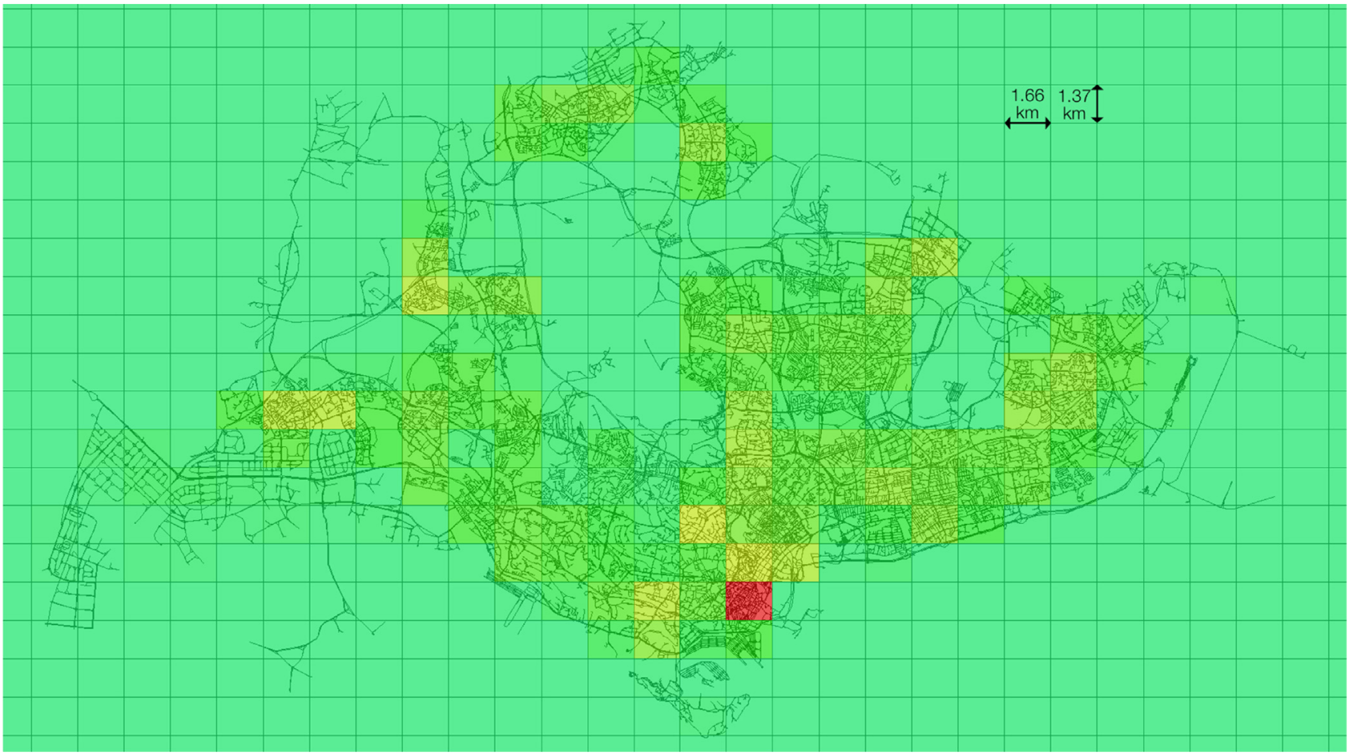


Fig. 5. Trip origins are fairly equally distributed across Singapore so it is difficult to determine best locations for charging stations.

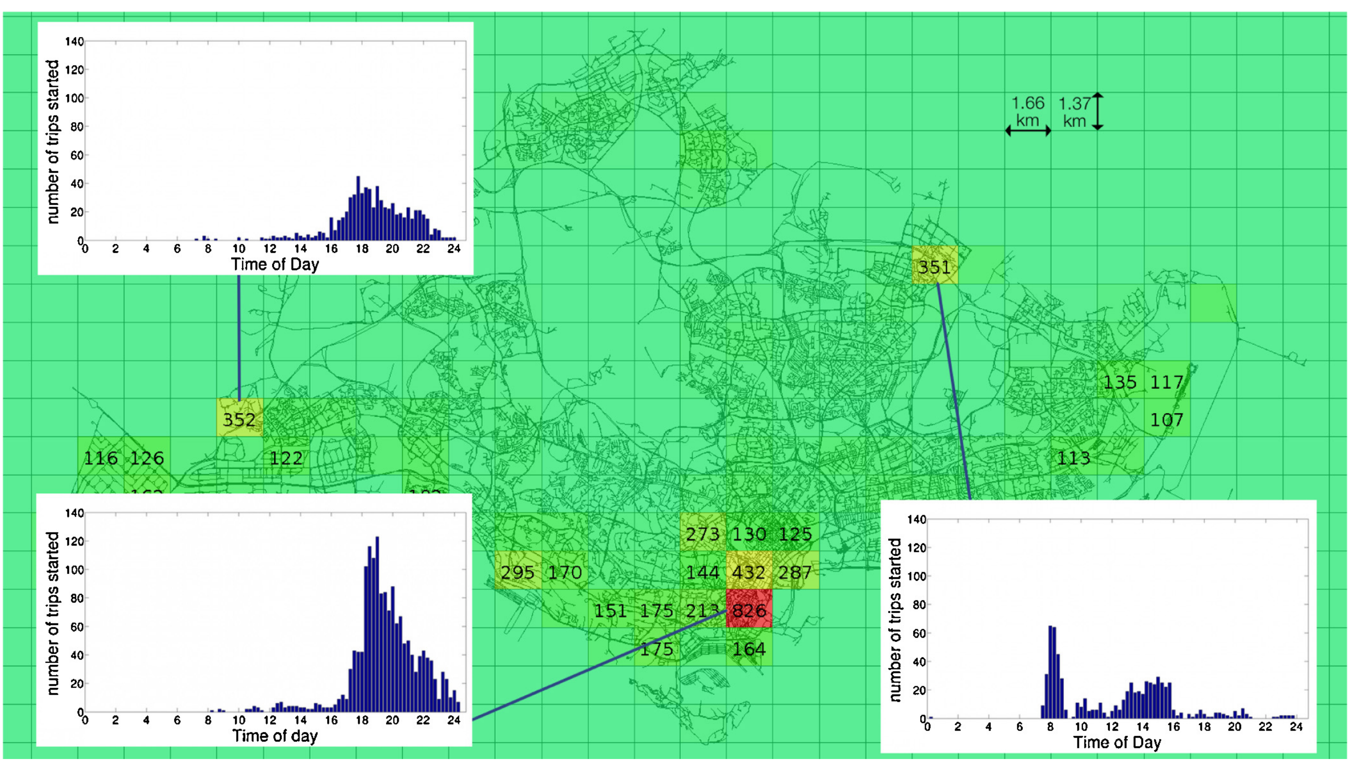


Fig. 6. This heatmap shows the last trip origins of vehicles which had less than 15% SoC at the end of day and were at this origin for more than 2 h (i.e., long enough to charge). It can be seen that some locations are clearly better suited for charging station placement. The histograms show the temporal distributions of checkouts of vehicles that end up with less than 15% charge.

6. Conclusions

In order to continue the rapid urbanization taking place today in a sustainable manner, a large scale transition to electro-mobility is probably necessary. However, this transition is hampered by a lack of charging infrastructure which, in turn, discourages consumers from buying EVs. In this paper, we used a nano-scale agent based traffic simulation to determine the viability of EVs in a city, given information on the road network and daily traffic patterns. Subsequently, a methodology for developing plans for charging infrastructure was proposed and demonstrated through a city-scale traffic simulation of Singapore. The traffic simulation has three major components: a vehicle model that simulates driver behaviour, vehicle movement and energy consumption; a road network model generated from real world data; and a traffic assignment model to generate realistic traffic patterns in the simulation from real world data.

Using the simulation it was determined that existing EVs will be able to satisfy 99% of the current daily traffic demands in Singapore on a single charge. The data from the simulation was then used to determine the ideal locations for charging stations so that range anxiety concerns of commuters could also be addressed. For more reliable results, it is necessary to get more detailed and more recent data on the road network and travel patterns in Singapore. Nevertheless, we believe the proposed methodology opens possibilities for new types of research that was traditionally not possible.

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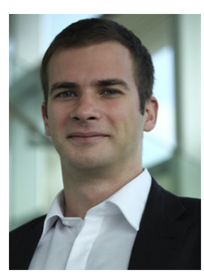

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