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Chapter 1

e-Quantum leap on a data highway: Planning for electric minibus taxis in sub-Saharan Africa's paratransit system

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Minibus taxis are ubiquitous in the developing cities of the Global South. This versatile, if somewhat chaotic, public transport system is now faced with the need to move to renewable energy. But the looming roll-out of electric vehicles poses a threat to the already fragile electrical grids of African cities. This chapter evaluates the energy requirements of decarbonisation and evaluates two types of data, passenger-based and vehicle-based, from research in South Africa that has modelled these taxis. Using these two data capture methods, we assess the energy requirements and charging opportunities for electric minibus paratransit in three African cities and compare the results of the two methods to assess their suitability for planning minibus taxi electrification.

1.1 Introduction

Paratransit is sub-Saharan Africa's main public transport system, carrying more than 70% of the daily commuters and providing a livelihood for many families [1, 2]. The modes are various, including even motorcycle or bicycle taxis, but most passengers use minibus taxis [3]. Powered by internal combustion engines, these vehicles contribute to greenhouse gas emission and air pollution.

Africa's paratransit differs in many ways from that of developed countries. In the latter, paratransit is usually a point-to-point flexible demand-responsive transport service with special facilities for transporting the elderly and the disabled [3, 4]. But in Africa it is an organically evolved, informal, market-oriented, self-organising service operating somewhere between private and public transport in terms of cost, scheduling, routes and quality of

service [5, 6]. In sub-Saharan Africa it consists of shared-ride, demand-responsive privately owned vehicles such as the minibus taxis of Johannesburg, Lagos, Kampala and Nairobi or Kampala's motor-cycle taxis ("boda bodas") and Nairobi's tricycle taxis ("tuk-tuks") [7, 8, 9]. Paratransit accounts for approximately 70%, 90%, 91%, and 98% of the road-based public trips in Johannesburg, Lagos, Kampala and Dar es Salaam, respectively [10, 11], and around 80% of these are by minibus taxi [11, 12, 13].

1.1.1 The "Quantum leap" in sub-Saharan Africa's paratransit

The public transport industry in sub-Saharan Africa underwent two fundamental organic changes in the last quarter of the twentieth century. The first was the shift from public to private, usually sole proprietorship because the World Bank's structural adjustment policies of the 1990s reduced financing to state-owned entities, many of which eventually collapsed [14, 15, 16]. The second was the gradual introduction of low-capacity (five-to-twenty seater) passenger-carrying vehicles to fill the public transport vacuum [1, 7, 9, 17]. These vehicles have been of various kinds, from the five-seater Ford Anglia of the 1970s, to the 10-seater Peugeot 204 of the 1980s, to the current 16-seater Toyota HiAce. The fourth and fifth generations (H100; 1989 and H200; 2004) of the Japanese Toyota HiAce have dominated the paratransit market in Africa since the 1990s, trading under several names depending on the country of assembly, such as Toyota Quantum in South Africa and Toyota Venture in Thailand.

The first big step forward – or "Quantum leap" – came when minibus taxis began to dominate the mobility lifestyle of the urban poor in sub-Saharan Africa. These taxis are unlikely to be phased out anytime soon, given their ubiquity and schedule flexibility, and the socio-cultural lifestyles of the urban poor. However, the environmental cost of running them is worrying. It has triggered discussions about the possibilities of transitioning to electric minibus taxis (eMBTs) as part of the global electrification and sustainability agenda. In this chapter, "minibus taxi" refers to an internal combustion engine vehicle unless "electric minibus taxi" or "eMBT" is specified.

1.1.2 Potholes in the data highway to decarbonisation

The development of low-carbon transport in cities is part of the global agenda to deal with possible climate change [18, 19, 20]. The IPCC (Intergovernmental Panel on Climate Change) estimated in 2014 that the transport sector generates 23% of the global energy related greenhouse emissions [21]. In sub-Saharan African cities, the deteriorating air quality resulting from ambient air pollution and a high concentration of particulate matter (PM_{2.5}) is partly attributed to vehicular emissions [22, 23, 24]. Akumu estimates the cost of air pollution in African cities to be as high as 2.7% of the GDP [25]. In the UN General Assembly's post-2015 development agenda, three of the seventeen Sustainable Development Goals, one, eleven and thirteen, are clean energy, sustainable cities and climate action [26]. Consequently, electrification is promoted as a low-carbon transport strategy to reduce combustion emissions. The transition from internal combustion engine (ICE) vehicles to electric-powered vehicles (EVs) is gradually increasing in developing countries. Some vehicle manufacturers are planning to phase out ICE vehicles in favour of EVs. A few isolated pilot EV projects have cropped up in sub-Saharan Africa, mainly focusing on micro-mobility (two- and three-wheelers, such as motorcycles and tricycles),

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but also on buses and private cars [27]. At the time of writing there was no known ICE to EV transition initiative targeting the paratransit industry, let alone the minibus taxis that are responsible for the vast majority of the public transport trips in the region.

To date, the literature on paratransit in sub-Saharan Africa focuses on sector governance [28] and regulation and reforms [17, 29], and seldom on operations [30], mobility characteristics [5], and future prospects of electric mobility integration [31].

Studies from China [32] and Europe [33] found that EVs are three times more efficient than ICE-powered cars and twice as efficient as hybrid cars (a vehicle powered by a combination of electricity and an internal combustion engine). This efficiency is partly achieved because the good braking systems and elimination of idling losses save energy for the actual EV movements [33]. Although debate continues on the economic and environmental trade-offs associated with EVs [34], evidence of sustainable EV deployment models also exists [35]. Some researchers argue that deploying EVs shifts gasoline usage to coal-fired power generation, exacerbating CO_2 emissions [34, 36]. However, EV proponents counter-argue that this effect can be reduced by a charging strategy that optimises the use of renewable energy sources such as solar photovoltaics [36, 37].

Two recent papers emphasise the need to decarbonise and electrify paratransit, but they also highlight the difficulties of achieving a more sustainable transport sector [18, 19]. To evaluate the readiness of three African cities to transition to electric minibus taxis, Odhiambo et al. [19] interviewed key stakeholders and concluded that the electrification of the most common mode of transport, namely paratransit, needs to receive increased attention, government support, and cross-sector collaboration for timeous uptake.

Collect and Hirmer [18] evaluated the readiness of paratransit in sub-Saharan Africa to transition to electric vehicles. They mention many benefits of the shift, but identify the lack of data as the main impediment to making the transition a reality [18]. They say that

for a sustainable transition to EVs, additional low-cost, clean generation will be required in many regions. Vital questions such as: "what is the potential demand?", "where and when will this demand occur?" and "how will consumers pay?" need to be answered. EV infrastructure planning, business model design, investment decisions, and policy making alike rely on the availability of adequate and reliable data to answer these questions. Such data are currently not well documented or aggregated in low-income countries, resulting in a data gap.

The words to focus on in this quotation are "adequate" and "reliable"; qualities that are often not applicable to data in developing counties. The literature reviewed above makes it clear that the road to electrification for transport in sub-Saharan Africa is far from smooth.

1.1.3 Two data collection methods

This chapter builds on the authors' investigation into the possibilities for solar charging of eMBTs in South Africa [38]. We assess the energy requirements of the paratransit system from the perspectives of two mobility data collection methods: using handheld mobile devices, and using GPS devices fixed in the taxis.

The first method, using the handheld mobile devices (often mobile phones) is commonly used by transport engineers in resource-constrained environments. This method involves field workers boarding the minibus taxis as passengers and tracing the routes for the duration of the trip. We show that although this type of data is readily available and often used, its usefulness in energy analyses is limited, for several reasons:

- It does not adequately reflect the mobility patterns from a vehicle perspective. It gives information on a particular route's energy requirements, which is less useful. However, with route frequency data, the route energy requirements with route frequency data can be extrapolated to obtain the aggregated energy needs for a transport system, which may be useful at a grid level.
- It is susceptible to errors introduced by the field workers' behaviour. They often start work late and go home early. They may be contracted to track for only a specified time of day for legal, oversight or convenience reasons.
- Although field workers may stick to their route and wait with passengers at stops, thereby capturing passenger waiting time, they are unlikely to capture the vehicle's waiting time. The vehicle stop time, rather than the passenger waiting time (see [5]), is crucial for energy analysis because the vehicle stops provide information about charging opportunities. An example of this is the first dataset evaluated below, which captures typical route information (origin, destination and temporal frequencies), but fails to specify how long the vehicle waits at formal and informal stops.

The second method which is slightly more invasive and has a higher setup cost, uses vehicle-fixed GPS trackers. The trackers continuously log and transmit their location and velocity to remote data collection centres through the communications network (usually cellular). This data is then made available from a cloud server either as timestamped GPS traces, or as processed timestamped trip information that captures the origin and destination. This method is much more useful for energy analysis than the first method as it adequately and reliably captures the vehicle's moving and stopping patterns.

This chapter builds a foundation for evaluating the eventual impact of eMBT transition on sub-Saharan African cities' electric grids, localised pollution, carbon footprint and taxi owners' profitability. We look specifically at the energy requirements of these vehicles, and the potential for installing charging stations at the many formal and informal stops. We explore the energy requirements of electric minibus taxis in an urban context, which includes paratransit between and within towns and metros.

We use two publicly available datasets. The first, called the "Digital Matatu" dataset, was collected with mobile phones in Kampala, Uganda, and Nairobi, Kenya, and stored in the GTFS (general transit feed specification) format [39, 40]. Although some useful information can be extracted from this dataset, we highlight the shortcomings and remaining challenges of using data captured by passengers on-board or at the roadside. The second consists of data from over a year of GPS vehicle tracking in Kampala and in Stellenbosch, South Africa. We analysed these datasets to assess the energy demands of minibus taxis and to explore the charging opportunities at the formal and informal stops. For both the datasets we used a micro-transport simulator.

1.2. *METHOD* **1.2 Method**

1.2.1 Data

Passenger-based data

The first dataset we used, downloaded from DigitalTransport4Africa, is for the cities of Kampala and Nairobi [39]. This dataset captures the minibus taxis' schedules, routes and stop locations. Importantly, it does so from a transport system rather than vehicle perspective. The focus is therefore on the route frequency, route length, origin location and destination location. Although this may seem a fully descriptive dataset, the temporal coverage is dependent on the data collection method, as we will show. The use of fieldworkers meant that the degree of scientific rigour and reliability varied considerably.

Table 1.1 shows the number of collectors, weeks used to capture the data, taxi routes captured, trips captured and surface area covered. If nothing else, it is clear that a lot of data was captured. Kampala and Nairobi have similar population sizes -4.0 million and 4.7 million. The minibus taxi numbers reported for the two cities were 25,000 and 15,000. The difference is because Kampala's paratransit is 63% minibus taxis (as opposed to other forms, such as motorcycles), whereas Nairobi's is only 43% minibus taxis (other forms being more common here) [41, 42, 43, 44].

| City | Collectors | Weeks | Routes | Trips | $\begin{array}{c} Area \\ [km^2] \end{array}$ | Ref. |
|--------------------|-----------------|--|-------------------------|--------------------|---|--------------|
| Kampala Nairobi | not specified 5 | $\begin{array}{c} 10\\ 24 \end{array}$ | $\substack{4,400\\264}$ | $92,262 \\ 35,640$ | $2,478 \\ 3,097$ | [45] [40] |

Table 1.1: Properties of the first dataset, captured by passenger data collectors.

Vehicle-based data

The second dataset was collected using tracking data from a fleet of eight minibus taxis in Kampala and nine minibus taxis in Stellenbosch. GPS trackers were installed in the vehicles, allowing full temporal coverage of the spatial location information. The dataset properties are listed in Table 1.2.

Table 1.2: Properties of the second dataset, captured by vehicle-based GPS trackers.

| City | Taxis | Weeks (after cleaning) | Daily distance [km] | $\begin{array}{c} Area \\ [km^2] \end{array}$ | Ref. |
|--------------|-------|---------------------------|------------------------|---|------|
| Kampala | 8 | 21 | 224 | $5,194 \\ 1,422$ | [46] |
| Stellenbosch | 9 | 29 | 228 | | [38] |

The Kampala part of this dataset consisted of GPS tracking data obtained over ten months from eight minibus taxis operating on routes in Kampala. The study wares is defined by a box with coordinates (0.170202, 32.181182) and (0.794505, 32.852554) and is shown with a heatmap of GPS traces in Figure 1.1a. It consisted of timestamped geographical coordinates, speed and direction, logged at one-minute intervals. We removed



Figure 1.1: Heatmaps of the two cities' GPS-tracking data.

irrelevant data from the dataset, such as public holidays and weekends, and days when a minibus taxi left the area of study. We were left with an average of 150 days of data per taxi.

The Stellenbosch part of this dataset consisted of GPS tracking data obtained over two years from nine minibus taxis operating on bi-directional routes connecting Stellenbosch with the northern suburbs of Cape Town and the town of Somerset West. The study area is defined by a box with coordinates (-34.229224, 18.656884) and (-33.786222, 18.969438) as shown in Figure 1.1b. The data was obtained from a local fleet management service provider, Mix Telematics. It consisted of timestamped geographical coordinates, speed and direction, logged at one-minute intervals. After cleaning the data we were left with an average of 201 days' worth of data per minibus taxi.

1.2.2 Minibus taxi mobility modelling from passenger-based data

For each of the routes defined in the manually collected data, the software extracted the route's sequence of stops. After this, for each of the routes, it generated simulated *route plans*. A route plan generates a path (a sequence of *roads* connecting the stops), which the simulated vehicle must follow to go from one stop to the next. The route-plan also specifies the time the vehicle must depart from each stop.

We identified a road network by downloading the OpenStreetMaps (OSM) raw data for the country in which each city lies [47]. We cropped the OSM file to define an appropriate section of the network for our study, creating a boundary box defined by longitude and latitude coordinates [48]. The software searched this chosen road network to find the paths that the simulated taxi should take along its route. We converted the cropped OSM file to a road network file which was readable by the mobility simulator, SUMO [49].

The algorithm used for solving the paths was SUMO's implementation of the Dijkstra

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algorithm [49]. This algorithm chooses between various optimisation objectives when solving for a path: time, distance, energy usage, etc. We chose to use distance, as it is the computationally cheapest optimisation [50]. However, for more realistic paths the *time* objective should be used instead. With the *distance* objective, the algorithm might choose short paths that go along roads with low speed limits and possible congestion. For example, it might choose a path through the city rather than along the highway. With the *time* objective, the algorithm might choose the highway option, which is longer in distance but shorter in time. This would be more realistic, because the taxi driver would prefer the quicker option.

For each route, the route plan was generated by traversing through the route's sequence of stops. For each stop, the nearest road on the road network from the stop's coordinates is found, and the shortest path from the road of the previous stop to the current road is calculated. This path is appended to the route plan being built. The route plan also specifies that the simulated vehicle should stop on the current road until the departure time of the current stop. This process is illustrated in Algorithm 1.

foreach city do

| foreach route do |
|--|
| Initialise the route-plan as an empty list; |
| foreach stop do |
| current_road := Find the nearest road to the stop's coordinates; |
| if previous_road was found then |
| Calculate the shortest path from previous_road to current_road; |
| Append this path to the route-plan; |
| Append stop's timestamp to the route. It will be the departure time from the current stop; |
| end |
| /* Store the current road for the next iteration. */ previous_road := current_road; |
| end |
| Save the route-plan; |
| end |
| end |

Algorithm 1: Route plan algorithm.

From the generated routes, we computed extra information that affects an electric vehicle's energy usage, such as the total distance, the road inclination and the road curvature.

1.2.3 Minibus taxi mobility modelling from vehicle-based data

Much more processing was required for the GPS-tracker data, since the raw data does not identify any routes or indicate which datapoints constitute a stop. We therefore did spatio-temporal clustering to identify the stop locations and times. After this, we generated the route plans by computing the paths between stops in preparation for electric minibus taxi modelling.

We ran the EV models independently in a micro-transport simulator (SUMO) [49, 51] and then recorded and analysed the vehicle's energy requirements for each simulated route.

We did three stages of spatial GPS data analysis to generate the mobility simulation data from measured GPS traces, using custom scripts written in Python. The first stage was visual inspection of the raw GPS data on a map to identify the main areas where the minibus taxis operated. The second stage was spatial clustering of the geo-locations to identify regions with dense points of interest, and then categorising these points and identifying GPS-related errors. We also removed errors introduced by divergent driver behaviour, such as taking a trip to a beach or other unusual behaviour. The third stage was using the identified stops and SUMO's ancillary routing function to generate the paths between consecutive stop events to use in a SUMO simulation with the built-in EV model.

Visual inspection of raw GPS data

We plotted an overlay heatmap showing the intensity variation of minibus taxi activity (based on the count of GPS data points) as shown in Figure 1.1. We could see four high-intensity areas: Stellenbosch, Kraaifontein, Mitchells Plain and Somerset West, which we interpreted as the epicentres of minibus taxi activity, a view that closely corroborates with the areas identified by an earlier study [52].

Spatial clustering and analysis

We used the DBSCAN (density-based spatial clustering of applications with noise) algorithm to group high-density closely related data points (or geo-locations), forming spatial clusters of data points that represented significant events (such as stopping and movement) during normal minibus taxi operations. We chose this algorithm because it is robust to outlier detection, can discover clusters with uneven densities and arbitrary shapes, and does not need prior knowledge of the number of clusters [53, 54]. For cluster analysis in this chapter, we used a Python implementation of the DBSCAN algorithm from the Scikit-Learn package [55]. The minimum cluster size was 70, and the maximum distance between neighbouring points in a cluster was 0.0002° [56].

We performed further analysis on each spatial cluster to identify sets of data points representing either a *stop event* or a *movement event* within the cluster's spatial extent. A stop event of a minibus taxi is closely related to a "stay point" as defined by Zeng et al. [57] and Damiani et al. [58]. Stop events are consecutive GPS locations within a cluster with a velocity below a threshold of 1 km/h.

Movement events (or "waypoints"), the cluster data points that do not belong to the "stop event" category, were preserved for use during minibus taxi route-plan generation in the eMBT model described below.

Generating routes

To simulate the mobility of minibus taxis between the high-intensity areas in the selected region and assess their energy requirements, the paths linking the identified stops were generated. A *path* is defined as a series of roads connecting two or more stop events, often starting and ending in different clusters. A simulated minibus taxi follows pre-selected paths as part of its daily route plan within the simulation boundary.

To generate the daily route plans, we again used stop events' cluster centroids, waypoints (GPS data representing moving events), the roads network and SUMO's shortest path Djikstra algorithm. The underlying road network infrastructure was again based on OpenStreetMaps (OSM) [59], which included the roads, intersections, speed limits and traffic-lights information. All GPS data points (including cluster centroids and waypoints)

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were snapped to the OSM's road network, and the shortest path between the origin and destination points computed using SUMO's implementation of the Djikstra algorithm [49].

For the passenger-based data, route-plans were generated for each route specified in the dataset. For the vehicle-based data, however, the routes were not specified in the data. Hence, route-plans were generated for each day recorded in the dataset.

Mobility model metrics

We developed a mobility model that could obtain the stop events which occurred in each spatial cluster. To generate the mobility patterns and also establish the charging potential, we had to identify the spatial clusters with the most stop events. We also did temporal clustering for each spatial cluster to find the times that these stop events occured. We also wanted to determine the total time that a minibus taxi typically remained stopped on a given day in order to calculate the charging potential. The following results were therefore generated to capture these metrics.

We first applied thresholds to filter out stop events with a duration above 8 hours or below 20 minutes. We did this to ensure that stop events irrelevant to our study did not skew the statistics. We grouped these stop events by the spatial cluster in which they occurred, and did temporal clustering within each spatial cluster to obtain spatio-temporal clusters.

For each spatio-temporal cluster, we generated a statistical summary, describing the total number of stop events, average stop arrival time, average stop duration, and the standard deviations therefrom. The statistical summary helped us to identify the spatial clusters with the most stop events, and the time that the stops typically occurred and their duration.

As a result, we ascertained that spatial clusters with a high number of stop events were situated near formal taxi stops (terminuses). Spatial clusters with lower counts were situated around intersections, or informal stops made en route to pick up passengers. Clustering the stop events temporally helped us identify the times at which these stops typically occurred.

We generated box plots of each eMBT's daily stop durations to show the overall stop duration per day, thereby showing how much time would be available for charging the eMBT.

1.2.4 The eMBT model simulation setup

To measure the temporal variation of power and energy usage, and the relationship between power consumption and eMBT speed, we set up a simulation model using a custom SUMO electric vehicle simulation module (SUMO EV). This model's parameters were specifically designed to be similar to those of the prevailing model of minibus taxi presently used in South Africa, the Toyota Quantum. Accordingly, the weight and front surface area of the eMBT model were taken from an existing Quantum. The rest of the parameters, summarised in 1.3, were approximated on the basis of recommendations by Fridlund et al. [60]

| Parameter | Value | Unit |
|-------------------------|-------|-------------|
| Height | 2.3 | m |
| Width | 1.9 | m |
| Front surface area | 4 | m^2 |
| Weight | 2,900 | $_{\rm kg}$ |
| Constant power intake | 100 | W |
| Propulsion efficiency | 0.8 | - |
| Recuperation efficiency | 0.5 | - |
| Roll drag coefficient | 0.01 | - |
| Radial drag coefficient | 0.5 | - |

Table 1.3: EV model parameters

This eMBT model was applied to the route plans generated in Sections 1.2.2 and 1.2.3. The simulation program initialised the eMBT model for each date that was simulated. For every second of simulation time, the simulator logged the energy consumption and speed of the eMBT as it progressed along its route plan.

1.3 Results and discussion

1.3.1 Passenger-based data

The passenger-based energy results are shown in Figure 1.2. Figure 1.2a shows the aggregated results for Kampala, in which all the individual routes in the dataset and their related frequencies were aggregated to estimate energy requirements for the paratransit system (minibus taxis only). The figure shows the power requirements throughout the day and the aggregated energy demand as the day progresses. Importantly, this only includes the routes covered in the dataset, and no extrapolation was done to include other routes. The figure shows a clear peak in the morning between 6 am and 9 am, followed by a plateau up to 6 pm, after which demand quickly decreases. The energy profile (power and aggregated energy) is shown for a 43 km route in Figure 1.2c.

Figure 1.2b. shows the aggregated results for Nairobi, again with all the routes and their corresponding frequencies aggregated for a system-level energy representation. The system profile shows the expected morning peak from 6 am to 10 am, a lull between 10 am and 3 am, and a longer peak from 3 pm to 9pm, after which the power quickly decreases.

The aggregated power profile is substantially lower than that of Kampala, which peaks at 280 MW, while Nairobi peaks at a mere 90 MW. This may be partly because Nairobi has fewer minibus taxis than Kampala, as noted earlier. However, a simple proportional calculation shows that the difference may also be partly because of under-representation in the passenger-based acquisition of routes. It is a drawback that we have no way of knowing the taxis' destinations unless they had passengers collecting data.

1.3.2 Vehicle-based data

The minibus taxi mobility modelling provided spatial clustering of the identified stop events while generating paths used to determine the power requirements of the individual eMBTs and the fleet.



Figure 1.2: Daily power and energy profiles of minibus paratransit systems in Kampala and Nairobi, from passenger-based data.

Energy demand

The output of the eMBT simulation is shown in Figure 1.3 for Kampala and Stellenbosch. A clear typical temporal profile is apparent for the minibus taxis in both cities, closely matching the expected peak traffic hours. This profile indicates the energy requirements of the eMBTs, and already hints at some charging potential during the evening – probably from grid power – and some during the middle of the day – preferably from solar power.

The mean instantaneous power demand profile of a working weekday in Kampala is shown in Figure 1.3a. "Power demand" refers to the net power drawn from the vehicle's battery. There is a morning peak demand period from 7 am to 9 am, with a peak mean value of 15 kW. A diminished demand with a mean of around 10 kW is observed from 11 am to 4 pm, constituting a period of reduced activity and demonstrating the potential for solar charging. A gradual increase to another pronounced mean peak value of 17 kW between 7 pm and 9 pm follows, and this flatter evening demand profile slowly declines to return to less than 3 kW by midnight. Complete inactivity is observed from midnight to



Figure 1.3: Summary of electrical demand for all the simulated eMBTs' daily power (instantaneous and rolling average) sampled per second, expressed per taxi.

5 am. This indicates that there is a period of around 5 hours for charging during night-time hours. It is clear that the taxis are active for a very long part of the day. This corresponds to the qualitative study done by Spooner et al. (p.29) [41] which showed that some taxi drivers in Kampala worked for more than 15 hours a day. The mean energy required per day was 220 kWh, and the mean distance was 224 km (obtained by integrating the power and speed profiles respectively).

The mean instantaneous power demand for a working weekday in Stellenbosch is shown in Figure 1.3b. There is a sharp demand peak period during the morning hours of 6 am and 9 am, with a peak mean value of 23 kW. A diminished demand with a mean of 5 kWh is observed from 9:00 am to 1 pm, constituting a period of substantially reduced activity, further demonstrating the potential for solar charging. This is followed by a gradual increase to a slightly less pronounced peak mean value of 21 kW between 5 pm and 6 pm. This flatter evening demand profile slowly declines to return to the trough of 6 kWh by 9 pm. Complete inactivity is observed from 11 pm to 5 am. Not only is the profile clearly defined, but the variation between taxis, shown by the minimum and maximum profiles in the shaded area, is minimal. The only substantial deviation is the increase in the maximum profile just after 9 pm. This is because some taxis start long-distance weekend trips on Friday evenings. [52, 61]. The mean energy required per day was 212 kWh, and the mean distance was 228 km.

The Kampala profile shows more variance in the power distribution, and also has less accentuated evening and afternoon peaks than the midday lull. This Kampala profile from vehicle tracking is substantially different from the passenger-based profile captured in Figure 1.2. The profile generated from manually tracked data falls away shortly after 6 pm. We believe this is due to field workers going home after the day's work, which erroneously creates the impression of a system with diminished activity from 6 pm onward. Relying on the data captured by field workers would therefore lead to a substantial error in energy estimations, exemplifying the crucial need for vehicle-based data collection.

The distribution of energy usage per day is shown in Figure 1.4a for each of the eight taxis in Kampala. Their energy usage is similar, with the median energy per taxi per day across all taxis ranging from 108 kWh to 335 kWh, with the mean of the medians equal to



Figure 1.4: Daily energy usage for each simulated eMBT.

220 kWh. The taxis travelled a mean distance of 224 km, leading to an energy efficiency of 0.98 kWh/km. For seven of the eight taxis there is a 75% probability that the taxi will use less than 314 kWh on a given day. For the eighth taxi, the 75th percentile energy-usage is 375 kWh. However, up to 491 kWh would be needed to meet the energy demand of *all* (non-outlier) days for all the taxis.

The distribution of energy usage per taxi per day, is shown in Figure 1.4b for the nine taxis in Stellenbosch. The taxis' energy usage is similar, with the median energy per day per taxi ranging from $189 \,\mathrm{kWh}$ to $252 \,\mathrm{kWh}$, with the mean of the medians equal to $215 \,\mathrm{kWh}$. For any given taxi, on $75 \,\%$ of the days less than $303 \,\mathrm{kWh}$ is used. Edight of the nine taxis, on all days, used less than $420 \,\mathrm{kWh}$, while remaining taxi used up to $490 \,\mathrm{kWh}$.

The results show that a maximum usable battery capacity of approximately 500 kWh would be sufficient for urban travel, if charging is limited to the stationary period before the day's first trip, and for 75% of the time a 303 kWh battery would be sufficient. This indicates that the demand is much bigger than the battery capacity of currently available passenger electric vehicles. To reduce the battery size and capital costs of the vehicle, it would be necessary for eMBTs to charge at various stops during the day. However, the results do seem plausible, as the mean energy efficiency of these minibus taxis (0.98 kWh/km) sits in-between the energy efficiencies of light electric vehicles and large electric buses [62]

1.3.3 Charging

A sizable eMBT fleet could place a substantial burden on the local electrical network and power generation capacity of countries in sub-Saharan Africa. The strain on the local electrical grid supplied by the utility could cause infrastructure and electrical supply problems, so we investigated the opportunities for charging these vehicles from solar photovoltaic systems. To discover the eMBTs' opportunities and requirements if they are to charge during stationary periods, we did a 24-hour analysis of the start times and the durations of stop events. The analysis shows what the average charger capacity should be if a vehicle is charged using only power from the local electrical grid. We applied a minimum stop duration of 20 minutes and a maximum stop duration of 8 hours per event to ensure that only valid operational stops would be identified and that drop or pick-up-and-go events were not included as charging opportunities. We chose the maximum of 8 hours because a taxi in normal service would be unlikely to stop for longer than that on a week day.

Figure 1.5 shows the distribution across days of stop events with the minimum and maximum stop duration thresholds applied. Figure 1.5a shows that the Kampala minibus taxis' cumulative stop durations vary considerably, with the median duration per day ranging from a minimum of 8 h for taxi T05 to a maximum of 12 h for taxi T08. Figure 1.5b shows that there is also a substantial variation in stop duration times between the taxis in Stellenbosch, with the median stop duration per day ranging from a minimum of 8 hours for taxi T3001, and a maximum of 11 hours for taxi T6000.



Figure 1.5: Daily durations of minibus taxi stop events with duration thresholds (20 minutes to 8 hours).

To calculate the charger capacity, we used a relatively high energy demand and a relatively short charging time for an averagely demanding situation. We used the average of the 75^{th} percentile of the energy usage, from Figure 1.4, and the average of the 25^{th} percentile of the 24-hour stop duration times, from Figure 1.5. For Kampala, these were 273 kWh and 6.7 h respectively to calculate a charger capacity of 40.6 kW. This assumes a constant charging profile for the sake of simplicity, as a real EV charging profile would require additional modelling. With these assumptions, 40.6 kW for 6.7 h would fully recharge a taxi on most days. For Stellenbosch, these were 247 kWh and 7.7 hours respectively to calculate a charger capacity of 32 kW. This is if we assume a constant charging profile and we are only charging from the local electrical grid supplied by the utility.

1.3.4 Data sources

The traditional domain of civil engineers is infrastructure. Transport engineers typically obtain information by employing people in two outdated ways, either to stand next to the road to record inflows and outflows or to get into vehicles to act as human carriers of tracking devices. These methods are particularly attractive in developing countries where operational traffic monitoring infrastructure is sparse and cheap labour is abundant. But, as mentioned in Section 1.1.2, this shortcut has many pitfalls.

Developments in vehicle tracking technology have changed the game. Although the setup cost is more, tracking devices have the substantial advantage that they are not

1.4. CONCLUSION

susceptible to human behavioural problems. For example, they don't wake up late, get tired and need eating breaks, and they do not sleep.

To illustrate the difference, in Figure 1.6 we show Kampala's energy profile from the two vantage points. The overlay shows the passenger-based energy profile, which was down-scaled by the number of taxis in Kampala (25,000 according to [41]), and our vehicle-based energy profile. The differences are stark. First, it is clear that the taxis started moving between 4 am and 5 am, before the fieldworkers managed to get on board. Second, the passenger-based profile grinds to a halt just before supper time. But we know that the minibus taxis in our samples happily chug away until after 9 pm.

Clearly, if we make assumptions about the power profile and energy requirements of electric minibus taxis from passenger-based data, we will miss the mark by a substantial margin. This adds weight to the statement by Collett and Hirmer that we quoted earlier stressing the need for adequate and reliable data [18].



Figure 1.6: Comparison of Kampala per-vehicle power profiles derived from passengerbased and vehicle-based data.

1.4 Conclusion

The threat of climate change has propelled an energy revolution from internal combustion engines to electric vehicles in the Global North. Influenced by market forces and supplier preferences beyond its borders, this wave will eventually sweep across the Global South with its organically evolved and notoriously chaotic paratransit systems and fragile electrical grids. Paratransit in the Global South has many unique characteristics, challenges and opportunities that will shape the eventual penetration of electric vehicles. This chapter focused on paratransit in the sub-Saharan region, which transports more than 70% of the region's commuters.

We considered how the dissimilar mobility characteristics of the minibus taxis, the mainstay of the paratransit in the region, will translate into electrical requirements. Also, since these vehicles park spontaneously at tacitly known stops of the drivers' choosing, for durations determined by passenger demand, the charging potential at these stops is unknown.

We also assessed two ways of modelling electrical energy requirements, passenger-based and vehicle-based.

We found that passenger-based data may be useful for determining the aggregate energy load of a whole city or a single route. However, these results could be wholly wrong if the passenger-based tracking is not reliable. Vehicle-based tracking provides a reliable means of determining the energy requirements of a vehicle, and with sufficient adoption it could be used to determine system demand too.

Our results showed that the electricity demand of the taxis was similar, with a nominal 250 kWh required per median day if no additional charging capacity is provided. This increased to 420 kWh when we included all days, except for one taxi, which required 490 kWh. The median stops per day ranged from 7.7 h to 10.6 h, suggesting considerable potential for charging.

The taxis with the shorter stopping periods, and hence the lower potential for charging, will need more energy because they are more mobile. Nevertheless, a nominal 41 kW charger will suffice when only charging only from the grid – if the grid is fully operational, which should not be taken for granted.

1.5 Further work

This chapter presents an informative and instructive view of how paratransit could be electrified, but challenges remain.

The first is the lack of sufficient-energy generating capacity to power the paratransit charging stations. The blackouts and load-shedding experienced in sub-Saharan Africa may hamper the transition from combustion engine powered minibus taxis to electric minibus taxis. Research should therefore explore the possibilities of harnessing alternative sources of energy such as wind and solar photovoltaic to power the electric minibus taxi charging stations. Second, although our simulation included micro-simulation of traffic scenarios, it would be prudent to expand the traffic models to include different scenarios for different cities and different modes of transport, such as motorbike taxis. Third, our eMBT model was extended from an existing EV model in SUMO, a transport simulator. Although the parameters were adjusted to reflect a minibus taxi, validation and potential further development of such a vehicle would probably provide more accurate results. Finally, the battery storage requirements for both the vehicle and roadside infrastructure have not been explored. These will have a large impact on business models and the viability of the transition.

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