USING TRACKING DATA AND AN ELECTRO-MOBILITY SIMULATOR TO ESTABLISH THE ENERGY REQUIREMENTS OF ELECTRIC MINIBUS TAXIS IN TSHWANE

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ABSTRACT

The minibus taxi (MBT) is the dominant form of public transport across Sub-Saharan Africa (SSA). With a growing global call for greener transport, MBTs are seen as a key sector of implementation. The electrification of MBTs entails many challenges, including limited electricity resources and the lack of understanding of MBTs' operational behaviour. In this paper, we estimate the electricity demand for future electric MBTs in the City of Tshwane, South Africa. We use existing origin and destination mobility data, which originated from vehicle-based tracking, and a micro-mobility simulation tool with an embedded electric vehicle model, called EV-Fleet-Sim. This simulation tool uses various SUMO packages to simulate mobility and calculate energy expenditure. The mobility dataset consists of various stop locations from a MBT fleet's daily operation. The simulator uses a routing model, a virtual map, and a virtual driver model to convert the origin and destination data to high-fidelity mobility traces. The results are used in the electro-kinetic model to estimate the vehicles' energy needs, from which charging opportunities can be derived. To illustrate this process and outputs, eight exemplar taxis with different operational patterns are selected for analysis. The results show a minimum and maximum median daily energy usage of 56 kWh and 215 kWh respectively, based on the mean observed daily distances travelled of 94 km to 330 km. While the energy demand varies significantly according to trip length and type of operation of the sub-fleet of 8 vehicles, clear morning and afternoon peaks are identified, along with charging opportunities during midday and at night.

1. BACKGROUND

Paratransit, including minibus taxis (MBTs), has increasingly been considered as an essential part of public transport systems in Sub Saharan Africa (SSA) (Ferro, 2015). It accounts for between 50-98% of passenger trips (Jennings & Behrens, 2017) with up to 80% of SSA population make use of paratransit for their daily commutes (Slocat, 2021).

The National Travel Survey in South Africa (NHTS, 2020) revealed that the minibus taxi is the third preferred mean of household trips across all modes, and is the first preferred mode for public transport users. According to NHTS 2020, transport modal share breakdown is "walking all the way" (41.7%), "private transport" (25.9%), "minibus taxi" (25.7%), "bus" (4.5%), and lastly comes "other" (1.5%) and "train" (0.7%). By province, a higher modal use of minibus taxis is reported for Gauteng Province (45,7%) followed by Mpumalanga (38,3%), and KwaZulu-Natal (38,2%)(Stats SA, 2019). The industry includes more than 200 000 taxis on South Africa's roads generating about R40 billion per year and providing approximately 300 000 direct and indirect job opportunities (GCIS, 2021).

The phenomenon has been questioned mostly for its formality and regulatory structure, service level, safety and customer satisfaction (Behrens, et al., 2016; Mccormick, et al., 2016; Gauthier & Weinstock, 2010). It is, however on the other hand, also acknowledged for providing several benefits for the operators and users amongst which entrepreneurial benefits, job creation and demand responsiveness nature of operation are obvious (Mccormick et al., 2016). These contradictories led to many integration and reform debates of the sector (Gauthier & Weinstock, 2010; Venter, 2013; Jennings & Behrens, 2017; Schalekamp & Klopp, 2018; Bruun & Behrens, 2016).

South Africa occupies the 14th position on the global greenhouse gas (GHG) emission rankings, mainly due to its reliance on coal for energy production (CarbonBrief, 2018). The transport sector in South Africa, the second largest emitter of CO_2, is responsible for approximately 14% of the national emissions and about 90% of the total fuel consumption. About 90% of these emissions are produced by road transport (Ahjum, et al., 2020; Slocat, 2021). Calls for decarbonising MBTs have thus emerged in response to the Paris Agreement in order to lower GHG emissions and to reduce oil dependency through the introduction of vehicle technologies such as electric vehicles (DoT, 2018). However, poor electricity resources and scarcity of data required for a sustainable transition towards greening the sector are pivotal challenges that need to be addressed (Collett & Hirmer, 2021). Ongoing research has thus started to identify and fill in the knowledge gaps needed for the electrification of MBTs of which the distribution of charging stations and energy required, and the potential impact on the already fragile electricity grids are key aspects.

Resent work has investigated the potential for MBT electrification in SSA and proposed methodologies and technologies to identify energy requirements and possible energy sources. Custom-built software was developed by Booysen et al. (2021) to assess the impact on the Ugandan grid of electrifying MBTs in Kampala and to investigate charging opportunities. Abraham et al. (2021) estimated the energy requirements and charging opportunities of nine electric MBTs in the Western Cape Province, South Africa. Using GPS tracking and spatio-temporal data, the authors assessed the effectiveness of using a photovoltaic charging system to reduce the burden on the electrical grid.

The effect that data collection methods and data reliability have on the accuracy of energy demand estimations was explored and discussed in Rix et al. (2022), who concluded that more reliable energy estimates could by obtained using vehicle-based tracking method rather than using passenger-based tracking method.

With the aid of the simulation tool developed by Abraham et al. (2022), called EV-Fleet-Sim (EV-Fleet-Sim, 2023), Hull et al. (2022) and Giliomee et al. (2022) investigated aspects related to the accuracy of energy consumption estimates in relation to GPS tracking methods; and assessed the virtual and actual manifestations of the physical infrastructure, the routing, and the driver and driving styles on the estimated energy expenditure.

A limitation of the work to date is that EV-Fleet-Sim has only been applied to small experimental datasets of MBT vehicle routes of up to 9 vehicles. It is necessary to extend this analysis to larger fleets of in-service vehicles that are more representative of fleetwide operational conditions.

2. CONTRIBUTION

In this paper, the authors show how a micro traffic simulation tool, called SUMO (SUMO, 2023a), can be used with an electro-kinetic model, called SUMO Electric (SUMO, 2023b), to determine energy requirements for electric minibus taxis (eMBTs) in the City of Tshwane. This software is packaged as EV-Fleet-Sim (EV-Fleet-Sim, 2023). The ultimate intention is to apply this to a representative sample of all MBTs operational in the city, in order to deliver insights on the fleetwide impacts of MBT electrification. In addition, this will, for the first time identify opportunities and constraints of rolling out such a transition on a citywide basis.

3. RESEARCH METHODOLOGY

The methodology used in this research is described in this section, starting with a description of the simulation tool followed by the available data and the procedure adopted to extract the required inputs for the tool.

3.1 Simulation Tool

EV-Fleet-Sim consists of various packages from a micro-traffic simulator called SUMO (SUMO, 2023a). This includes a routing function, virtual driver model and electro-kinetic model. EV-Fleet-Sim then processes the results generated by SUMO in various output graphs and datasets. This process is summarised in the flow chart in Figure 1.

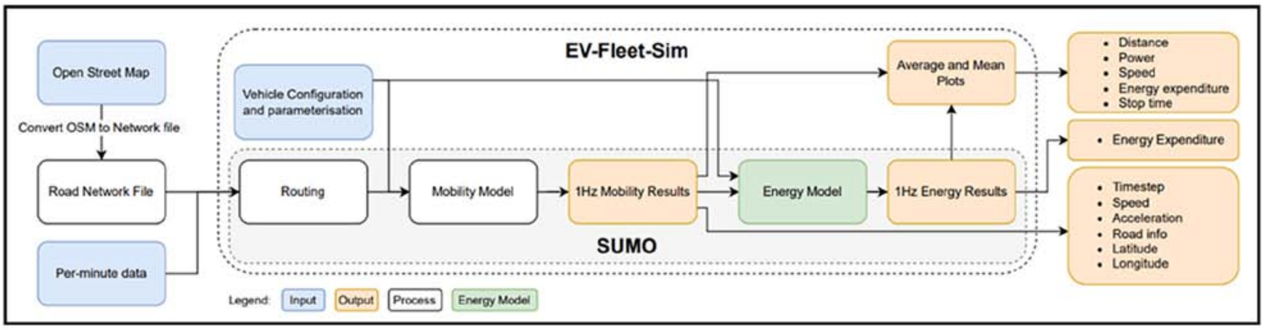


Figure 1: A flow diagram of EV-Fleet-Sim input and outputs (Giliomee et al., 2022)

Input data is required in the form of GPS waypoints. This dataset must include a timestamp, latitude, longitude, altitude and speed information. Along with a road network file from Open Street Maps (OSM, 2023), a routing function from SUMO uses the input data to determine a route between the given waypoints. However, it is shown by Giliomee et al. (2022) that the network file provided by Open Street Maps is not always complete. The extent of the incomplete road network in the area covered by the dataset in this study is unknown.

Along with the routing function, SUMO uses a driver model to convert mobility data from 1/min samples to 1/sec samples through interpolating mobility simulation. This is done by simulating micro-mobility in-between input data points. Traffic features in the road network file also have an impact on this modelling. Through this, the inputted timestamp, latitude, longitude and altitude information is virtually up-sampled to 1 Hz mobility data. In addition, other parameters such as velocity and acceleration are also added in the virtual mobility dataset.

The electro-kinetic model used in the simulation model is called SUMO Electric. This is based on a model proposed by Kurczveil et al. (2014). It uses the virtual 1Hz mobility dataset and calculates the power and energy required from the vehicle to move from one waypoint to the next. This is an energy-based model as it uses the difference in potential and kinetic energy between samples in its calculation, as opposed to a physics-based model which calculates force and the subsequent energy output.

Results from the simulation are aplenty. From the 1Hz simulated mobility data generated by SUMO, EV-Fleet-Sim creates various graphs and box plots ranging from daily distance covered to power and energy offtake and speed profiles. It is important to understand that all results are generated by various packages within SUMO, where EV-Fleet-Sim only further processes it.

3.2 Data

Data used in this study were obtained from iSAHA, an entity that provides management and business solutions that mainly focuses on Transport and Health related projects. iSAHA conducted an Electronic On-Board survey for the City of Tshwane for the purpose of analysing operation business values for minibus taxis in the city and determining the effects of the implementation of the Tshwane Rapid Transit (A Re Yeng) on their market (iSAHA, 2015). The data captured daily operation and passenger counts for 205 minibus taxis from 27 May to 30 October 2014. Data on the daily trips and stops for each taxi are available and provide - among other information - the date, number, route, income, and duration of trips. The stops data, which provide information on the sequence, stop time, passenger count, and geographic coordinates of stops in each trip, constitute the main inputs for EV-Fleet-Sim that rely on the stop time and location of each stop. Although somewhat dated, the data are still deemed sufficiently representative of the core of MBT operations in the city, given that industry transition and replacement strategies linked to the A Re Yeng deployment have not yet materialised.

The data preparation process started with analysing the existing trip data to understand the variation in taxi operational patterns. MBTs were thus categorised into four groups based on the total daily travel distances to reflect the percentage of taxis that travelled less than 100 km (category 1), between 100 and 200 km (category 2), between 200 and 300 km (category 3), and more than 300 km (category 4). The percentage of MBTs in each category is illustrated in Figure 2 which shows that more than 70% of taxis in the dataset fall in the intermediate range categories, i.e., taxis travelled between 100 – 300 km.

Taxis within each category were then further classified based on the average number of trips per day to identify the operational characteristics of each MBT in the dataset. It was found that taxis with a smaller average number of trips per day travelled longer average distances per trip than those with greater average number of trips within the same category of daily travelled distance. This suggests that taxis with a fewer average number of trips have an intercity type of operation while those with a higher average number of trips of the same distance category are of urban operating typology. This result has been confirmed visually by looking at the origins and destinations of these trips using the available coordinates of trips and the Quantum Geographic Information System (QGIS) software (QGIS, 2023). Two MBTs were selected from each category for simulation to reflect the variation in the operational characteristics of intercity and urban travel typologies which are illustrated in Table 1. The table also provides information on the number of days of data gathering for each taxi as well as the average total distance travelled. Input data for the simulation was prepared for each taxi using the stops dataset and the QGIS software.

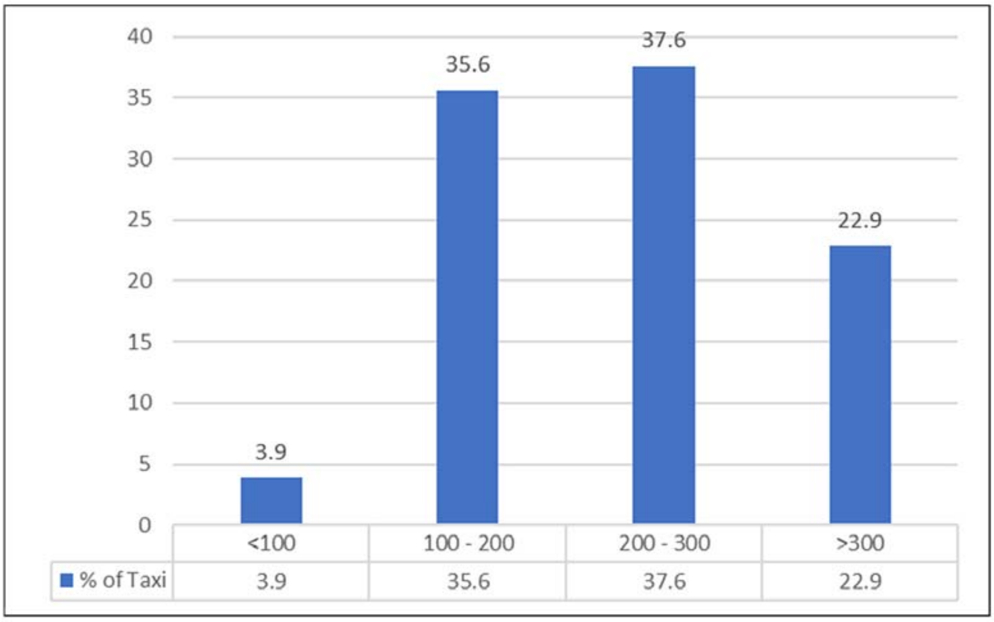


Figure 2: Categories of MBTs based on the average total daily travel distance

Table 1: Characteristics of the eight selected MBTs for simulation

Category by daily distance travelled	**(1) <100 km**		**(2) 100-200 km**		**(3) 200-300 km**		**(4) >300 km**	
Taxi code	**C005**	**L010**	**C010**	**L009**	**E011**	**P007**	**T013**	**G002**
Type of operation	Urban	Intercity	Urban	Intercity	Urban	Intercity	Urban	Intercity
No. of days of data gathering	3	1	2	5	3	5	5	2
Av. No of trips /day	20	3	22	5	24	8	20	8
Av. Distance travelled/trip (km)	5	32	8	32	10	31	18	41
Av. Total distance travelled /day (km)	93	95	170	139	241	222	356	304

A heatmap of input data points from all the MBTs investigated in this paper is shown in Figure 3, reflecting the geographical extent of taxis operation throughout the days of data gathering. Figure 4 illustrates the differences in daily operation of taxis of group 3 (200-300 km), where we can easily see the urban travel pattern of taxi E011 and the intercity travel pattern of taxi P007 as an example. The simulation was run and output results were generated.

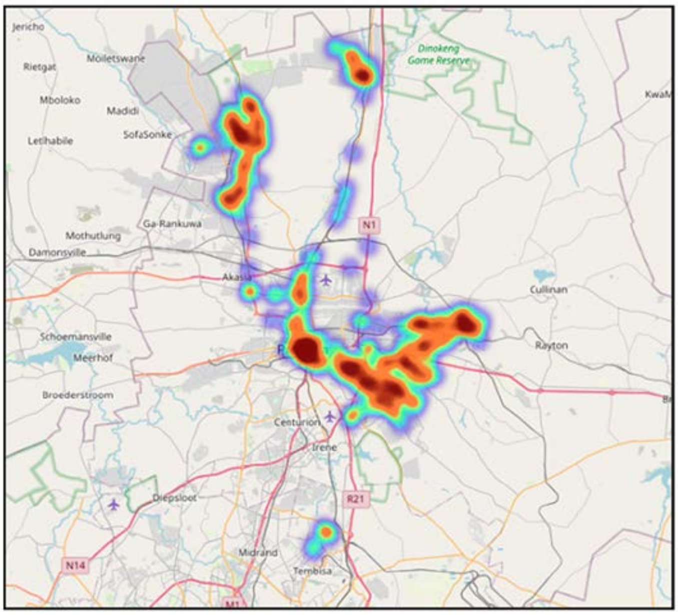


Figure 3: Heatmap of all the input data-points

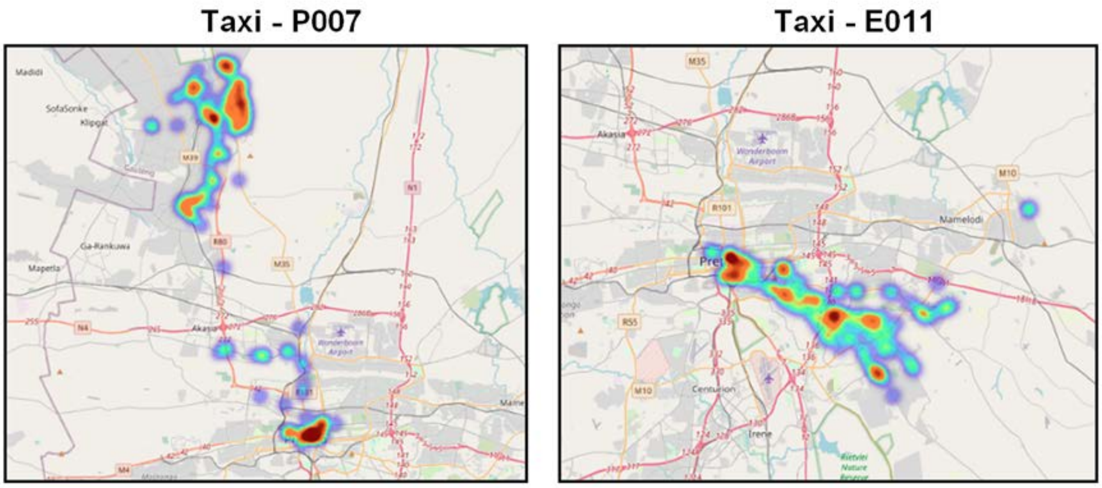


Figure 4: Illustration of the operational pattern of MBTs of group 3 (200-300 km)

4. RESULTS

The simulation tool outputs a variety of results pertaining to the simulated eMBTs. This includes, among others, results on the average rolling distance, power draw from the battery, and estimated energy consumption. This is presented both per taxi and as a fleet average. In addition, it is shown for each day and as an average across the total timespan of the input data. This section presents results of the simulation for individual taxis as well as for each defined taxi category to explore the relationship between operational characteristics and energy use.

4.1 Individual MBT Analyses

4.1.1 Energy and Power Draw from Battery

From the simulated mobility dataset generated by SUMO and SUMO Electric, power and energy offtake from the battery for every sample in the simulated 1Hz dataset can be seen. EV-Fleet-Sim uses these results to generate various graphs for easy analysis. Firstly, we look at the daily energy usage for each eMBT, which is presented in the form of a boxplot. These results are shown in Figure 5 and in detail in Table 2. Considering the fleet of the 8 eMBTs, it is found that a minimum daily energy demand of 17 kWh is estimated for the intercity taxi L009 from the second category. However, this can be seen as an outlier, with the next minimum daily energy demand being 53 kWh. A maximum of 277 kWh daily energy demand is determined for the urban taxi T013 from the fourth category. The mean daily energy demand for all taxis in the dataset is found to be 131 kWh, across an average distance of 180 km. The variance in operational patterns of MBTs, which leads to a variance in their energy requirements, is evident from this result. This indicates the importance of a segmentation approach when exploring the opportunities of electrifying the MBTs and to plan roll-out strategies.

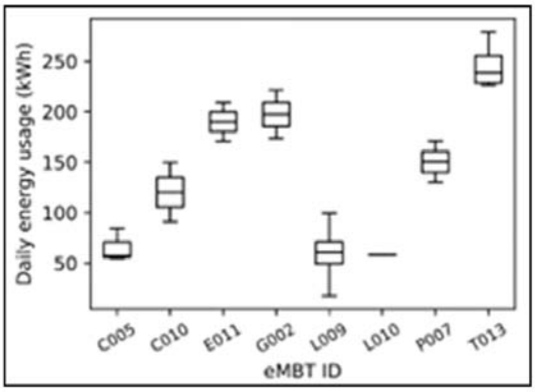


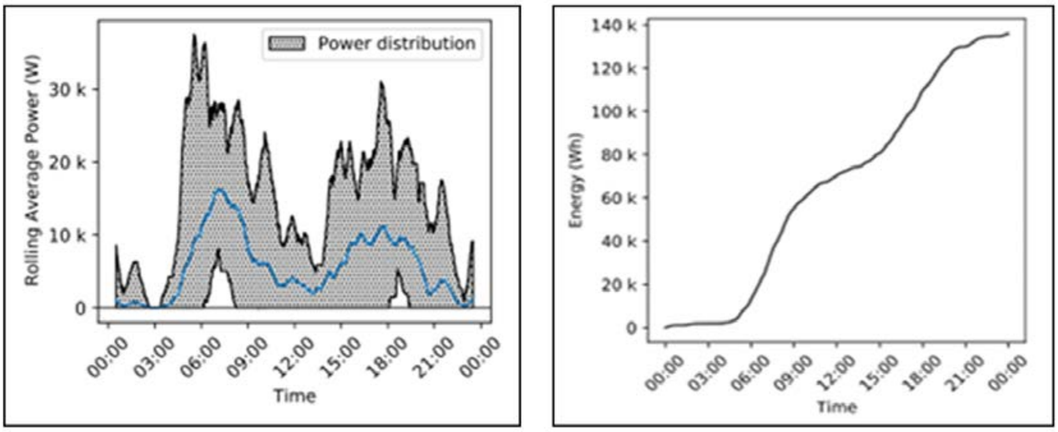
Figure 5: Box plot of daily energy usage of simulated eMBTs

Table 2: Daily energy usage of simulated eMBTs

Category	Taxi code	Operation type	Min. daily energy used (kWh)	Max. daily energy used (kWh)	Median energy used per day (kWh)	Mean energy used per day (kWh)
1	**C005**	Urban	53	81	56	**56**
	L010	Intercity	56	56	56	
2	**C010**	Urban	86	144	115	**87**
	L009	Intercity	17	99	60	
3	**E011**	Urban	165	205	185	**165**
	P007	Intercity	119	163	145	
4	**T013**	Urban	225	277	238	**215**
	G002	Intercity	171	216	193	

Power and energy profiles from all analysed MBTs are compared in terms of the timestamps of each datapoint. EV-Fleet-Sim uses this to create mean power and energy profiles for a 24-hour period. For all eight taxis used as input, the mean and distributive power draw from the battery is shown in Figure 6a, with the cumulative mean daily energy used per simulated eMBT shown in Figure 6b.

Although a large variation in power draw from the vehicle battery across all vehicles is seen in Figure 6a, which suggests variation in operations, two clear operational peaks are identified in the morning and late afternoon. This suggests that although MBTs have different operations, they still roughly follow the same temporal pattern. This is also evident from the cumulative energy profile, where a higher gradient is seen during peak operation.



(a) Mean and distributive daily power profile (b) Mean daily energy profile

Figure 6: Mean and distribution of daily power and mean energy draw from the battery of all 8 simulated eMBTs

4.1.2 Charging Opportunities

From Figure 6, operational patterns and charging opportunities can be derived. Subsequently, the timing of peak grid impact can be estimated. Concluding peak operational times, MBTs return to the rank and refuel (or recharge in this context) for the following operational peak. In the context of this paper, downtime is seen as a charging opportunity for eMBTs. From Figure 6, these times are estimated as 10:00 to 14:00 during the day, and 21:00 to 04:00 the following morning over nighttime.

Furthermore, charging opportunities can be identified by analysing the mean daily distance profile. EV-Fleet-Sim constructs profiles of mean daily distance versus time for each simulated taxi, as shown in Figure 7. The stationary times, and subsequent charging opportunity, of the taxis the day can be identified from these profiles. Distances travelled and the routing of the simulated eMBTs in SUMO will further be discussed in detail in section 4.2.3.

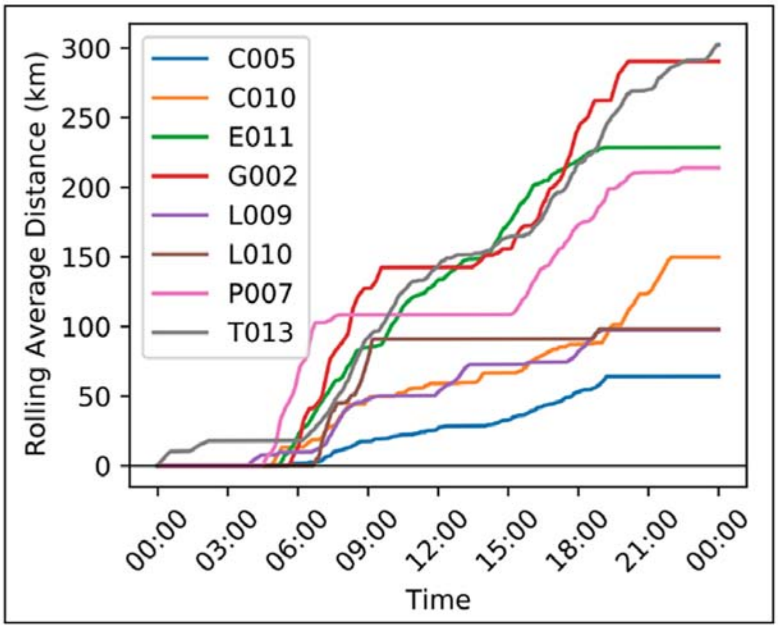


Figure 7: Mean daily distance profile of each simulated eMBT

However, it would not be accurate to determine a grid load profile from these results. For this, additional data regarding charging stations, the number of chargers and charging speed is required. This is recommended as future work and further addressed in the conclusion.

4.2 Groups Analyses

4.2.1 Energy and Power Draw from the Battery

In Table 2 we have shown summaries of the energy demand results for each vehicle, which are further examined in the box plots shown in Figure 4.

Table 2 provides details on the minimum and maximum daily energy used by each eMBT in the fleet, as well as the mean energy required by each group of taxis. It is seen that the total energy requirements for eMBTs directly correlates with the distance travelled, with 56 kWh used by the first category and 215 kWh for the fourth category.

Also seen from this, is that urban trips require more energy than intercity trips; apart from those who travel short daily distances, which consumed the same amount of energy. This is due to the constant breaking and acceleration associated with urban driving. This uses significantly more energy opposed to driving at a constant velocity, such as with intercity driving.

4.2.2 Charging Opportunities

From analysing each taxi's individual battery power draw profile, we further assess their peak operational times. From this, we specify charging opportunities according to urban or intercity operational profiles.

Although the specific power draw stated in the simulation results is not relevant to city and electrical infrastructure planning, it gives an indication when the taxi is active or not. The value itself would only be useful in the case of defining proposed parameters for the powertrain of an eMBT.

The morning operational peak is determined as 07:30 to 10:00 for urban trips, and 05:30 to 07:30 for intercity trips. Here, a clear separation can be made between the charging opportunities of taxis doing intercity and urban trips, as current data shows a taxi only does one or the other. The afternoon/evening peak for the two operational profiles overlaps slightly. For urban trips, peak operational time is found to be between 15:00 and 21:30, where 16:00 to 18:30 is estimated for intercity travel.

The results show a variance in peak operational time for the different trip types. However, as we are working with a limited dataset, more investigation is suggested with a larger number of MBTs to confirm the peak operational times and subsequent charging opportunities. With the inclusion of charging station information, grid impact can further be determined.

From the battery power draw profile for each taxi, along with the mean daily distance profile, inactive times of taxis can be derived for the 24-hour period. A summary of times the taxi had zero power draw from the battery, indicating inactivity, is shown in Table 3. This shows 7 out of the 8 MBTs to have stationary times of around 7 hours at night, and 5 having stationary times of at least 1.5 hours during the day.

Table 3: Inactive periods of simulated eMBTs

MBT category	Taxi code	Inactive periods over 24 hours				
		1st	2nd	3rd	4th	5th
1	**C005**	19:40 - 05:00 (≈ 9 hrs)	-	-	-	-
	L010	19:20 - 06:00 (≈ 10 hrs)	09:40 - 18:00 (≈ 9 hrs)	-	-	-
2	**C010**	22:30 - 04:20 (≈ 6 hrs)	12:00 - 12:20 (≈ 30 min)	14:30 - 14:46 (≈ 15 min)	-	-
	L009	19:31 - 03:20 (≈ 8 hrs)	05:40 - 06:00 (≈ 2 hrs)	10:00 - 11:00 (1 hrs)	14:00 -15:15 (≈ 1.5 hrs)	16:30 - 17:00 (≈ 1.5 hrs)
3	**E011**	19:30 - 04:40 (≈ 9 hrs)	-	-	-	-
	P007	22:40 - 04:00 (≈ 7 hrs)	08:15- 14:30 (≈ 6 hrs)	-	-	-
4	**T013**	02:40 - 05:40 (≈ 3 hrs)	-	-	-	-
	G002	20:40 - 05:00 (≈ 10 hrs)	10:00 - 01:00 (3 hrs)	-	-	-

These stationary periods, in addition to information on their spatial distribution, gives an indication of the charging opportunities for eMBTs. This includes locations of charging stations, the number of charging points, and charging speed (power).

4.2.3 Distance and Routing

By comparing the measured daily distance travelled to that of the routing algorithm in the simulation, as shown in Table 4, it is clear that the routing function by SUMO is not perfect. This highlights both the shortcomings of simulations and the importance of high frequency measured data. As only stop locations are used as input to the simulation, the actual routes taken between these stops are unknown to the simulation. As described by Rix et al. (2022), the SUMO routing algorithm used EV-Fleet-Sim aims to find the shortest path between two input data points. As the measured distance covered by the MBTs exceed that of the simulated distance, it is clear that taxis do not always take the shortest route. This shortcoming of the simulation tool has previously been investigated by Giliomee et al. (2022), where they quantified the effect this has on the total daily energy usage. Improving on this inaccuracy is recommended as further work on the simulation tool.

Table 4: Measured distances vs simulated distance from the simulation tool

MBT category	Urban trips			Intercity trips		
	Taxi code	Measured distance (km)	Simulated distance (km)	Taxi code	Measured distance (km)	Simulated distance (km)
1	**C005**	93	64	**L010**	95	98
2	**C010**	170	149	**L009**	139	97
3	**E011**	241	228	**P007**	222	213
4	**T013**	356	290	**G002**	304	302
Average distance (km)		**215**	**183**		**190**	**177**

5. CONCLUSION AND RECOMMENDATIONS

The work presented in this paper represents an initial attempt towards planning for the roll-out of the electrification of minibus taxis (MBTs) in the City of Tshwane, South Africa. Two activities needed early on are to develop tools to help estimate the energy requirements of electrified vehicles, and to identify typical operational patterns and routes that can help to understand the impacts of the electrification process on the already fragile national grid. This paper demonstrated both tasks. A segmentation approach has been applied to a readily available GPS tracking data to explore the opportunities of electrifying the MBTs using the EV-Fleet-Sim simulation tool. The tool generated estimates for the energy demands for a fleet of 8 simulated eMBTs, given their different trip and operational typologies. The taxi trips were segmented into four different categories based on the average distances travelled as well as on their operational pattern as urban or intercity trips. Urban trips are found to consume more energy than intercity trips. It is estimated that this is due to the nature of the constant breaking and accelerating driving style observed in urban scenarios. Such results, expanded to larger fleets of representative vehicles, will help transport planners to devise and evaluate implementation strategies for incremental electrification of the MBT fleet.

The EV-Fleet-Sim simulation tool provides detailed information on the energy demands of future electric minibus taxis (eMBTs). A mean energy demand of 130 kWh per day is found across the fleet of 8 taxis. Additionally, the minimum and maximum daily energy demand for the shortest and longest distance-based categories is found to be 56 kWh and 215 kWh, respectively

Across all 8 taxis, a morning peak of between 05:30 to 10:00 and an afternoon peak of 15:00 to 21:30 is seen. Seven of the 8 taxis reported a night stationary time of more than 7 hours, with 5 taxis having at least 1.5 hours stationary time during the day. These stationary times indicate the potential for charging opportunities for future eMBTs. When comparing charging opportunities to the national electrical grid load profile, it is seen that these times coincide with a reduced demand. Nonetheless, with the fragile nature of the current electrical grid, the additional strain cannot be supported. Also seen is charging opportunities during the day, which indicates the possibility of incorporating solar charging stations. Thus, careful planning is required if eMBTs are to be adopted in South Africa. Synchronising charging times and load with grid and solar power availability is paramount. Furthermore, we suggest a segmented approach of electrifying the MBTs according to their operational pattern.

The EV-Fleet-Sim software generates detailed outcomes on the energy and power profiles for the simulated eMBT fleet. It provides a powerful means for assessing MBT electrification requirements and planning according to different operational characteristics. However, a maximum usefulness of the tool may only be achieved by the presence of sufficient and accurate data. Further work is needed on understanding the minimum requirements for such data to address limitations in data sources, and in simulation tools. We recommend that further research should be conducted as an extension to the work done in this paper to include more taxis from each of the defined distance-based categories. Additionally, attempting other operational-based segmentation of the available datasets in order to obtain a holistic overview of the electrification potential of the industry.

6. ACKNOWLEDGMENTS

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