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Simulation of Electric Mobility Concepts

- Swappable batteries and battery swapping stations -

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ABSTRACT: This paper investigates the comparative performance of swappable battery electric vehicles (SBEV) with battery swapping stations (BSS) and electric vehicles (BEV) with stationary charging stations (CS) in an urban traffic scenario using the large-scale activity-based simulator MATSim on the city of Hamburg, Germany, to assess user behavior across various EV system specifications. Focusing on user experience and operational efficiency, we hypothesize that BSSs offer shorter charging times for users compared to CS. Key variables under investigation include charging speed, battery capacity, number of battery sockets per vehicle, and charging capacity per station. A primary objective is to identify critical break-even points at which one infrastructure type demonstrates improved performance over the other, providing insights into optimal deployment strategies regarding station density and product specifications. These findings aim to support operators in making data-driven decisions on electric vehicle infrastructure, contributing to efficient urban mobility systems.

KEY WORDS: Electric Mobility, Simulation, Swappable Batteries, Network Analysis

1. INTRODUCTION

The rapid adoption of electric vehicles (EVs) has intensified the need for efficient charging infrastructure to support urban mobility systems. Two primary approaches to EV charging infrastructure are stationary charging stations (CS), for conventional battery electric vehicles (BEV) and battery swapping stations (BSS) for swappable battery electric vehicles (SBEVs). BSSs offer a distinct operational advantage by allowing for rapid battery replacement, thereby reducing vehicle downtime. Additionally, they enable more controlled charging cycles, minimizing battery degradation and enhancing grid stability through predictable, off-peak charging. Furthermore, BSSs facilitate high-frequency energy bidding, granting grid operators increased flexibility in energy management.

This study aims to compare the performance of BSSs and CSs in urban EV networks, focusing on key metrics such as user charging times and operational efficiency. We hypothesize that BSSs will result in shorter charging times and improved scalability compared to CSs. To test these hypotheses, we use the MATSim simulation framework, which provides a detailed representation of mobility patterns within a dynamic urban transport network.

Our analysis is based on the Open Hamburg (Germany) Scenario [1], which uses detailed traffic and mobility data from 2019. The simulation integrates a broad range of transport modes, including private, commercial, and freight traffic, and is validated using real-world traffic counts, public transport timetables, and travel data from multiple sources.

By adapting MATSim's existing UrbanEV [1] [2] module to incorporate swappable battery functionality, we model the

[1] https://github.com/TUMFTM/UrbanEV

operational differences between BSSs and CSs under various infrastructure and demand scenarios.

Previous studies have investigated the optimal placement of battery swapping stations using a combinatorial optimization technique, efficiently handling large infrastructure networks but relying on simplified user behavior assumptions [3], [4]. In a another study MATSim has been applied to evaluate vertiport placement decisions for urban air mobility (UAM) in conjunction with multi-modal transport systems, demonstrating its useability for bi-level optimization problems in dynamic transport networks [5]. This current study builds on these works by incorporating more realistic mobility patterns using MATSim on a scenario with calibrated CS and BEV information.

The primary goal of the present study is to identify critical thresholds where BSS outperforms CSS or vice versa under varying conditions of station density, charging capacity, and user demand. These results will offer valuable insights for mobility service providers, helping to support product specifications and EV infrastructure decisions for dense urban environments.

2. BATTERY SWAPPING STATIONS

2.1. Technology Overview & Applications

Honda developed the battery pack "Honda Mobile Power Pack e: (MPP)" (Fig. 1) and BSS "Honda Power Pack Exchanger e:" (Fig. 2). Battery packs and swapping stations are operated within a service called BaaS (Battery as a Service), where users can exchange their empty battery packs quickly at one of many BSSs distributed in a city to minimize recharging efforts. The concept can be used for different small mobility products like eMopeds or electric tricycle taxis (“rickshaws”). Several demonstrations using Honda’s BSSs have been conducted in South East Asia.

Eventually, the Honda MPP is supposed to power a wider range of products, also including business applications such as electric micro-excavators for use at construction sites, small electric propulsion systems for use as marine outboard motors, or generators for both indoor and outdoor usage. Although the generality of purpose of MPPs for applications beyond mobility constitutes an additional utility for users, this study concentrates on the effects of swappable batteries on mobility patterns limited to small scale BEVs, that can equip up to two MPPs.

2.2. Outlook on Mobility Domain in Europe

In Europe particularly, we observe a growing demand for electrification in both B2C and B2B services such as scooter sharing, and last mile delivery (e.g. parcels, groceries). This is partly driven by societal movement and partly by the political sphere. As for the latter, following European directives, local authorities of cities formulate future mobility concepts (dedicated ‘Sustainable Urban Mobility Plans’), aiming for carbon neutrality through increased electrification of urban traffic.

Consequently, European countries like Spain, Germany, the Netherlands, France and Italy are among the biggest eMoped markets in the world already. To provide suitable products for electrified personal and business transportation, Honda Europe has started selling the eM1e, an eMoped powered by one MPP, though has not introduced BSSs in Europe yet. Instead, MPPs are currently being charged by customers via single-MPP charger systems. Since charging downtimes are a well-documented critical decision parameter for commercial users of electrified vehicles (who need to maximize operational availability of their fleets), Honda investigates the desirability of BaaS solutions in conjunction with BSSs.

＜Specifications of Honda Mobile Power Pack e:＞	
External dimensions (mm)	Approx. 298×177.3×156.3
Battery type	Lithium-ion battery
Rated voltage	Approx. 50.26V
Rated capacity	26.1Ah/1314Wh
Weight	10.3kg
Charging time	Approx. 5 hours

Figure 1: Key features of Honda Mobile Power Pack e:[2]

Product name		Control Unit (C-BEX)	Extension Unit (Ex-BEX)
Compatible battery		Honda Mobile Power Pack e:	
Frequency (Hz)		50/60	
Rated power consumption (kW)		6.5	
Weight (kg)		361	360
External dimensions (mm)	W × H × D	960 × 1,820 × 758	
Connecting power supply (V)		Japan model: 3-phase 2-wire 200 India model: 3-phase 4-wire 400	
Cooler		○	○
Monitor		○	–
communication function		○	–
NFC authentication device		○	–

Figure 2: Key features of Honda Power Pack Exchanger e:[3]

[2] https://global.honda/newsroom/news/2021/c211029beng.html

[3] https://global.honda/newsroom/news/2022/p221025eng.html

3. APPROACH

In the following the methodology employed in this study is explained, which integrates the MATSim simulation framework and the scenario-specific adaptation of the UrbanEV module [2] to compare BSSs and CSs under varying urban mobility conditions. The approach leverages MATSim's capability to model agent-based mobility behavior while incorporating dynamic infrastructure modifications.

3.1 Activity-Based Transport Simulation (MATSim)

MATSim is an open-source, agent-based transport simulation platform designed to model large-scale traffic scenarios over a 24-hour period. The activity-based approach in MATSim simulates individual agents' daily activity plans, consisting of a series of trips and activities (Fig. 3). Each agent selects from available transport modes (e.g., car, bicycle, public transport) to optimize their activity plan. Optimization is achieved through a co-evolutionary algorithm, where agents iteratively adjust their decisions, such as transportation modes, departure times, and routes, based on achieved utility scores from previous iterations. The system converges towards a Nash equilibrium, ensuring that no agent can improve its utility on its own.

For this study, the Open Hamburg scenario [1] serves as the base model, offering a validated representation of urban mobility using diverse data sources, including public transport timetables (GTFS), freight, and commercial transport demand, and sociodemographic data. The scenario includes multiple transport modes covering 10% of the city population, corresponding to 755,258 agents. A detailed explanation of the activity pattern calibration, the traffic and demand validation processes can be found in the literature [6], [7].

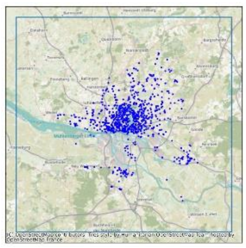
To evaluate the performance of BSS, the MATSim UrbanEV module was adapted to incorporate swappable battery functionality. The simulation assumes identical user behavior across CS and BSS systems, with both BEV and SBEV users selecting charging or swapping stations based on availability, travel and previous charging/swapping duration. This assumption enables direct comparability between the two systems. Battery and charging specifications are derived from Honda MPP data (Fig. 1 and Fig. 2), allowing the modified UrbanEV module to simulate both traditional charging and battery-swapping processes for BEVs.

The simulation is parameterized to focus on typical workdays, capturing 24-hour mobility patterns. Road network and public transport data are derived from OpenStreetMap and GTFS, while travel times are validated using navigation service provider data. Freight and commercial transport are integrated in the simulation as traffic participants, but not considered in the usage of CS and BSS systems.

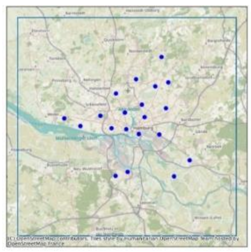
Figure 3: Example of a daily activity chain of an agent

3.2 Experimental Set-up

This section describes the experimental setup designed to evaluate the impact of battery swapping stations (BSSs) compared to conventional charging stations (CSs) in the Hamburg scenario modeled using the MATSim framework. The goal is to assess the operational differences in waiting times, station utilization, and detour distances.



(a) CSs



(b) BSSs

Figure 4: Open Hamburg scenario with limited action space for agents (blue rectangle).

Scenario Definition

The study compares two distinct simulation scenarios:

- Conventional Charging Scenario (BEV + CSs): All electric vehicle agents operate as BEVs with a battery capacity of 40 kWh and rely on 1154 real-world CS locations (Fig. 4a)
- Swapping Scenario (SBEV + BSSs): BEVs are replaced by SBEVs, and CSs are substituted with a variable number of BSSs distributed across the network (Fig. 4b)

This experiment design allows for comparison of infrastructure effectiveness under identical mobility demand conditions.

The distribution of the positions of 1154 real CSs for BEVs used for the following study is shown in Fig. 4a. This configuration will be compared to a scenario with the CSs replaced by a variable number of BSSs, e.g., distributed based on a k-mean clustering approach, as shown for 20 stations in Fig. 4b.

Agent Charging & Swapping Behavior

Each agent follows a state-of-charge (SOC) decision-making process based on a calibrated logistic function from real-world data [8], determining when an agent seeks swapping.

The time in station consists of:

- Waiting time: Time spent queuing before charging/swapping
- Charging/swapping time: Time required for charging/swapping

A key hypothesis is that swapping events (SBEV + BSS) yield significantly lower total service times than conventional charging (BEV + CS), improving operational throughput and user experience.

Sensitivity Analysis & Parameter Variation

The study systematically evaluates how BSS infrastructure parameters influence performance by conducting a two-stage sensitivity analysis:

1. BEV vs. SBEV Station Utilization: Analyzes station occupancy and reduction potential using the real-world CS data for benchmarking
2. BSS Configuration Variations: Evaluates different setups by varying (base specifications highlighted in bold):
    - Total number of BSS stations (20, **50**, 100)
    - Available MPP sockets per BSS (21, 31, 41, **51**)
    - Battery capacity per vehicle (**1.3 kWh**, 2.6 kWh)
    - Charging power per socket (**0.26 kW**, 0.52 kW)
    - Number of MPPs per vehicle (**2**, 4)

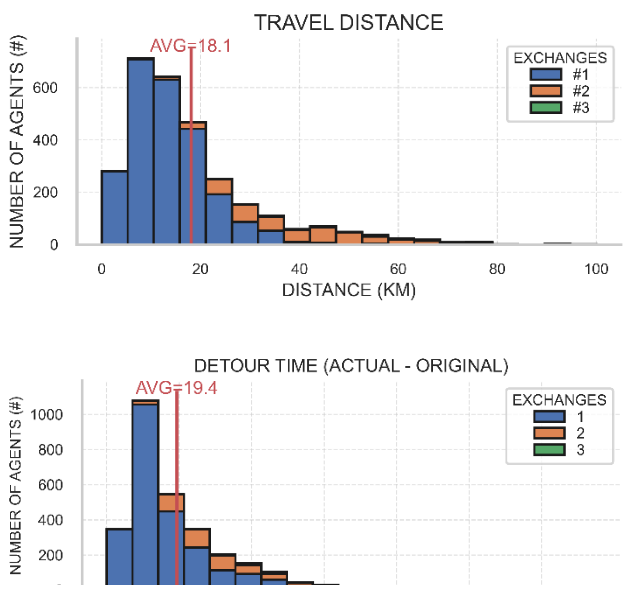


Figure 5 Distribution Travel Distance (upper figure) and Detour Time (lower figure) for SBEV users with 50 BSS.

The tested values, including MPPs per vehicle, battery capacity, and charging power, are chosen for generalized scenario analysis. While some values as the base battery specifications align with realistic, others are set arbitrarily for our traffic simulation to explore system dynamics and assess parameter sensitivities.

4. RESULTS

This section presents a quantitative assessment of swappable battery electric vehicles (SBEVs) versus conventional battery electric vehicles (BEVs) using the MATSim UrbanEV module. The results are based on the Hamburg urban transport network simulation, providing insights into operational feasibility, system efficiency, and the impact of large-scale SBEV adoption.

4.1 Travel and Detour Distance Analysis

Fig. 5 presents the distribution of detour distances for SBEV users seeking a battery exchange for 50 BSS stations. The upper part of Fig. 5 shows the distribution of total travel distances for SBEV users, indicating that most users require only one battery swap, while only long-distance travelers require multiple exchanges. The lower part of Fig. 5 compares travel detour time for SBEVs with and without a battery exchange, showing that the average detour time remains below 20 minutes.

This suggests that while longer trips necessitate more exchanges, most daily travel distances require at most one battery exchange. Even with increased detour lengths, our study shows that the vast majority of cases are manageable with up to three battery exchanges.

4.2 Charging and Swapping Duration Comparison

The primary advantage of SBEVs is their reduced total station service time compared to conventional BEVs. Figs. 6 and 7 compare the total station dwell time (including waiting time and charging/swapping time) across different battery swapping stations

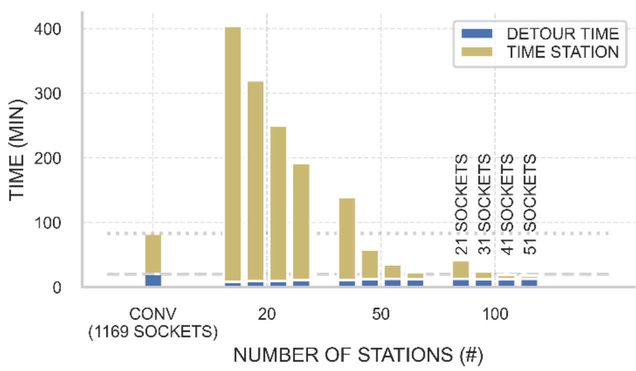


Figure 6 Effect of Station Socket Number on Waiting Times for BEVs and SBEVs

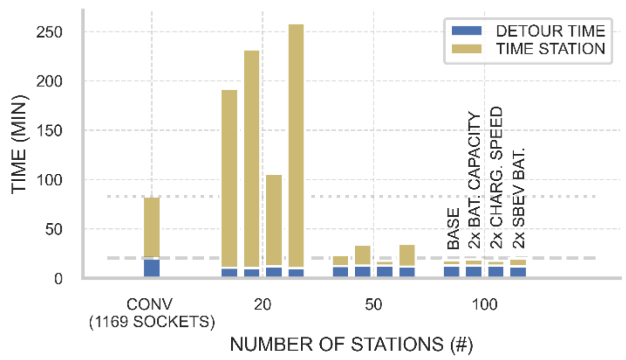


Figure 7 Effect of SBEV Specifications on Waiting Times for BEVs and SBEVs for 51 Sockets

(BSS) configurations, considering station density and available swapping sockets.

Those findings indicate that with a configuration of 50 BSSs equipped with at least 31 sockets per station, the station dwell time drops below the conventional CS scenario. This configuration corresponds roughly to 775 parallel charging events which is notably fewer than the 1169 sockets (equivalent to parallel charging events) of the conventional charging. This highlights a significant advantage of BSS configurations: lower infrastructure requirements for achieving comparable or improved service levels. Moreover, increasing the station capacity further reduced the dwell times, as shown in the scenario with 100 stations. These findings allow an estimation of the necessary BSS network size to match or exceed conventional service levels, and provide insights into how scaling the capacity improves station efficiency.

The difference in the detour time compared to the conventional implementation [2] from methodological differences in station selection. For BEVs, a CS is selected based on proximity to the agent's next destination. Consequently, agents in our simulation might experience slightly shorter detours. A more detailed investigation is necessary to determine which behavior is more realistic, particularly considering the potential for utilizing charging time for other activities, a factor not covered in this study.

Fig. 7 extends this analysis by evaluating the impact of battery capacity, charging power, and onboard battery quantity:

- Doubling the charging power has the most significant effect, reducing the waiting times by up to 30% compared to the base scenario
- Increasing battery capacity has mixed effects: Fewer exchanges are required, but longer charging times increase station occupancy, negatively affecting BSS turnover efficiency
- Doubling the number of SBEV sockets leads to longer battery downtimes in BSS, reducing station efficiency most despite a higher overall vehicle range

These findings highlight a trade-off between battery capacity and station throughput, emphasizing that system-level efficiency depends mostly on charging speed. Simply increasing battery capacity or sockets numbers creates a bottleneck in the throughput due to longer charging times.

4.3 No-Waiting Rate and Maximum Waiting Time

Fig. 8 depicts the station utilization saturation points, showing the fraction of users who experience zero waiting time at different BSS station densities (20, 50, 100 stations). The No-Waiting Rate information extends the previous findings from Fig. 6, indicating the fraction of agents arriving at a BSS without waiting. With 50 stations, only scenarios with doubled charging speed achieve No-Waiting Rate of around 100 %. Additionally, the Max Total Time, combining waiting and detour times, confirms that doubling charging speed significantly impacts both metrics. The 100% No-Waiting Rate can, for the other scenarios, only be achieved roughly through increased battery capacity or onboard battery quantity for 100 stations.

However, this study does not consider the cost trade-offs between infrastructure expansion and battery capacity improvements. Further detailed analysis is necessary to evaluate the economic feasibility of expanding charging capacity versus increasing battery size.

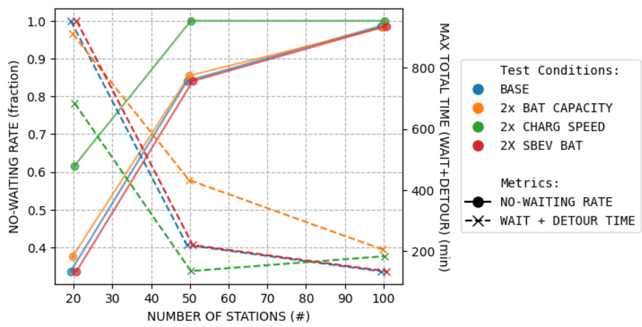


Figure 8 No-Waiting Rate Across Different Battery Densities (BSS) Configurations for 51 Sockets

5. Conclusion

This study quantitatively compares swappable battery electric vehicles (SBEVs) and conventional battery electric vehicles (BEVs) using an agent-based transport simulation (MATSim) applied to the Hamburg urban context. The analysis reveals substantial operational benefits of SBEVs, particularly through reduced station dwell times and enhanced infrastructure efficiency. A critical insight is that increasing charging power significantly outperforms strategies focused solely on enlarging battery capacity or adding more sockets, both of which tend to introduce throughput bottlenecks.

The key advantage of SBEVs lies in decoupling charging from vehicle downtime, enabling higher system flexibility and reducing infrastructure demands compared to conventional charging stations (CSs). Our results demonstrate that a strategically optimized battery swapping station (BSS) network—specifically, at least 50 stations with 31 sockets per station, can deliver equivalent or superior service quality with fewer resources. Additionally advantages are, which are not taking into account in this study could be, controlled off-vehicle charging which could facilitate battery lifecycle management, reduce degradation, and enable integration with renewable energy and dynamic electricity pricing schemes.

Nevertheless, the transition to widespread SBEV adoption hinges upon several unresolved factors, notably infrastructure planning precision, economic feasibility, and end-user acceptance. The trade-offs between charging speed, battery capacity, and station density must be carefully balanced to avoid diminishing returns. Future research should explicitly focus on demand-responsive station management to dynamically mitigate peak-load issues and rigorously evaluate associated economic implications. Furthermore, the transferability of findings to other urban contexts and the implications of extensive SBEV integration for grid stability and energy systems warrant in-depth investigation.

Overall, this study showed on a large-scale city assessment that using SBEVs can be a compelling alternative to conventional BEVs, provided infrastructure planning is optimized and supported by economic analyses and policy measures.

REFERENCES

[1] T. Schlenther et al., ‘Simulation-based investigation of transport scenarios for Hamburg’, *Procedia Comput. Sci.*, vol. 201, pp. 587–593, 2022

[2] L. Adenaw and M. Lienkamp, ‘Multi-Criteria, Co-Evolutionary Charging Behavior: An Agent-Based Simulation of Urban Electromobility’, *World Electr. Veh. J.*, vol. 12, no. 1, p. 18, Jan. 2021

[3] T. Jatschka et al., ‘A General Cooperative Optimization Approach for Distributing Service Points in Mobility Applications’, *Algorithms*, vol. 14, no. 8, p. 232, Aug. 2021.

[4] T. Rodemann et al., ‘Optimizing the positions of battery swapping stations-Pilot studies and layout optimization algorithm’, presented at the The International Electric Vehicle Technology Conference, Yokohama, Japan, 2023.

[5] S. Brulin and M. Olhofer, ‘Bi-level Network Design for UAM Vertiport Allocation Using Activity-Based Transport Simulations’, presented at the The International Electric Vehicle Technology Conference, Yokohama, Japan, 2023.

[6] K. W. Axhausen and ETH Zürich, *The Multi-Agent Transport Simulation MATSim*. Ubiquity Press, 2016.

[7] S. Hörl and M. Balac, ‘Synthetic population and travel demand for Paris and Île-de-France based on open and publicly available data’, *Transp. Res. Part C Emerg. Technol.*, vol. 130, p. 103291, Sep. 2021

[8] Z. Fotouhi et al., ‘A General Model for EV Drivers’ Charging Behavior’, *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 7368–7382, Aug. 2019