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New simulation tool of electric taxi services for analysis of charging infrastructure placement

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1. Introduction

The world is currently seeing a shift away from fossil-fuel-based transportation to transport options powered by alternative means. Electric vehicles (EVs) are playing a major role in the decarbonisation of transport systems, especially in countries where electricity can be generated sustainably. While charging systems for EVs are getting more efficient and faster, an alternative approach to conventional plug-in charging for EVs is by wirelessly charging using inductive power transfer (Covic and Boys 2013). Here, charging pads can be embedded in the road surface and charge vehicles that are stationary above the pads, or even moving vehicles – there may be no need plug in or even to stop the vehicle. This wireless technology improves convenience for EV users. If EVs can charge on the road, they may be able to have smaller battery capacity, hence lower weight leading to higher vehicle efficiency. While it may not be feasible in the near future to universally embed charging pads under the road surface, an initial approach to the rollout of wireless charging infrastructure could be to install charging pads targeted at groups of high-mileage transport users. One such example group is taxis as they drive long distances every day and are often early adopters of efficient vehicle technologies such as EVs. EV taxi drivers would benefit from the convenience of being able to charge on-the-go as long as charging infrastructure is placed strategically. We aim to develop an understanding of what kind of infrastructure would be required to support the operations of a taxi service that either operates exclusively with EVs or at least has a large portion of EVs available.

In some locations electric taxi (e-taxi) services are already operational and optimal placement of charging systems has been studied for these locations based on observed taxi movements and charging demand (Tu, et al. 2016). If only a conventional (non-electric) taxi service exists in a location, a data-driven approach can be taken (Yang, Dong and Lin 2016; Hu, et al. 2018) to analyze whether electrifying a taxi fleet is feasible based on the ability to cover past (conventional) taxi trajectories. Asamer, et al. (2016) develop an optimization model for e-taxi charger locations assuming that good locations for charging are where many (conventional) taxi trips start or end, without consideration of when e-taxis would actually need to charge or how many chargers are needed. The approaches outlined above are unable to take into account timing and convenience of charging, or how e-taxis may adjust their trajectories in response to provision of charging infrastructure in certain locations, which we want to consider in an optimization-simulation approach. We are interested in understanding how to best support the transition of a taxi service from conventional vehicles to EVs. This means we cannot draw on data on charging demand from an existing e-taxi service. Instead, we are developing a simulation tool that allows us to simulate the operations of a taxi service based on location and time of passenger requests that are then serviced by taxis moving through the system. The simulation models the behavior of e-taxis, including their charging needs and ability to service requests based on battery state-of-charge (SOC). We can thereby develop an understanding of spatio-temporal demand for charging, which in turn will enable us to develop an optimization-simulation approach in the future to identify where chargers are needed, what types are needed, and that allows for calibration of charging infrastructure such as charging power levels. Similar optimization-simulation tools are also being used to optimize operations in other fields such as ambulance services (Ridler, Mason and Raith 2022).

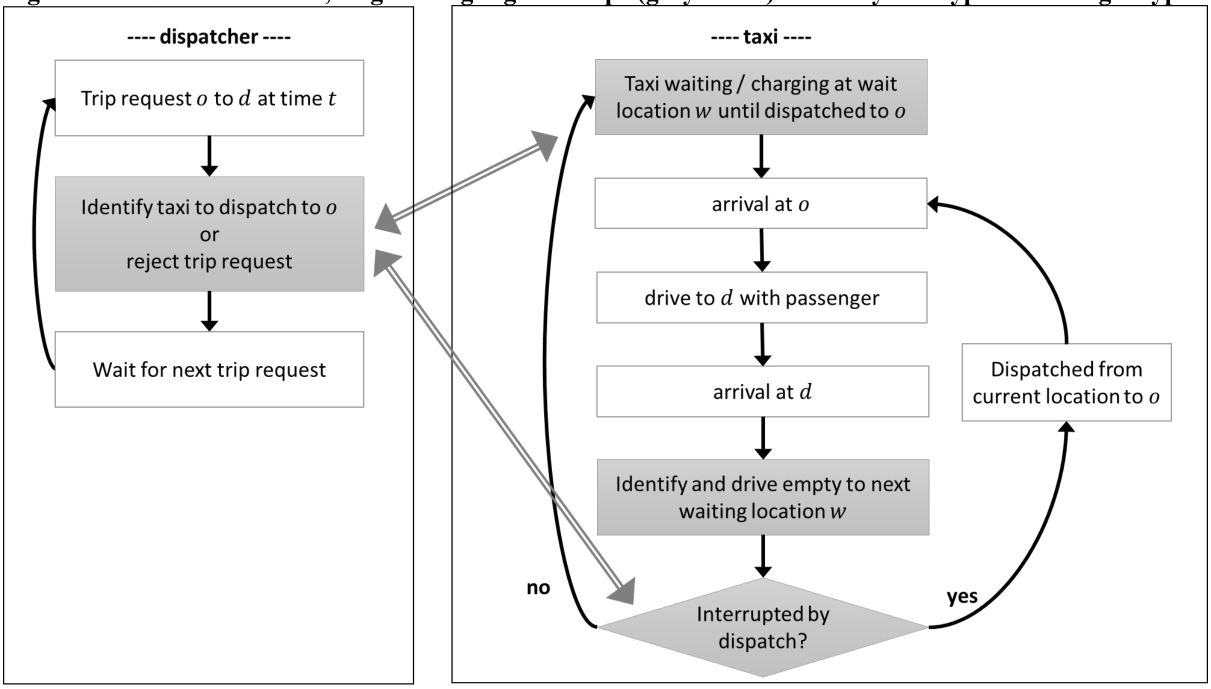
While there appear to be no commercial taxi simulators, we note that other simulation tools for transport-on-demand services, taxis and e-taxis have been developed. Bischoff and Maciejewski (2014) develop a model of e-taxi operations in MATSim assuming mixed or electric-only fleets, that slow / fast chargers are available at all taxi ranks, and assuming different dispatch scenarios. Similarly, Jäger, Wittmann and Lienkamp (2017) develop a taxi simulation in Java (using a framework called JADE) that is calibrated for regular combustion vehicles and then applied to e-taxis, enabling a comparison of the two simulated systems. Simulation software does not appear to be publicly available in either case. Adenaw and Lienkamp (2021) present an updated version of the latter implemented in MATSim. Our presented approach stands out in the choice of language (Julia), and ability to draw on open-source data (OpenStreetMap). It enables us to capture and track features of an e-taxi services as required, will permit easy integration with optimization tools and will eventually be made available open-source.

2. Methodology e-taxi simulation

Our **E-T**axi **SIM**ulation (ETSIM) is a discrete event simulation, as described in the following. It is assumed that there is a number of taxis available somewhere in the system. A prospective passenger either hails a taxi from a taxi rank, or places a call with a call centre that then dispatches a taxi to the requested pick-up location. The dispatched taxi travels to pick up the passenger and drives them to their destination. Once a taxi arrives at the destination, the passenger disembarks, and the taxi is idle. An idle taxi can either pick up another passenger, if there is a passenger request that needs to be serviced, or it can return to a waiting location, such as a taxi rank of its choice. In case of an e-taxi, before accepting a passenger, an additional consideration is whether the taxi is able to transport a passenger to their destination, that is whether there is sufficient battery SOC for the trip and return to a charging station. Otherwise an e-taxi may need to reject a potential passenger, which is especially undesirable in case of lucrative (long) trips. An idle taxi's choice of waiting location may be affected by the popularity of the location, i.e. how many passengers start their journey at or close to a waiting location, the need to re-charge their battery and convenience of doing so. ETSIM enables us to track metrics such as SOC throughout an e-taxi's working day, rejected passenger trips due to insufficient SOC or because a taxi is charging, utilization of chargers, additional driving required to reach chargers, etc. This will ultimately enable us to develop an integrated optimization-simulation approach to optimize location and type of charging infrastructure.

We chose to implement ETSIM in Julia as it is a modern programming language that is known for its ease of use and speed. It also has powerful packages available that support simulation (SimJulia) and optimization (JuMP).

Figure 1: ETSIM flow chart; Logic in highlighted steps (grey boxes) varies by taxi type and charger type.



The flow chart in Figure 1 outlines the process of ETSIM for general taxi operations. Firstly, the dispatcher logic on the left of Figure 1 outlines how a taxi trip request from a trip origin o to trip destination d is processed at simulation time t. A suitable taxi is identified and dispatched to pick up the passenger at their origin o. If this is not possible within some time frame (e.g. all taxis are busy or have insufficient SOC), the trip is rejected. The dispatcher then waits for the next trip request. The taxi logic is shown on the right of Figure 1. Taxis wait at a waiting location w, such as a taxi rank until they are dispatched to pick up a passenger at location o (this location could be the taxi rank where the dispatched taxi is already waiting, in which case it arrives at o to pick up the passenger immediately). The taxi then drives to destination d. Upon arrival the taxi determines their next waiting location w and starts driving towards it. A taxi driving without a passenger can be interrupted and dispatched to pick up another nearby passenger. If this does not occur they eventually reach their waiting location w. Some of the decision making logic in the simulation differs between e-taxis and regular taxis, and for wireless and plug-in charging, as outlined below. This affects the highlighted elements in the flow chart (Figure 1). SOC plays a major role when making decisions for e-taxis. We define three parameters, SOC_{charge}, the SOC level threshold below which e-taxi drivers will seek to charge immediately, SOC_{max}, which is the SOC level to which drivers will charge at a plug-in charger and SOC_{min}, which is the minimum charge level at which a wirelessly charging taxi will accept a passenger trip.

Taxi – Identify and drive to next waiting location: Regular taxis and e-taxis with sufficient charge will seek out a taxi rank to wait at based on a utility function that takes into account distance to rank, popularity of rank, and the number of taxis already waiting there. If $\mathrm{SOC} < \mathrm{SOC}_{charge}$ e-taxis need to charge urgently, and will drive to the closest taxi rank that has a charger available. Once a taxi in need of an urgent charge arrives at a rank it will charge immediately at an available charger. If there is a plug-in charger, the taxi charges until SOC_{max} is reached and then joins the queue at the rank from where it can be dispatched. If there is a wireless charger available the taxi joins the queue *while charging* (as long as a charger is available at their current position in the queue). If there is only a wireless charger, the e-taxi will join the queue while charging, or wait for an available charger. A wirelessly charging e-taxi can be dispatched once a charge level of SOC_{min} is achieved. If not dispatched, it will continue charging until the battery is full, even when the battery reaches an SOC beyond SOC_{max}. A queueing e-taxi with full battery can block access to a wireless charger.

Dispatcher - Identify taxi to dispatch: Taxis dispatched from a rank are always the first in the queue (unless it is a wirelessly charging e-taxi and has not yet reached SOC_{min}). The taxi to be dispatched will be chosen from a rank if the passenger's origin location o is at a rank. Otherwise the taxi closest to o will be dispatched, which is either a nearby driving taxi without passenger, or a taxi at a nearby rank. If an e-taxi is to be dispatched, this can only happen if it has sufficient SOC for the whole trip and subsequent return to a charging location. E-taxis that need to charge ($\mathrm{SOC} < \mathrm{SOC}_{charge}$) cannot be interrupted while driving to a charging location.

ETSIM tracks SOC for each individual e-taxi in the simulation. It is currently assumed that e-taxi energy consumption is proportional to distance driven, and that there is no energy consumption when not driving. More sophisticated energy consumption models could be implemented and may be more appropriate in locations with extreme temperatures, significant hills, or inner-city start-and-stop traffic. Charging can be modelled by a non-linear charging time function.

The following input data is required by ETSIM:

- Road network: can be sourced from OpenStreetMap https://www.openstreetmap.org
- Passenger trip data: This is ideally historical data for a regular or e-taxi service, which provides trip origin and destination (mapped to the road network) as well as time of trip request. It is assumed taxis travel along the shortest path from origin to destination.
- Taxi ranks: location, capacity, number and type of chargers.
- Number of taxis operating: Can be derived from a taxi shift plan.

ETSIM Output: The simulation tracks various metrics of interest such as the number of passenger requests that could not be serviced as no taxi was available, the waiting and charging time of taxis, the number of passenger requests a taxi had to turn down due to insufficient SOC, etc. We can track any metric we require since ETSIM is a purpose-built simulation.

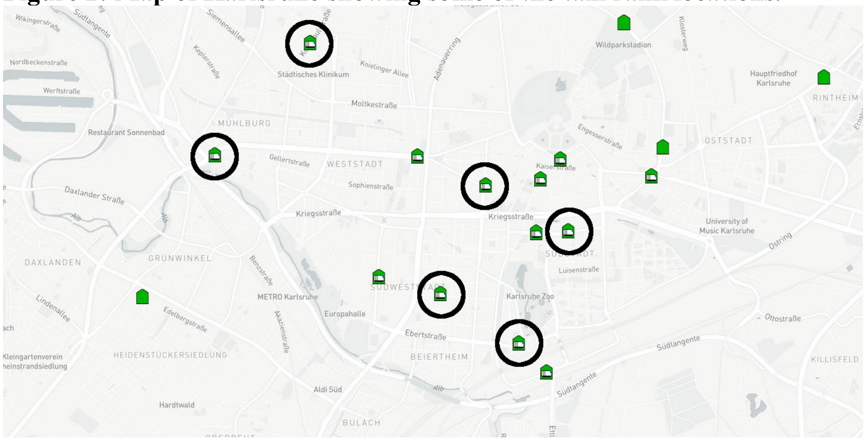
ETSIM Implementation details: ETSIM is implemented in the Julia programming language, which is known for its relative ease of use, speed and versatility. The simulation itself uses the SimJulia package. We are currently developing a browser-based visualization that will help visually analyze simulation results and make it easier to verify correctness of simulation logic and to communicate results to potential users and practitioners.

3. Case study Karlsruhe

We present a case study of the taxi operations in the city of Karlsruhe, Germany, see Figure 2. There is a single central taxi management unit in the city. In accordance with German legislation, taxis are required to drive back to a taxi rank after each passenger trip. Passengers can hail a taxi at one of the ranks, or they can arrange to be picked up by a taxi at a different location. There are 26 taxi ranks (shown as green houses in Figure 2), where the busiest one is located next to the train station almost at the bottom of Figure 2. Ranks have limited capacity for waiting taxis and the number of (simulated) chargers available (wireless and plug-in) varies by rank. There is a varying number of taxis operating depending on time of day.

We have a dataset of taxi trip requests over a four week period in summer 2017. Taxis cover a total daily average of about 200 km with many short trips. We assume there are only e-taxis with an energy consumption of 25 kWh per 100 km and a battery with 35 kWh capacity.

Figure 2: Map of Karlsruhe showing some of the taxi rank locations.



It is assumed that plug-in chargers have a maximum charging power of 50 kW. For wireless inductive charging, we assume a very conservative additional energy loss of 10% and charging power of 20 kW. In ETSIM chargers are located at eight of the 26 taxi ranks, ranks with chargers are circled in Figure 2 (nine of the ranks, including two with chargers, are located outside the map area). We set $\mathrm{SOC}_{charge} = 60\%, \mathrm{SOC}_{max} = 80\%, \mathrm{SOC}_{min} = 30\%$ relative to battery capacity.

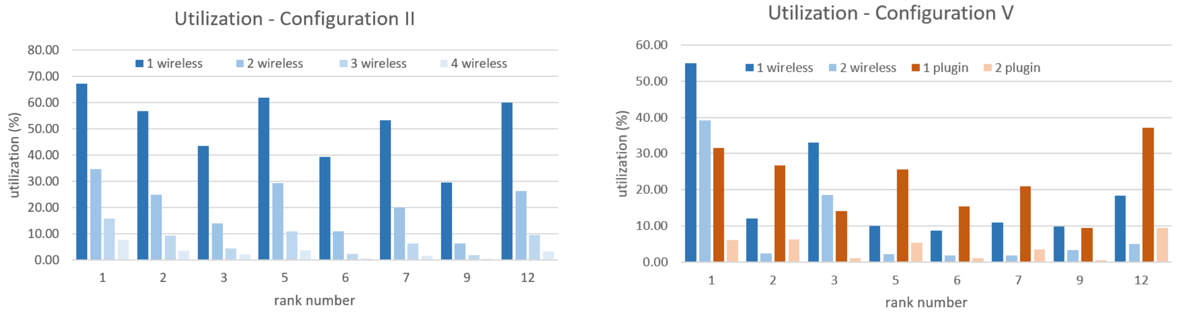
As a case study we run the simulation repeatedly over a time period of one week during which there are 11,775 taxi trips. The number of chargers and their type can be varied. In an initial experiment we place the same number of chargers at each rank that is equipped with chargers leading to the five configurations listed in Table 1. We can make a few observations for our preliminary experiments. Firstly, when charger numbers are low (two wireless or plug-in chargers), many trip requests cannot be serviced due to unavailability of a taxi with sufficient SOC (Row *Missed trips* in Table 1). Since plug-in chargers are modelled to have a higher charging power, fewer trips are missed with plug-in chargers compared to the same number of wireless chargers. It is interesting to note that even fewer trips are missed when plug-in and wireless charging is combined in Configuration V. However, with plug-in chargers taxis cannot join the queue and may end up with longer wait times after charging. Wireless charging can occur conveniently while waiting. In Configuration II, for instance, there are almost 9,000 instances where taxis request a charger (while waiting in queue), while in Configuration IV there are only 2,606 requests when an e-taxis request to charge urgently. In Configuration V there are even fewer urgent charge requests for plug-in chargers (1,880) as more wireless charging occurs while taxis wait in the queue. These initial results show that it may be a to combine convenient wireless charging that can occur while queueing with faster plug-in charging for e-taxis with low SOC.

Table 1: Number of chargers at each taxi rank and some simulated metrics

Configuration	I	II	III	IV	V
Wireless	2	4	-	-	2
Plug-in	-	-	2	4	2
Missed trips	2,276	1,316	115	103	77
#charge requests / %waits	9,015 / 30.7%	9,840 / 5.5%	2,601 / 11.5%	2,606 / 0.5%	W: 5,934 / 30.5% P: 1,880 / 7.4%
Avg wait time (min)	7.44	5.11	6.93	3.32	W: 6.09 P: 5.34
Total energy (kWh)	17,883.0	19,761.2	24,460.6	24,334.3	W: 6,775.5 P: 17,884.2

Various metrics can be tracked throughout the simulation. For example, Figure 3 shows utilization of each of the chargers at the various ranks equipped with charging under Configurations II and V. It can be seen that wireless chargers generally have high utilization under Configuration II, although this can drop off quickly for the other chargers at a rank. In Configuration V, wireless charger utilization is much lower for some ranks, and utilization of plug-in chargers drops off quickly as well, likely due to faster charging and the fact that e-taxis only charge urgently but not casually while waiting in queue for their next trip. We can also see here that some ranks have particularly high utilization of both types of chargers, which indicates that rearranging chargers between ranks could improve performance of the system further. We observe that a wireless charger is only rarely being blocked by a waiting taxi that is not charging as its battery is already full. This happens no more 1.3% of the time, in the worst case.

Figure 3: Charger utilization for Configurations II (wireless only) and V (mixed).



We can also analyze taxi operations. Table 2 shows some metrics collected for the first five taxis in Configuration V (mixed charging). The second column of Table 2 shows wait time in the taxi queue (min). A significant amount of time is spent waiting for the next trip, while taxis generally do not wait long for a plug-in charger (last column). On average, e-taxis spend 34.22% of their queueing time waiting for a charger, which is not surprising as they always seek to charge wirelessly while in the queue. The table also shows that taxis make 18.11 plug-in charge requests on average (third column). In comparison, more wireless charge requests are made as taxis seek to charge wirelessly whenever waiting in the queue. Taxis often have to wait for wireless chargers when they are blocked by other taxis.

Table 2: Number of chargers at each taxi rank and some simulated metrics in Configuration V

Taxi	Queue wait time (min)	#charge requests	#times taxi had to wait for charger	Total wait time to charge
1	308.32	W: 65 / P: 22	W: 20 / P: 2	W: 128.33 / P: 7.88
2	207.77	W: 45 / P: 18	W: 14 / P: 0	W: 68.56 / P: 0.00
3	285.24	W: 68 / P: 21	W: 20 / P: 2	W: 82.96 / P: 4.52
4	320.79	W: 67 / P: 27	W: 23 / P: 1	W: 199.34 / P: 7.26
5	344.15	W: 68 / P: 25	W: 20 / P: 4	W: 140.53 / P: 39.95
Avg	319.71	W: 59.34 / P: 18.80	W: 18.11 / P: 1.40	W: 110.31 / P: 7.48

4. Future work

Our ultimate goal is to be able to use ETSIM to understand how to best design and support an e-taxi service in a location where taxis are currently exclusively or predominantly conventional vehicles (or hybrids). ETSIM can help us understand where there is a need for charging, whether an e-taxi service can operate reliably despite limited battery capacity, and how charging is best integrated into an e-taxi, etc. Particular aspects of interest are whether there is an advantage in integrating queueing and charging, and to develop a better understanding of what specifications wireless chargers would need to meet to be able to support e-taxi operations while giving drivers confidence in using an EV rather than a conventional vehicle. We chose to develop ETSIM in Julia as it allows the seamless integration of optimization and simulation, which will enable us to optimize system parameters to find best value for money investment options for charging infrastructure, and thereby identify how to best support the transitioning of an existing taxi service to higher or exclusive use of EVs. In the shorter term, there are several details in ETSIM that could be improved (dispatcher and taxi decision making logic, taxi charging and queueing, real-time travel times, energy consumption model, etc), including the choice of some of the core parameters in the simulation such as charging power, energy loss and the SOC levels that are core to the simulation logic.

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