Fuel and Infrastructure Options for Electrifying Public Transit: A Data-Driven Micro-Simulation Approach

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MAIN BODY

Transportation electrification has been widely regarded as an effective initiative to reduce carbon emissions and therefore public transit, as a principal contributor in the transportation sector, has undergone tremendous changes for electrifying [1, 2]. Electric vehicles (EVs) have been widely introduced into the bus fleet, but there are some issues with battery electric buses (BEBs), such as long recharging time (which leads to the low operational efficiency of the whole bus fleet). It has been recently argued that hydrogen buses (HBs) might be a more promising option for electrifying public transit system, as their refueling time could be much shorter. However, the cost of hydrogen buses and stations, as well as operation cost of HBs, might be extremely high. It remains unclear if introducing HBs instead of BEBs into the bus fleet could be more feasible from both technical and economic perspectives. To fill the research gap, this paper will investigate which fuel option (electricity or hydrogen) would be more feasible for electrifying public transit system and how to deploy charging/refueling facilities accordingly.

In this study, we mainly used a trajectory dataset containing 10,508 buses with 3,3042,553 records collected in Shenzhen on Oct 22, 2013 (see Fig. 1 for the layout of bus stops in Shenzhen). Its key fields include bus ID, timestamp, longitude, latitude, and instantaneous speed. We simulated how BEBs and HBs move on the bus network and consume energy with information (e.g., speed) extracted from the GPS trajectory dataset, according to the bus timetable. Based on the simulation, we can figure out the spatiotemporal distribution of charging/refueling demands, which can be further used as key inputs of charging/refueling facility location optimization models. In the charging station location optimization model for BEBs, we considered two objectives, namely minimizing the system cost (including vehicle cost, facility cost and energy cost), and maximizing the level of service (i.e., minimizing the average delay time per bus trip). In particular, the model considered possible queuing of BEBs at charging stations and the availability of different charger types (i.e., fast and slow chargers); while in the hydrogen station location optimization model, we only considered the system cost as the objective, as HBs could get refueled as fast as petrol buses and thus it would be easy to maintain the initial level of service. To solve these two models, we used the simulated annealing (SA) algorithm, which is a random search method and was initially proposed by Kirkpatrick et al. to address discrete optimization problems [4].

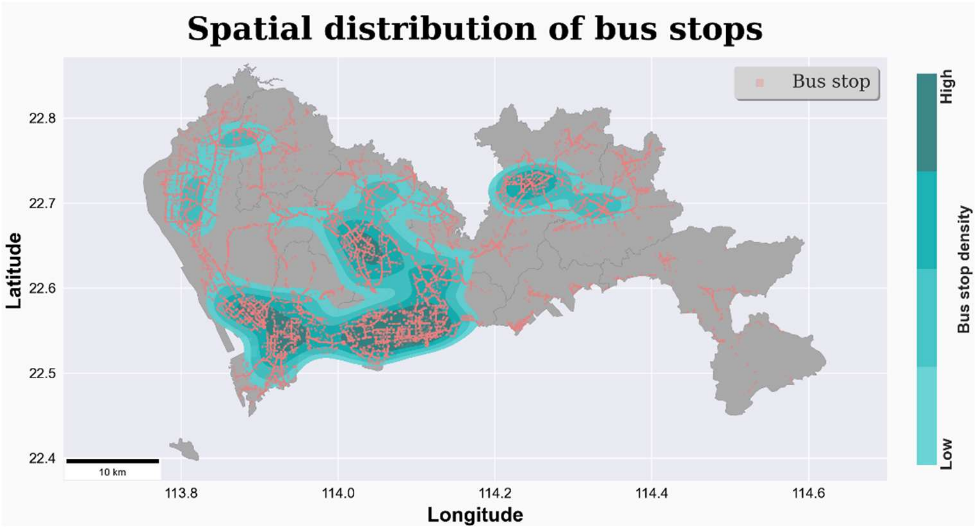

Fig. 1. The spatial distribution of bus stops

Fig. 2 shows the distribution of the number of bus trips by hour of the day, suggesting that most bus trips occurred between 6 am and 9 pm, and the number of trips peaked twice at around 10 am and 5 pm. These were consistent with commuting patterns on a typical working day.

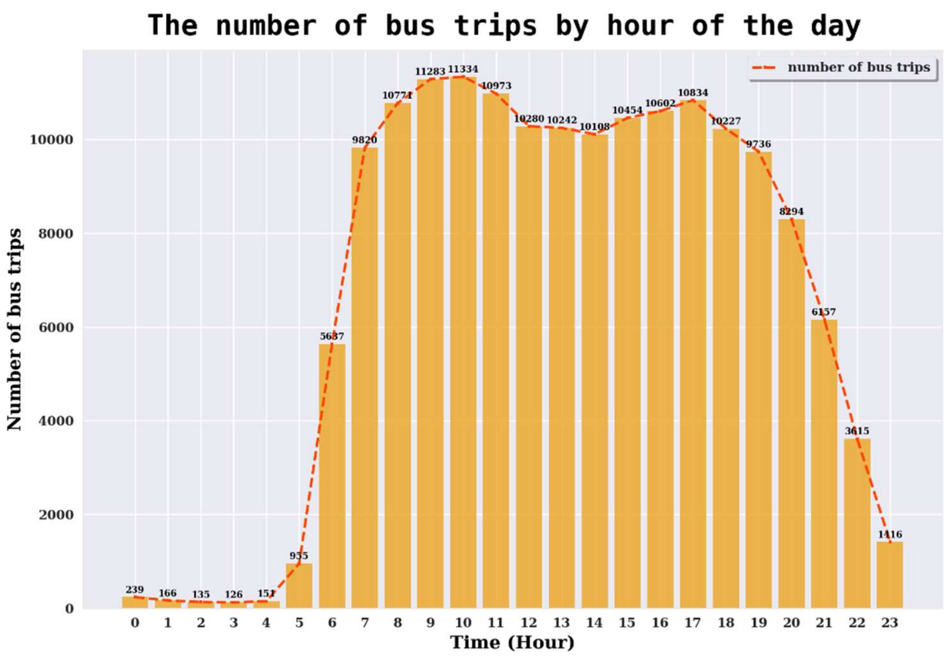

Fig. 2. The number of bus trips by hour of the day

Fig. 3 and Fig 4 show the spatial distribution of charging/refueling demands with density and intensity in the BEB and HB scenarios, respectively. Specifically, we first generated demand points where BEBs/HBs had potential charging/refueling demand. A demand point with a low SOC indicates a high intensity and is presented by a dark red point in the map. Further, the kernel density analysis was applied to explore the spatial patterns of demand points: those areas in dark blue indicate a higher demand density (i.e., more demand points). Note that the demand points of BEBs were generated based at start/end bus stops; while those of HBs were generated along bus routes. The spatial demand patterns suggested that the refueling demand of HBs were in the central and southwest areas; while the charging demand of BEBs were in the central and northwest areas.

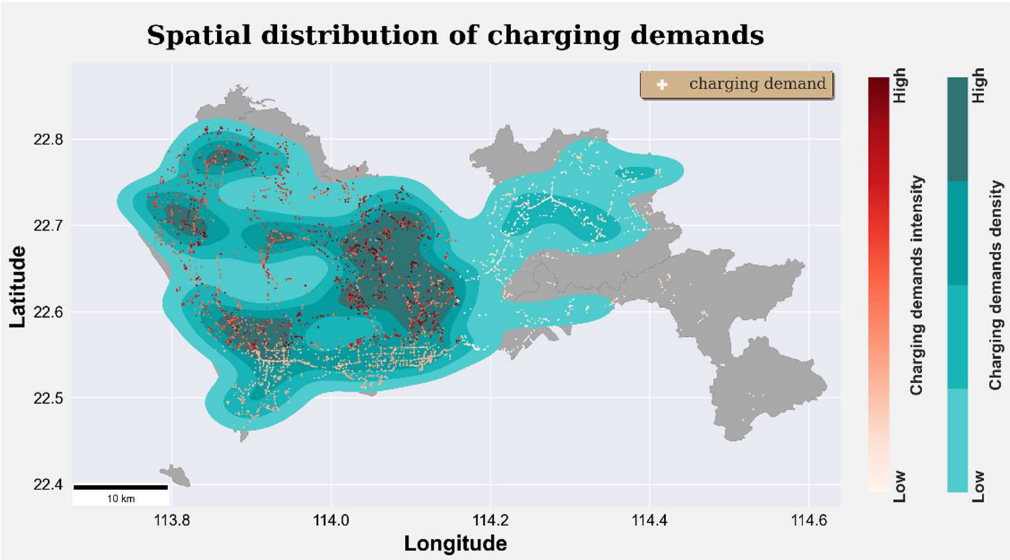

Fig. 3. Spatial distribution of charging demands in the BEB scenario

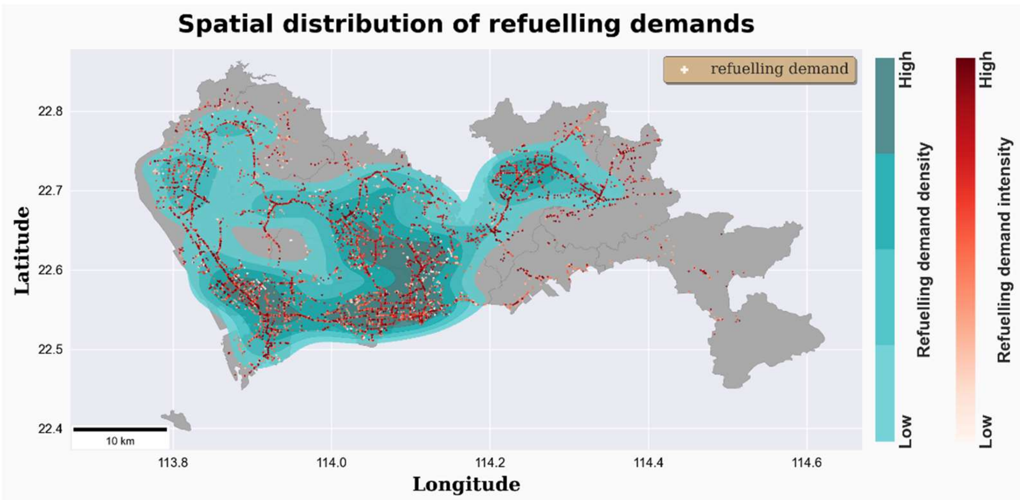

Fig. 4. Spatial distribution of refueling demands in the HB scenario

Table. 1 summarized key outputs of the two facility location optimization models. We found that the system cost in the HB scenario tended to be much higher than the BEB counterpart although the HB scenario has no delay time. For example, in the BEB scenario with 359 charging stations to be deployed, the average charging delay time per bus trip in the whole system was only around 0.9 minutes; while its system cost was approximately 3070.64 million yuan which was only about 65.8% of the hydrogen counterpart. Furthermore, by comparing the BEB scenario with 408 and 455 charging stations to be deployed, we found that adding more charging stations had almost no improvement on operational performance of the whole bus fleet when charging stations are sufficient.

Table 1. Comparing BEB scenarios against the HB scenario

Cost	Description	BEB scenarios					HB scenario
		BEB scenario 1	BEB scenario 2	BEB scenario 3	BEB scenario 4	BEB scenario 5	
Charging/refueling stations to be deployed	The number of charging/refueling stations to be deployed	243	315	359	408	455	75
Vehicle cost (Million yuan)	The cost of BEBs or HEBs purchase and maintenance			**2,338.96**			2,888.40
Charger cost (Million yuan)	The cost of chargers purchase and installation	28.16	38.61	44.14	49.78	57.43	**N/A**
Station cost (Million yuan)	The cost of building charging/refueling stations	181.5	235.5	269.25	304.5	339	140.63
Energy cost (Million yuan)	The energy consumption cost for completing operation tasks			**407.85**			1,597.23
Travel to station cost (Million yuan)	The cost of travelling between charging/refuelling stations and demand points.	12.34	10.92	10.44	9.72	9.32	36.13
System cost (Million yuan)	The sum of all the above costs	2,968.81	3,031.84	3,070.64	3,110.81	3,152.56	4,662.39
Level of service (Minute)	The average delay time per bus trip caused by charging	4.5	1.62	0.9	0.65	0.64	**N/A**

Furthermore, Fig. 5 and Fig. 6 show the spatial distributions of charging/refueling stations in the HB and BEB scenarios, respectively (note that here we used the BEV scenario with 359 charging stations to be deployed as an example, as it tended to better tradeoff between the system cost and efficiency). We also conducted a kernel density analysis to explore the spatial patterns of facilities. Overall, the southwest area needs more charging/refueling stations in both BEB and HB scenarios; while there was a higher density of charging stations in the central area in the BEB scenario. These spatial patterns were consistent with the patterns of demand/refueling demand points (see Fig. 3 and Fig. 4).

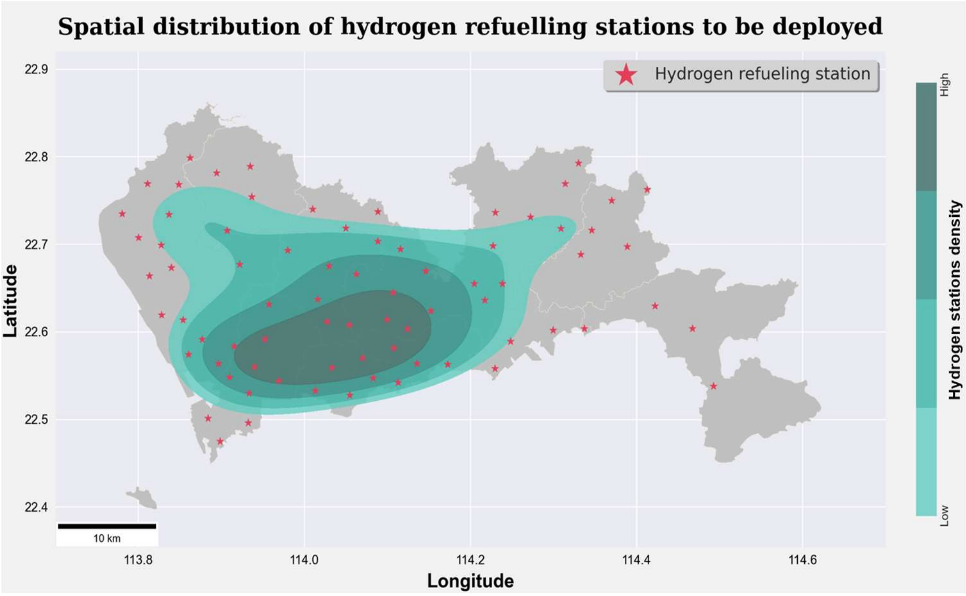

Fig. 5. Spatial distribution of refueling stations in the HB scenario

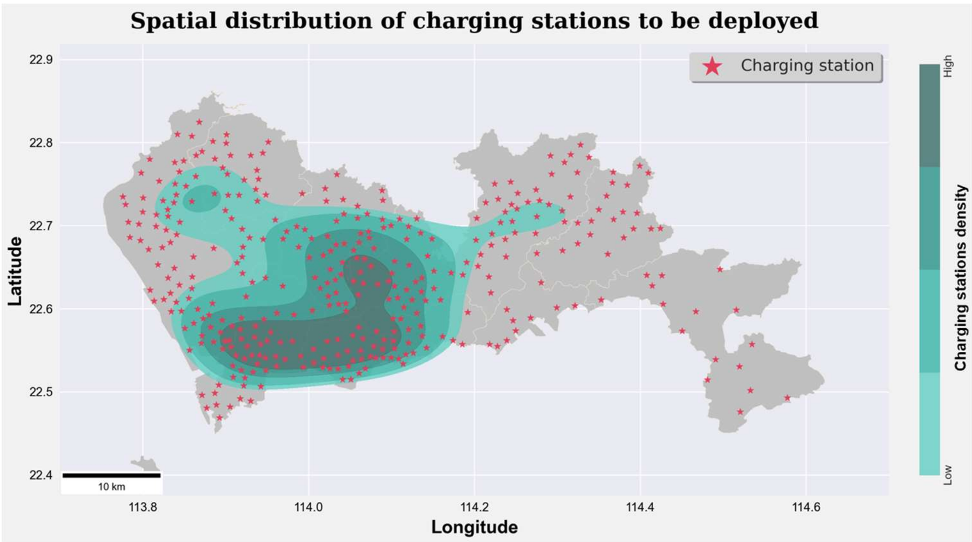

Fig. 6. Spatial distribution of charging stations in the BEB scenario

To summarize, this paper proposed a data-driven micro-simulation approach to compare fuel options (electricity or hydrogen) for electrifying public transit, using real bus operation information extracted from a GPS bus trajectory dataset in Shenzhen. The spatial charging and refueling patterns of BEBs and HBs were different, resulting in different layouts of charging/hydrogen stations. The simulation results suggested that given almost the same level of service to maintain, the system cost of the HB scenario could be 48% higher than that of the BEB scenario. Therefore, HBs would not be an economic option for electrifying public transit in Shenzhen. However, in our future work, we will further explore how different model parameters (e.g., costs of HB and stations) would influence outputs of interest (e.g., the system cost and efficiency).

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