Computing our way to electric commuting in Africa: The data roadblock

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Abstract

In the information age, the value of good data can hardly be overstated. Unsurprisingly, a severe lack thereof is seen as a pothole on the road to the decarbonisation of Africa's paratransit – the mainstay of the region's transport. Data acquisition in transport used to be concerned with the temporal flow rates and volumes of passengers and vehicles on sections of roads. This was done with surveys and vehicle counting. Separately, vehicle mobility data has been used for vehicle health monitoring, driver behaviour monitoring and vehicle recovery. For paratransit in Africa, where passenger counts and routes are unknown (and fluid), and where data acquisition is tedious, standardised passengers with tracking applications on phones are extensively used for this purpose. This brings the meaning of "good data" in this region of low and lower-middle-income countries into focus. Given the long ranges and fast refilling times of combustion engine vehicles, manufacturers and fuel outlets had hitherto existed in a symbiotic relationship without the bondage of mobility pattern information. However, in the era of electrification, battery-powered vehicles and their specifications and limitations have become inextricably coupled to road-side infrastructure through their mobility patterns due to their lower range and slower charge times. The infrastructure energy supply side can be modelled with dated passenger-based or roadside-based gathered data, assuming unchanged patterns. But, the charging potential calculations requires stationary rather than moving times. Moreover, energy demand per point is effectively that of an individual vehicle, which depends on spatio-temporal mobility patterns and battery capacity. Intermittent renewable energy generation further complicates this time variant challenge. In this paper we use a public passenger-based data set that is normally used to characterise routes, which has over 300 000 trips, to establish the energy requirements of seven cities in Africa - Abidjan, Accra, Cairo, Freetown, Harare, Kampala and Nairobi. The results show that the peak demand per city varies wildly, apparently with the reliability of the city's data, with realistic peaks of 100 MW to 300 MW. Although the results give an indication of the supply side requirements, it highlights the problem with using incomplete and/or unreliable data to estimate a city's peak load, which points to a need for vehicle-based data acquisition to adequately answer the question, or at least validate, the results.

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1. Introduction

"In light of the climate crisis, transport systems globally need to be decarbonised. This is particularly challenging in Sub-Saharan Africa (SSA) where transport systems are poorly characterised due to a lack of data, which contributes to hindering investment. We call for a more systematic approach to data collection to support the sustainable transition to electric vehicles in SSA."—Collett and Hirmer [1] in *Nature Sustainability.*

Over the years, *paratransit* has become one of the most dominant forms of transport in Africa, providing countless jobs and cheap transport for millions of people every day. Paratransit is a mode of informal public transport, owned by small operators, and which does not follow fixed schedules or routes, but rather adapts to passenger demand. Paratransit is characteristic of African cities, and accounts for over 70 % of the modal share (excluding non-motorized modes of transport) [2].

Although paratransit in the region takes various forms, such as minibus taxis, motorcycle taxis and tuk-tuks [3], minibus taxis in particular have become ubiquitous throughout Africa. They are able to carry many passengers and, moreover, they are available at low-cost, as second-hand imports from developed countries. [4, p. 348] Unfortunately, this has led to the system being fraught with old, under-maintained vehicles, causing a serious environmental concern. One study done on 12 African cities found that the average age of minibus taxis was 15 years [5]. Powered by internal combustion engines, these vehicles contribute greatly to the emission of greenhouse gases and a general decline of air quality in African cities [1].

Part of the reason that Africa's public transport is in this state is that there has been very little regulation on the paratransit industry. The paratransit industry originated from the collapse of state-owned public transport throughout the continent, during the restructuring of World Bank policies in the 1990s [5–7]. As a result, paratransit grew organically to fill this vacuum. By the time governments sought to control the transition, the system had already grown to a size that made it resistant to change [2, 8].

Although there is a lack of regulation, it does create the advantage that the system has low barriers to entry, encouraging small-business to enter the market. However, taxi operators also misuse this freedom to cut-costs in taxi-maintenance in order to squeeze profits from this relatively flooded market. At the same time, the urban poor have resigned to the poor standards of transport due to the fact that they cannot afford any better.

Some countries have made various interventions to try to improve the quality, safety and environmental footprint of these vehicles. While some of these countries have attempted to establish control through regulation, this has often resulted in pushback by the paratransit sector. In other cases, countries have tried to financially subsidise the sector to upgrade their fleets. This has been successful in economically advanced countries such as South Africa, which incentivised taxi owners with around USD 7500 when they scrapped their old taxis [2]. However, in most African countries, paratransit subsidies do not exist and would be unaffordable by the government [5].

Some countries have also tried to override the paratransit industry by competing against it with more formal modes of mass transit, such as metro rail, bus rapid transit, etc. However, these have been fraught with poor government spending, poor integration with existing paratransit, and general incompatibility with the dynamic transport needs of the urban poor. All this has led to formal mass transit being a burden on the tax-payer. [9]

In order to improve the state of transport in the future, a different approach needs to be taken. Sustainable mobility needs to be achieved hand-in-hand with paratransit, using computer optimisation. One paradigm through which to achieve sustainable mobility is the three-pronged "Avoid-Shift-Improve" approach [10, 11]. This paradigm follows three steps. The first is to *avoid* redundancy. For example, this can be done by reducing redundant taxi trips through computer optimisation. The second step is to *shift* to alternative technologies (e.g. electric vehicles). The software presented in this paper can be used to investigate the energy demands of various technologies to select the best alternative. Finally, the last step is to continuously improve the new technology through various efficiency upgrades. For example, an electric paratransit system can be enhanced with more/faster charging stations, integration of solar energy charging, and more efficient vehicles. All three of these steps require adequate data in order to drive the process.

Unfortunately, attempts at capturing paratransit data is surprisingly scarce, leading to poor decision making [1]. A few known attempts conducted in Africa are summarised in Table 1, and is outlined in more detail in the following paragraphs.

The paratransit data capturing approaches can be grouped into four categories: vehicle-based tracking, passenger-based tracking, roadside-based counting and household travel surveys.

We have found that, out of these various paratransit data collection methods, the *passenger-based tracking* method has become the most prevalent. A list of many such datasets can be found in [15] in addition to the seven datasets used in this article (listed in Table 2). In order to compile this data into a consumable digital format, several standards could be considered. Most of the datasets made use of the *General Transit Feed Specification* (GTFS), which is an open format used for digitally specifying public transport routes and schedules. Additional datasets were collected by a company called *GoMetro* [15] who use their own custom specification. However documentation of their specification could not be found, and the GTFS standard is

Table 1: Paratransit data-capturing methods

Methods	Strengths	Weaknesses
Vehicle-based Tracking: A selected number of minibus taxis are installed with GPS tracking devices. The tracking devices log the position and speed of the taxi at various points in time. (Examples: [12, 13])	• Data is collected on a per-taxi basis. This allows one to analyse the net energy that a taxi uses on any day of operation. • The times that the taxi makes stops between routes is known, allowing one to analyse how long the taxi has to charge on any day of operation. • The data is extremely robust since it is collected continuously and the taxi's day plan is recorded repeatedly. Hence, the data is updated continuously.	• GPS traces do not inform where and when a particular route stops and ends. Neither does it inform when a taxi stopped to deliver passengers (as opposed to stopping at a traffic light). Further data analysis needs to be done on the collected data to make it useful. • Capital cost can be extremely expensive. • Tracking devices are liable to theft. • High technical expertise required for installation and maintenance.
Passenger-based Tracking: Hired personnel are deployed into the paratransit system with mobile tracking devices. They travel in each of the routes that exist in the paratransit system, logging data regarding the stop locations and times along the route. (Examples: refer Table 2, [14, 15])	• Requires very little consultation with paratransit operators. • Minimal technical expertise required. • Can be cost-effective in countries where uneducated labour is relatively cheap, if updating the dataset is not planned.	• Takes very long to obtain sufficient data quality. Certain routes may take very long to traverse, and need to be taken multiple times in order to obtain confidence in the data. • Data is collected on a per-route basis rather than per-vehicle. Therefore, no information will be available regarding the exact itinerary of each of the taxis. • Data needs to be manually updated periodically.
Roadside-based Counting: Hired personnel are hired to stand at a particular location (e.g. a paratransit terminal) and count the number of paratransit vehicles passing or stopping at that location. (Examples: [16–18])	• Requires very little consultation with paratransit operators. • Minimal technical expertise required. • Can be cost-effective in countries where uneducated labour is relatively cheap, if updating the dataset is not planned.	• No information on the exact itinerary of each of the taxis. • Data needs to be manually updated periodically.
Household Travel Survey: Hired personnel are deployed to households in the region of study. Households then answer a questionnaire regarding their travel patterns. (Examples: [19])	• Can be cost-effective in countries where uneducated labour is relatively cheap. • Requires very little consultation with paratransit operators. • Minimal technical expertise required.	• Data is presented at a very high level. Data is presented in an origin-destination based format. No vehicle-based or route-based data. • Data capture takes a lot of time, and might be difficult if sufficient respondents can not be obtained for the study. • Data needs to be manually updated periodically.

more widespread globally. This paper therefore makes use of the available GTFS data to:

- Forecast electric paratransit energy demands in the various paratransit systems.
- Evaluate the GTFS method's suitability for electric paratransit forecasting.
- Validate if the quality of currently available GTFS paratransit data is acceptable.

This paper specifically focuses on minibus taxis, since that particular mode of paratransit is the most prevalent across Africa [2]. While the various GTFS datasets contained various modes of paratransit, the minibus taxi was the only mode present in all the available GTFS datasets.

GTFS was originally developed for formal public transport systems, which have predetermined timetables and routes. In the case of paratransit, schedules and routes are fluid and based on the demand. Hence, it becomes necessary to collect sufficient data in order to synthesise "typical" routes and schedules within a boundary of confidence. The GTFS standard has provisions to capture (1) The shapes of the various routes, (2) location, arrival time, and duration of stops along each route, and (3) what times of the day a taxi departs on each route.

The popular approach for capturing this data for paratransit systems is the one pioneered by *The Digital Matatu Project* [20]. This approach employs data collectors equipped with mobile phones who ride on the taxis to collect data. As the data collector makes a trip on a particular route, the mobile phone records the path taken, and the data collector will make a record when the taxi stops to drop off or pick up passengers. The process is very manual. The advantage of this is that very little permission is required from the taxi association to collect data, as nothing is installed on the vehicles. As a result, the capital cost of the data capture is minimised.

However, there are some major disadvantages with this approach. First of all, the data is only valid for as long as the paratransit system continues to follow the same movement patterns. However, in reality, paratransit movement patterns often adapt to the evolving demand of its customers. Therefore, data will need to be re-captured at regular intervals in order to keep the dataset up to date. Although unskilled labour is often cheap in Africa's developing countries, the cost can quickly compound due to the number of man-hours required to collect the data. This could be the reason that none of the datasets we analysed have been updated since their initial release.

DigitalTransport4Africa (DT4A) [14] is a recent concerted effort to collect GTFS data for paratransit systems in African cities. The collection of datasets are hosted online, and can be used by the public for free. Furthermore, the collection can easily be contributed to by the public, allowing for the public to add their own GTFS data and request corrections to existing datasets. This has facilitated rapid growth to the size of the collection. Currently, the site hosts GTFS data for the paratransit systems of 12 African cities. The quality of this data will be evaluated in this paper, and the data will be used to estimate Africa's readiness for EV taxis, while at the same time highlighting how the state of the art in paratransit data collection can be improved for future EV evaluations.

In sum, this paper will use the DT4A paratransit datasets to project the amount of energy that would be required for electric paratransit in various African cities. The paper seeks to answer a few questions from this data. Firstly, from the perspective of the grid: how much additional energy would the system require, and what would the peak load be on the grid? Secondly, from the perspective of the vehicle: what battery size would be required, and what are ideal times for the taxi to stop and charge? Finally, the paper will discuss the suitability and reliability of using this data to answer these questions. If it is found that GTFS data is not descriptive enough to answer some of our research questions, the paper will suggest alternative data schemes or suggest how the current data scheme can be improved.

Our custom-built software, which we call *EV-Fleet-Sim*, was used to obtain the results in this paper. This software and its source code can be downloaded from the following website: `https://gitlab.com/eputs/ev-fleet-sim`. We publish the software for free use and modification, subject to the terms of the GPLv3 license. The data [14] is also publicly available, allowing for easy reproduction of the results.

2. Method

GTFS datasets were obtained for ten African cities from DigitalTransport4Africa [14]. These datasets described the schedules, routes, and stop locations of minibus paratransit. Although the methods described in this paper should be extendable to any other form of public transport that can be described in the GTFS specification, minibus paratransit is quite unique in that it is highly unregulated. Because of this, the compilers of these GTFS datasets were required to do their own data collection in order compile their GTFS datasets. This meant that varying approaches were used in this process, each with varying degrees of scientific rigour and reliability.

2.1. Data Reliability Analysis

Therefore, the first step was to inspect the datasets and the methods used to compile them, in order to evaluate their reliability. This was done in a systematic way. As discussed in the introduction, a few methods of paratransit data-collection exist. By reading through the literature surrounding each dataset and contacting the various dataset compilers, it was possible to obtain the details of the methods used to collect the data behind seven of the ten datasets.

In the case of this study, all the datasets were compiled using the approach of deploying human data-collectors into the field. We selected a couple of metrics that could be used to give an idea of how the data was collected and how much effort was put into collecting the data and keeping it up to date. The chosen metrics include:

- Whether data-collection was *passenger-based* or *roadside-based*:
  - *Passenger-based* data collection means that the collectors boarded the minibuses as passengers, and recorded data by travelling the various routes.
  - *Roadside-based* data collection means that the collectors stood at the various terminals, recording the frequency at which taxis arrive and depart.
- Months since last update: Indicates whether the dataset is being kept up to date.
- Number of human data collectors: More data collectors would indicate more effort put into collecting the data.
- Number of weeks of data collection: A longer data collection period would indicate more effort put into collecting the data.

We tabulated these metrics for each of the seven cities in order to compare the rigour with which their data was captured. Furthermore, we classified the effort behind each dataset into three categories: high, medium and low.[*1]

However, in order to make a fair comparison of the reliability of the datasets, it was also necessary to capture metrics that would illustrate the size of each dataset. A larger dataset would naturally require more effort to capture. Hence, another table was generated with the following metrics to get a context of the size of each dataset.

- Number of routes: The data capturers would need to make at least one trip on each route of the paratransit system. Hence, more routes there are, the more effort required to complete the data capturing project.
- Number of trips per day: Each day, multiple trips are taken on a particular route. This metric summarises how many trips are taken per day across all the routes of the transport system.

[*1] We classified datasets with less than 50 man-weeks as low effort, less than 100 man-weeks as medium effort, and above 100 man-weeks as high-effort.

- Geographic spread of the transport system: This is the area in km^2 of the transport system, as derived from the dataset. This is calculated by creating a bounding box from the minimum and maximum coordinates that are recorded in the transport system's route definitions, and calculating the area of that bounding box. A larger geographical spread would indicate that the routes are longer. A longer route, would probably require more time to capture than a shorter route.

We therefore classified the size of each dataset as small, medium or large. For example, a dataset with many routes and a large geographic area, would be classified as "large".[*2]

From these classifications, it was possible to evaluate the reliability of each of the datasets. This was done by comparing the effort to the dataset size. If the level of effort was less than the dataset size, then the dataset's reliability was classified as "low". If the effort was equivalent to the level of the dataset size, then it's reliability was classified as "medium". If the effort exceeded the level of the dataset size, then it's reliability was classified as "high". For example, a dataset with with of a medium size would have its reliability classified as "low" if the effort was low, "medium" if the effort was medium, and "high" if the effort was high.

2.2. Minibus taxi mobility modelling from data

For each of the cities, the following method was used to create a simulation-ready model from the data:

The first step was to obtain geographical data that would describe the road network and terrain that the paratransit system operates in. We were able to utilise a free dataset developed by OpenStreetMap [21]. The download server stores the data as one file per country. Therefore, we were forced to download the data for the whole country in which the city lies [22]. For each of the routes defined in the GTFS file, we searched for the coordinates of the smallest possible rectangular bounding box which would enclose all the routes of that city. We then cropped the geographical data to the bounding box, using the *OSMConvert* program [23]. This would extract only the appropriate section of the data for our study, greatly reducing simulation overhead. This geographical data was then converted to a simulation-ready road network using the *Netconvert* program [24].

The software searched this road network to find the exact *path* (sequence of roads) that the simulated taxi must follow to go from one stop to the next. The location of these stops were extracted from the GTFS file [25]. The times and sequences of the stops were also extracted and combined with the paths generated in order to create *route plans*, files which direct the movement of the electric vehicle model during the simulation.

[*2] We multiplied the routes with the area (in km^2) for each of the datasets. If the resulting value was below 200 thousand, it was classified as small. Values below 400 thousand were classified as medium, and values above 400 thousand were classified as large.

The Dijkstra algorithm was used for solving the paths [24]. 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 [26]. 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 was 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.

2.3. The Taxi EV model

With the route plans established, the next step was to define an electric vehicle model that can follow the route plans. The model would need to be configurable and use the route's distance, road inclination and curvature to evaluate the electric vehicle's energy usage.

The SUMO software [24] was used for this purpose. The electric vehicle model built into SUMO allows the user to set various parameters. Since the focus of this study is minibus taxis, a common minibus taxi, namely the Toyota Quantum, was used as a basis for the EV parameters. The following model parameters were chosen from the Quantum's geometry:

Height: 2.3 m, width: 1.9 m, front-facing surface area: 4 m^2, weight: 2900 kg.

We approximated the rest of the parameters according to the recommendations by Fridlund and Wilen [27]. These include:

Constant power intake: 100 W, propulsion efficiency: 0.8, recuperation efficiency: 0.5, roll drag coefficient: 0.01 and radial drag coefficient: 0.5.

The software initialised the EV model for each route that was defined in the GTFS file. The EVs followed the route plans, obeying all speed limits, traffic signals, etc. as defined in the road network. For every second of simulation time, the simulator outputted the energy consumption and speed of the EV as it progressed along its route.

The simulation resulted in energy and power usage profiles of each of the routes. The GTFS file defines a *frequencies.txt* file. This file indicates the frequency at which new trips commence on each route, for various periods of the day. For example, a new trip may commence on a particular route every 30 minutes from 6 AM to 8 AM, and every 10 minutes from 8 AM to 9 AM. Based on this frequency data, the results were replicated for the trips on each of the routes.

With an average of 45,000 daily minibus taxi trips per city, the volume of output data from the simulation was substantial. Our goal was to obtain useful metrics that would summarise this data. The first metric we considered was the total power usage profile of the whole electric minibus paratransit system. Such a profile would indicate how much power the system would require at various times of the day. This profile would be indispensable, for example, for identifying the peak strain that the electric fleet would have on the grid. It could also indicate what times this strain would occur.

We calculated this profile as follows: First we retrieved the power-vs-time results of each trip, to generate power profiles of each trip. For each route, we aggregated power profiles of the trips done on that route, to get the total power profile of the route. Finally, we aggregated the power profiles of all the routes in the taxi system, to get the total power profile of the city's taxis. The profile was plotted with respect to time.

In addition to the power usage characteristics, the energy usage of the minibus taxi system was also of interest. The power profiles obtained in the previous step were integrated with respect to time, in order to obtain energy-vs-time profiles. The net energy profile of the minibus taxi system of each city would give an estimate of the total daily energy usage, how much energy was saved due to regenerative braking, and how much energy would be used between times of relative inactivity.

Finally, for each city, box plots were created to show the median energy usage of the routes, as well as the spread of energy usage across the various routes of the city.

In order to verify the results, we generated a table of the characteristics of paratransit in the various cities. The simulation results were compared to these characteristics to see if they corresponded. We chose characteristics about the city that would indicate the magnitude of its transport needs. The following metrics were chosen for this purpose:

- Number of taxis: A higher number of taxis would indicate that there are probably more trips to be serviced, and hence more energy would be required.
- Number of inhabitants: A city with more inhabitants would have higher transport needs, and, hence, more energy usage could be expected.
- Modal split of minibus paratransit: If a higher percentage of trips are taken via minibus taxis, as opposed to other modes, the energy usage would be higher.

After further investigation, we found that some of the cities did not have reliable, up-to-date statistics on the number of taxis. We therefore used the remaining two metrics to classify the expected energy demand as high, medium or low.[*3]

3. Results and discussion

This section will discuss the results obtained from the various steps of the methodology. It will first attempt to investigate the reliability of the data. After this, it will use the data reliability investigations to discuss what can be expected from the simulation. The simulation results will then be presented, and correspondence with the data reliability investigation will be highlighted. Finally, the simulation results will be verified with the verification metrics discussed in the methodology. Throughout this section, we will suggest reasons for data reliability issues and the consequences thereof.

3.1. Data Reliability Analysis

Since the various datasets were collected by different independent entities, the effort taken varied for each set. Table 2 captures a few metrics that indicate the method, recency, and rigour with which each dataset was collected. For each city, we evaluated the effort made to capture the data based on these metrics. Many data collectors and many weeks of data collection would imply that more effort was taken in the data collection process.

Due to the fact that four of the seven datasets were missing sufficient documentation, we were unable to populate some of the cells. Unfortunately, this reduced our ability to interpret the reliability of the data.

[*3] If the product of the population size and the modal split was below a threshold of 1.5 million, we classified the expected energy demand as low. If it was below 2.5 million it was classified as medium, and if was above 2.5 million it was classified as high.

Table 2: Data collection method, recency, and rigour

City	Approach	Months since last update	Number of Collectors	Number of Weeks	Reference	Effort
Abidjan	Onboard + Static	2	7	~ 24	[16]	High
Accra	Onboard + Static	36	6	~ 5	[17]	Low
Cairo	Onboard	42	19	–	[28]	Low
Freetown	–	27	–	–	[29]	Low
Harare	Onboard	29	–	2	[30]	Low
Kampala	Onboard	15	–	10	[31]	Medium
Nairobi	Onboard	27	5	~ 24	[20]	High

The table shows that the Abidjan dataset has a high effort rating. This was due to the fact that they did more man-weeks of work ($7 \times 24 = 168$ man-weeks) than any other dataset. We considered datasets with limited documentation also deficient in reliability. For each missing metric we assigned the worst value found in the other populated rows. As a result, Freetown and Harare were classified as low effort.

Furthermore, all the datasets provided paratransit data only for a "typical weekday". In other words, the dataset did not express variation between days of the week, nor did it express the variation between seasons of the year. If the data was more descriptive, perhaps we could quantify how much less active taxis are on the weekend, when compared to the midweek, and how much later taxis start operating during Winter, when compared to Summer.

Although the datasets had these various issues, they were all relatively up to date. Only 1 dataset (Cairo) had not been updated in last three years.

However, effort alone is insufficient as a proxy for taken is not enough to evaluate the reliability of a dataset. This is because a large dataset requires proportionally more effort in the data collection. Therefore, we needed to have an idea of the size of each dataset. We computed various metrics which indicated the size of the datasets. Based on these metrics we classified the datasets as small, medium and large. This is shown in Table 3.

Table 3: Size and scope of the datasets.

City	Number of routes	Daily number of trips	Geographic spread (km^2)[*4]	Dataset Size / Required Effort	Reliability
Abidjan	73	8890	1850	Small	High
Accra	277	49 214	1356	Medium	Low
Cairo	94	29 000	4150	Medium	Low
Freetown	69	16 954	530	Small	Medium
Harare	486	86 733	4639	Large	Low
Kampala	369	92 262	2478	Large	Low
Nairobi	136	35 640	3097	Large	Medium

Finally, we were able to classify the reliability of each of the datasets. For example, the Abidjan data collectors took a lot of effort in producing their dataset, although the measured paratransit size was small, instilling high confidence in the reliability of the dataset. On the other hand, with Harare, although the dataset was large, little effort was put in, resulting in an apparent low reliability. These classifications are shown in the last column of Table 3.

We can expect datasets with a high reliability to produce results that are more verifiable.

3.2. EV Simulation Results

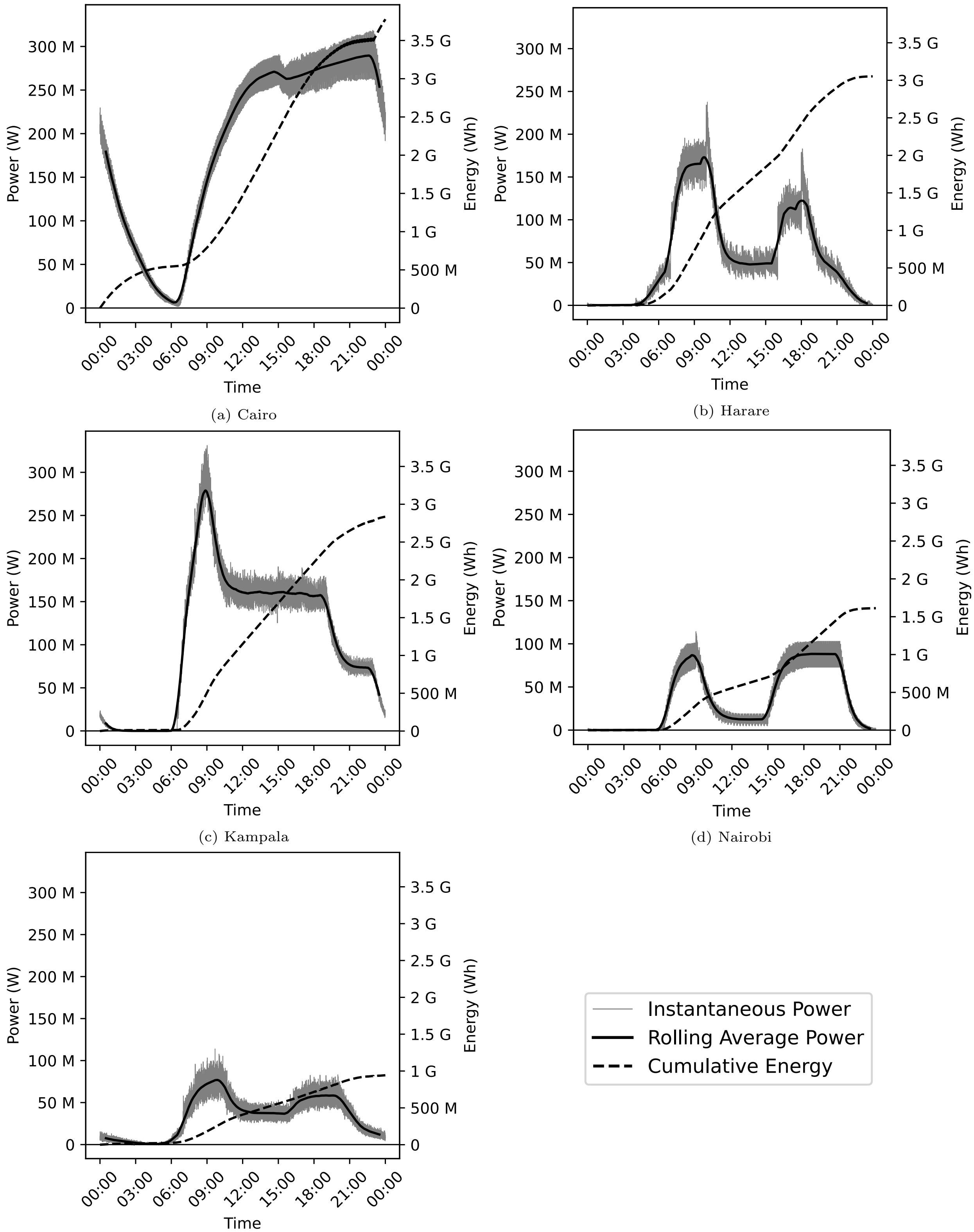
We took the seven datasets and ran it through our custom EV-Fleet-Sim simulation program. This yielded the power and energy profiles shown in Figure 1.

Four of the cities (Harare, Kampala, Nairobi and Freetown) have a peak in their power profile in the mid-morning hours (around 9 am). All of these except one (Kampala) also have an evening peak of power usage (at around 6 pm).

Cairo on the other hand displays a different power usage profile. Unlike the other cities, Cairo is North of the Sahara dessert. It is possible that its geographical differences have different living/mobility patterns.

The remaining two cities (Abidjan and Accra), do not have any peaks in their power profiles. Rather, they appear flat with low power consumption profiles. This corresponds with the fact that the geographical spread of the cities are small as indicated by Table 3. It could also indicate that the cities make use of other

[*4]Simulation size was determined by creating a rectangular box that bounded all the routes defined in the dataset, and then computing the box's size.



(a) Cairo

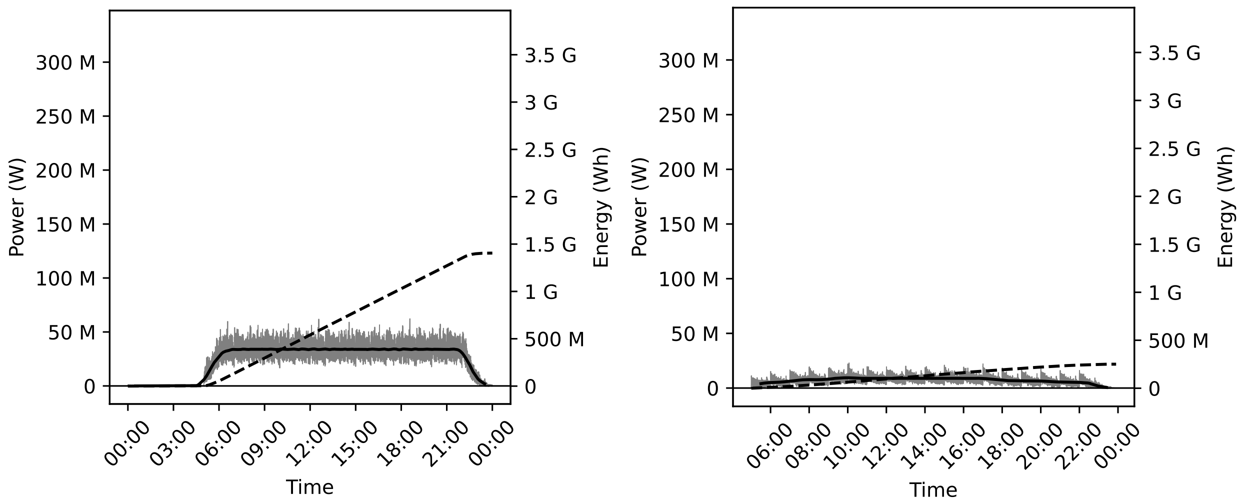
(b) Harare

(c) Kampala

(d) Nairobi

(e) Freetown

Figure 1: Daily power and energy profiles of the minibus paratransit systems. (Contd. on p. 15)



(f) Accra

(g) Abidjan

Figure 1: (Contd. from p. 14) Daily power and energy profiles of the minibus paratransit systems.

modes of transport to satisfy the bulk of their mobility demands. Both these cities are situated close to one another geographically, in North-West Africa. Freetown, the remaining city from North-West Africa, also has a low overall energy usage like Abidjan and Accra.

The total energy demand of each of the simulation scenarios is summarised in Table 4. These values will be used in order to perform verification. We will use data from an alternative source to approximate the energy requirements of each of the cities, and compare them to the results found in Table 4.

Table 4: Summary of simulation results.

City	Daily Energy Usage (MWh/day)
Cairo	3778
Harare	3053
Kampala	2835
Nairobi	1612
Accra	1405
Freetown	943
Abidjan	250

We also generated box-plots (Figure 2) which indicate the per-route energy usage of each paratransit system. If each route was apportioned a dedicated fleet of vehicles to service that route, the box plots show how much energy the fleets would use. Consequently, if each route was apportioned a dedicated charging station for its fleet, the box plots indicate how much energy the charging stations would require from the grid. Of course, such a scenario would be sub-optimal, but it was the only scenario we could conjure up that would allow the GTFS data to be useful on a disaggregated level.

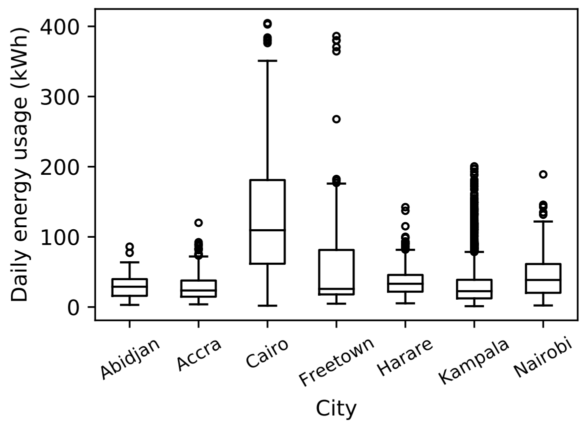


Figure 2: Daily energy usage of the routes of each city

3.3. Results Verification

In order to verify the results and see if they corresponded to what could be expected in reality, the taxi energy demands were categorised as high, medium or low based on the city's population size and the taxi modal split, as gathered from independent data sources. These are shown in Table 4. As shown in the table, Cairo is expected to have a high energy demand due to the fact that it has an extremely large population that relies on taxis. Conversely, Freetown is expected to have a low energy demand due to the fact that it has a relatively small population, and they don't rely on taxis much, as indicated by the low modal split.

Table 5: Paratransit characteristics of the cities.

City	Number of taxis[*5]	Number of inhabitants (Mil.) [32, 33]	Modal split (%)[*6]	Reference	Expected Energy Demand
Abidjan	5000	4.7	23	[34, 35]	Low
Accra	15 000	4.8	33	[36, 37]	Medium
Cairo	15 000	21.3	20	[28, 38]	High
Freetown	5000	1.2	23	[39]	Low
Harare	100 000	2.9	60	[40, 41]	Medium
Kampala	25 000	4.0	63	[42, 43]	High
Nairobi	15 000	4.7	43	[44, 45]	Medium

[*5] Refers to the *total* number of operational minibus taxis. Approximate values.

[*6] Refers to the number of trips that are taken by taxi, as a fraction of the total *motorised* trips.

We see that, for the most part, the energy usage from the simulations (in Table 4) correspond with the expected energy demands (in Table 5). For example, we see that Cairo has the highest simulated energy usage, and it also has a high expected energy demand. Abidjan has the lowest simulated energy usage, and it also has a low expected energy demand. The only results that did not correspond perfectly were Harare and Kampala. Harare had a higher simulated energy usage than expected, while Kampala had a lower simulated energy usage than expected. This can be attributed to the fact that both of those datasets had a low reliability rating in Table 3.

We can therefore say that GTFS data can be used to give a rough estimate of the order of magnitude of a paratransit system's energy demands. However, due to the current state of data quality, they are likely to be unreliable for quantifying the exact energy demands.

Our original intention was to approximate the expected energy demand using the number of taxis in each paratransit system. However, this proved to be difficult due to unreliable figures we found for this metric. In most of the countries, the transport authorities did not publish a figure on this metric. We therefore relied on independent sources, who's figures did not agree. For example, Harare's transport authority did not publish any figure on the number of taxis, and the figure of 100 000 which we found from an independent source seems extremely disproportionate when one takes into account the city's population size. In addition, that figure was the most recent we could find, although it is from 2002. This highlights, once again, the need for some level of systematic data collection.

Reliable statistics on the number of taxis would have also been useful for downscaling the power/energy profiles in Figure 1, in order to get the average taxi's energy demand. In the following paragraphs, we will nevertheless downscale the Kampala profile by the number of taxis in order to compare its power profile to one we computed from independently gathered, reliable, vehicle-based paratransit data. [46]

3.4. Discussion: Passenger-based data shortcomings

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 Table 1, 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 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 3 we show Kampala's energy profile from the two vantage points.

The overlay shows two plots. One is the passenger-based power profile from Figure 1c, which was downscaled by the number of taxis in Kampala (25 000, as shown in Table 5 [42]). The second plot is a *vehicle-based* power profile of Kampala obtained from Booysen et al. [46]. 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 see in the vehicle-based profile that the minibus taxis 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 a more systematic approach to data collection for the purpose of planning decarbonisation of paratransit [1].

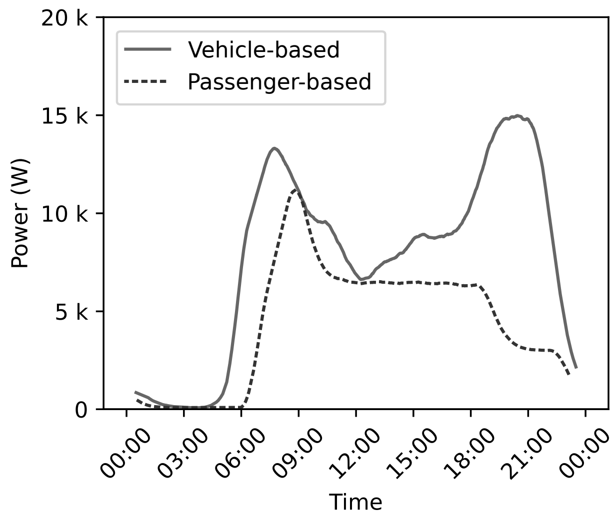


Figure 3: Comparison of Kampala per-vehicle power profiles derived from passenger-based and vehicle-based data.

4. Conclusion

Climate change is forcing the world to adapt to new, cleaner technologies, especially in the transport sector, which contributes a large share of carbon emissions. Developed countries have committed to ambitious plans to reduce their emissions in the short term, and are turning away from fossil fuel vehicles. Eventually, developed countries will be compelled to do the same, and must be prepared for such big changes.

This paper prepares for this eventual migration by providing a method for modelling and simulating electric paratransit, Africa's most used mode of motorised transport [2]. Using this method, this paper has attempted to establish the energy requirements that paratransit would have on the electric utilities of several cities across Africa. Publicly available GTFS data was used for the simulations, in order to evaluate how the state of the art can be improved for future evaluations, and whether the approach of paratransit data collection should be changed.

The first objective was to the establish the net energy demand that the paratransit systems would have on each of the cities. This was plotted in Figure 1 and summarised in Table 4. Although, the presented method was able to obtain the net energy demands of the paratransit systems, our evaluation of the data collection processes revealed a few quality issues that have hurt our confidence in the data. Therefore, we demand for more rigour in future paratransit data collection projects. Despite this, the results can still serve as an *indication* of what the future energy demand would look like.

The profiles give a rough idea of what the taxis' movement profiles would look like. Four of the cities (Harare, Kampala, Nairobi and Freetown) indicate that the highest energy demand of the taxis are at around 9 AM. This would indicate that taxis have a period of high activity in the so-called "morning rush". It is clear therefore that taxis need to be adequately charged overnight in order to sustain this high-activity period. Three of these cities also indicate a high-activity period in the evening. This would mean that the taxis may also need to charge around midday when there is a period of relative inactivity.

Although we know the periods of relative inactivity, we don't know exactly how long the typical taxi stops. This is because the data does not capture the individual taxis' itineraries. Rather, it gives the perspective from an infrastructure, passenger demand, and traffic modelling point of view. Specifically, it captures the itinerary and frequency of each route and assumes that taxis will be available to service the route. Therefore, since we do not know when the taxis stop, it is not possible to know exactly when and how much the peak strain on the electric grid would be due to the charging of the vehicles. In order to do this, tracking data of the individual taxis will be required. At best, with this data, we have an indication that the peak charging strain on the grid would be approximately the peak power usage from the electric vehicles, but offset a few hours earlier to the hours of inactivity.

If there was tracking data of the individual taxis, we would know exactly which routes they service during the day, and how long their breaks are between routes. We would then be able to profile the individual taxis' daily energy requirements which would be useful for calculating the battery size required for the taxis. This would have also been possible to find this metric through the GTFS data, if we knew the number of taxis operating the paratransit systems. However, statistics on the number of taxis operating in the cities are unreliable.

Finding the battery size would be important, since a mass roll-out of electric taxis would provide the electric network with a distributed energy resource. Essentially, the grid can use the batteries of vehicles connected to the grid as a buffer in which to store excess energy that is generated and draw energy when needed. A tariff scheme could help taxi owners to make a profit when they provide this service to the electric grid. To know exactly how much of a benefit this service would have on the grid, again we would need to know the battery size of the taxis and the times that the taxis stop to connect to the electrical network. At best, the results which could be generated from the GTFS data could give only a rough indication of the size of the total distributed energy resource at the grid's disposal. Assuming that each taxi's battery size is the approximately the same as its energy demand, then the total paratransit system would provide the grid with a distributed energy buffer equivalent to its energy demand (as found in Table 4).

Similarly, to evaluate the renewable energy generation capacity that is needed to supplement the grid to charge the taxis, we would need to know the stopping times of the taxis. Since most renewable energy resources are time variant, the exact stopping times are important. From the GTFS data, we have identified that, in some of the cities, the taxis have a dip in activity at midday, which presents and opportunity for charging from solar energy. However to quantify exactly how much solar resource is required, the stopping times need to be known.

In conclusion, the GTFS data that seems to be the state of the art in paratransit data capture is useful in giving us an idea of the total energy requirements of a paratransit system, in giving *indications* of the supply-side energy requirements, in *estimating* the distributed battery resource available to the electric network, and in *identifying opportunities* for charging the taxis through renewable energy generation. However, the data quality needs to be improved in order to establish enough confidence in the data to *quantify* these energy requirements and opportunities with a scientific level of accuracy. More rigour needs to be applied when collecting the data, possibly by increasing the number of field workers and the number of times data is collected on each route. The results clearly show that it is not possible to identify the per-vehicle energy requirements from GTFS data. Although an attempt was made to scale down the power profile by the number of taxis, we found that the result did not correspond satisfactorily with independently gathered GPS tracking data. This has highlighted the issues of human data collection, calling for a more systematic, autonomous approach in data capture. With all this in mind, the authors recommend that future data collection efforts employ the vehicle-based strategy (e.g. through GPS trackers). Through higher quality data driving the process of decision making, we can finally compute our way towards sustainable mobility in Africa.

References

[1] K. A. Collett and S. A. Hirmer. Data needed to decarbonize paratransit in Sub-Saharan Africa. *Nature Sustainability*, 4(7):562–564, 2021. ISSN 2398-9629. doi: 10.1038/s41893-021-00721-7. URL `https://rdcu.be/ckzez`.

[2] R Behrens, D McCormick, and D Mfinanga. *Paratransit in African cities: Operations, regulation and reform.* Routledge, London, 1 edition, 2016. ISBN 9781315849515. doi: 10.4324/9781315849515.

[3] Daniel Ehebrecht, Dirk Heinrichs, and Barbara Lenz. Motorcycle-taxis in sub-Saharan Africa: Current knowledge, implications for the debate on “informal” transport and research needs. *Journal of Transport Geography*, 69:242–256, 2018. ISSN 0966-6923. doi: https://doi.org/10.1016/j.jtrangeo.2018.05.006.

[4] Raffaello Cervigni, John Allen Rogers, and Irina Dvorak. *Assessing Low-Carbon Development in Nigeria : An Analysis of Four Sectors*. World Bank, Washington, DC, 2013. URL `https://openknowledge.worldbank.org/handle/10986/15797`.

[5] Ajay Mahaputra Kumar, Vivien Foster, and Fanny Barrett. Stuck in traffic : urban transport in Africa. Technical report, Washington, DC: World Bank, 2008. URL `http://documents1.worldbank.org/curated/en/671081468008449140/pdf/0Urban1Trans1FINAL1with0cover.pdf`.

[6] Ajay Mahaputra Kumar. Understanding the emerging role of motorcycles in African cities : a political economy perspective. Technical Report 13, Washington, DC: World Bank, Washington, DC, 2011.

[7] Robert Cervero and Aaron Golub. Informal transport: A global perspective. *Transport Policy*, 14(6): 445–457, 11 2007. ISSN 0967-070X. doi: 10.1016/J.TRANPOL.2007.04.011.

[8] Gail Jennings and Roger Behrens. The case for investing in paratransit: Strategies for regulation and reform. 1 2017. URL `https://trid.trb.org/view/1660898`.

[9] Dominic Stead and Dorina Pojani. The Urban Transport Crisis in Emerging Economies: A Comparative Overview. In Dorina Pojani and Dominic Stead, editors, *The Urban Transport Crisis in Emerging Economies*, pages 283–295. Springer International Publishing, Cham, 2017. ISBN 978-3-319-43851-1. doi: 10.1007/978-3-319-43851-1_14.

[10] Transformative Urban Mobility Initiative. Sustainable Urban Transport: Avoid-Shift-Improve (A-S-I), 2022. URL `https://www.transformative-mobility.org/assets/publications/ASI_TUMI_SUTP_iNUA_No-9_April-2019.pdf`. [Online; accessed 15. Feb. 2022].

[11] Jakub Galuszka, Emilie Martin, Alphonse Nkurunziza, Judith Achieng’ Oginga, Jacqueline Senyagwa, Edmund Teko, and Oliver Lah. East Africa’s Policy and Stakeholder Integration of Informal Operators in Electric Mobility Transitions—Kigali, Nairobi, Kisumu and Dar es Salaam. *Sustainability*, 13(4), 2021. ISSN 2071-1050. doi: 10.3390/su13041703.

[12] Innocent Ndibatya and M J Booysen. Characterizing the movement patterns of minibus taxis in Kampala’s paratransit system. *Journal of Transport Geography*, 92:103001, 2021. ISSN 0966-6923. doi: 10.1016/j.jtrangeo.2021.103001.

[13] C.J. Abraham, A.J. Rix, I. Ndibatya, and M.J. Booysen. Ray of hope for sub-Saharan Africa's paratransit: Solar charging of urban electric minibus taxis in South Africa. *Energy for Sustainable Development*, 64:118–127, 2021. ISSN 0973-0826. doi: https://doi.org/10.1016/j.esd.2021.08.003. URL https://www.sciencedirect.com/science/article/pii/S0973082621000946.

[14] DigitalTransport4Africa. Data, 2021. URL https://git.digitaltransport4africa.org/data. [Online; accessed 17. Oct. 2021].

[15] Dirk du Preez, Mark Zuidgeest, and Roger Behrens. A quantitative clustering analysis of paratransit route typology and operating attributes in Cape Town. *Journal of Transport Geography*, 80(C), 1 2019. doi: 10.1016/j.jtrangeo.2019.1. URL https://ideas.repec.org/a/eee/jotrge/v80y2019ics096669231830807x.html.

[16] Abidjantransport, 2021. URL http://doc.digitaltransport.io/abidjantransport. [Online; accessed 7. Nov. 2021].

[17] Transitec. Recording, Mapping and Analyzing the Performance of Paratransit Services. Feb 2018. URL https://git.digitaltransport4africa.org/data/africa/accra/-/blob/f04f2f1209f4235a832c7008463bd6eb019e32a2/papers/0844_170-gui-ssd-2-AM3_guide.pdf.

[18] Jacobus Petrus Snyman. *Establishing and applying road classification and access management techniques on Bird street in Stellenbosch, South Africa*. PhD thesis, Stellenbosch: Stellenbosch University, 2020.

[19] StatsSA. P0320 - National Household Travel Survey, 2020, Mar 2021. URL http://www.statssa.gov.za/?page_id=1854&PPN=P0320&SCH=72769.

[20] Sarah Williams, Adam White, Peter Waiganjo, Daniel Orwa, and Jacqueline Klopp. The digital matatu project: Using cell phones to create an open source data for Nairobi's semi-formal bus system. *Journal of Transport Geography*, 49:39–51, 2015. ISSN 09666923. doi: 10.1016/j.jtrangeo.2015.10.005.

[21] OpenStreetMap Contributors. OpenStretMap Data, Feb 2022. URL https://www.openstreetmap.org.

[22] Geofabrik. OpenStreetMap Data Extracts, Jan 2022. URL https://download.geofabrik.de. [Online; accessed 7. Jan. 2022].

[23] marqqs. osmctools, Jan 2022. URL https://gitlab.com/osm-c-tools/osmctools. [Online; accessed 7. Jan. 2022].

[24] Pablo Alvarez Lopez, Michael Behrisch, Laura Bieker-Walz, Jakob Erdmann, Yun-Pang Flötteröd, Robert Hilbrich, Leonhard Lücken, Johannes Rummel, Peter Wagner, and Evamarie Wießner. Microscopic

Traffic Simulation using SUMO. In *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, pages 2575–2582. IEEE, 11 2018. URL https://elib.dlr.de/127994/.

[25] Pedro R. Andrade, Rafael H M Pereira, João Pedro Bazzo Vieira, dhersz, and Marcus Saraiva. ipeagit/gtfs2gps: v1.5-4, September 2021. URL https://doi.org/10.5281/zenodo.5501855.

[26] Rhyd Lewis. Algorithms for Finding Shortest Paths in Networks with Vertex Transfer Penalties. *Algorithms*, 13(11), 2020. ISSN 1999-4893. doi: 10.3390/a13110269.

[27] Joakim Fridlund and Oliver Wilen. Parameter Guidelines for Electric Vehicle Route Planning, 2020.

[28] TICD and TfC. How can Transit Mapping contribute to achieving Adequate Urban Mobility? The Case of Cairo, Egypt. 2017. URL https://git.digitaltransport4africa.org/data/africa/cairo/-/blob/ae279a3097e0c1aa1f99003acf0724f0da947778/Research%20&%20Policy%20Papers/TfC_TICD_How%20can%20Transit%20Mapping%20Contribute%20to%20achieving%20AUM%20(28-11-2017)%20Resource%20Center.pdf.

[29] Dunstan Matekenya, Xavier Espinet Alegre, Fatima Arroyo Arroyo, and Marta Gonzalez. Using Mobile Data to Understand Urban Mobility Patterns in Freetown, Sierra Leone. 2021. URL https://openknowledge.worldbank.org/bitstream/handle/10986/35033/Using-Mobile-Data-to-Understand-Urban-Mobility-Patterns-in-Freetown-Sierra-Leone.pdf. Policy research working paper 9519.

[30] Travis Fried. Readme, 2019. URL https://git.digitaltransport4africa.org/data/africa/harare/-/blob/178fa08537240b8a3faf8f2d172186b600fa1244/README.md.

[31] Transport for Cairo. Kampala and Parantransit street usage study, Sep 2020. URL https://transportforcairo.com/2020/09/01/kampala. [Online; accessed 7. Nov. 2021].

[32] G. Falchetta, M. Noussan, and A.T. Hammad. Comparing paratransit in seven major african cities: An accessibility and network analysis. *Journal of Transport Geography*, 94:103131, 2021. ISSN 0966-6923. doi: https://doi.org/10.1016/j.jtrangeo.2021.103131. URL https://www.sciencedirect.com/science/article/pii/S0966692321001848.

[33] United Nations, Department of Economic and Social Affairs, Population Division. World Population Prospects 2019, custom data acquired via website, 2019. URL https://population.un.org/wpp/DataQuery. [Online; accessed 10. Aug. 2021].

[34] Leonard Johnstone and Vatanavongs Ratanavaraha. Public transport initiatives in west africa, a case study of abidjan. *Int J Geomate*, 19:197–204, 2020. URL https://www.geomatejournal.com/user/download/1929/197-204-5529-Leonard-Aug-2020-72.pdf.

[35] Amakoé Adoléhoumé and Alain Bonnafous. Urban transport microenterprises in abidjan. 2001. URL https://openknowledge.worldbank.org/bitstream/handle/10986/9805/28537findeng186.pdf?sequence=1.

[36] Albert M Abane. Travel behaviour in ghana: empirical observations from four metropolitan areas. *Journal of Transport Geography*, 19(2):313–322, 2011. URL https://www.sciencedirect.com/science/article/pii/S0966692310000347?casa_token=83Ql-exFglMAAAAA:4DPySIPY3i2OGVA1f1vciAJ_EockuCqouKLMLbroyc03H4kqQaaFB3r7MQk90LB0g_cxeF09ol0.

[37] A Kumar, EA Kwakye, and Z Girma. What works in private provision of bus transport services—case study of accra and addis ababa. In *11th Conference of CODATU*, 2004. URL http://www.codatu.org/wp-content/uploads/What-works-in-private-provision-of-bus-transport-services-case-study-of-Accra-and-Addis-Ababa-A.-KUMAR-E.A.-KWAKYE-Z.-GIRMA.pdf.

[38] Mohamed El Esawey and Ahmed Ghareib. Analysis of mode choice behavior in greater cairo region. Technical report, 2009. URL https://www.researchgate.net/profile/Mohamed-Elesawey/publication/282134483_Analysis_of_Mode_Choice_Behavior_in_Greater_Cairo_Region/links/594e304a0f7e9be7b2da7963/Analysis-of-Mode-Choice-Behavior-in-Greater-Cairo-Region.pdf.

[39] B Koroma, D Oviedo, Y Yusuf, J Macarthy, C Cavoli, P Jones, L Caren, and S Sellu. City profile: Freetown: Base conditions of mobility, accessibility and land use. 2021. URL https://discovery.ucl.ac.uk/id/eprint/10122487/1/TSUM_CityProfile_Freetown.pdf.

[40] Tatenda C Mbara. Activity patterns, transport and policies for the urban poor in harare, zimbabwe. *Final country report.[En ligne.] www. transport-links. org/transport_links/filearea/documentstore/305_Zimbabwe% 20Final% 20Report*, 2002. URL http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.1003.6243&rep=rep1&type=pdf.

[41] Abraham R. Matamanda, Innocent Chirisa, Munyaradzi A. Dzvimbo, and Queen L. Chinozvina. The political economy of zimbabwean urban informality since 2000 – a contemporary governance dilemma. *Development Southern Africa*, 37(4):694–707, 2020. doi: 10.1080/0376835X.2019.1698410. URL https://doi.org/10.1080/0376835X.2019.1698410.

[42] Dave Spooner, John Mark Mwanika, Shadrack Natamba, and Erick Oluoch Manga. Kampala bus rapid transit: Understanding kampala's paratransit market structure, 2020. URL https://www.researchgate.net/profile/Dave-Spooner/publication/342233740_Kampala_Bus_Rapid_Transit_Understanding_Kampala's_Paratransit_Market_Structure/links/5ee9f250a6fdcc73be82f860/Kampala-Bus-Rapid-Transit-Understanding-Kampalas-Paratransit-Market-Structure.pdf.

[43] Susan Watundu. Urban household road travel demand and transport mode choice: the case of kampala, uganda. 2015. URL http://publication.aercafricalibrary.org/handle/123456789/2077.

[44] Jennifer Graeff. The organization and future of the matatu industry in nairobi, kenya. *Paper prepared by Center for Sustainable Urban development, earth Institute, Columbia University, New York*, pages 1–3, 2009. URL http://www.vref.se/download/18.53e8780912f2dbbe3a580002295/1377188299857/Organization+and+Future+of+the+Matatu+Industry.pdf.

[45] Eric Bruun, Romano Del Mistro, Yolandi Venter, and David Mfinanga. The state of public transport systems in three Sub-Saharan African cities. In Roger Behrens, Dorothy McCormick, and David Mfinanga, editors, *Paratransit in African Cities: Operations, Regulation and Reform*, chapter 2. Routledge, New York, 1 edition, 2016. ISBN 9781315849515. doi: 10.4324/9781315849515.

[46] M. J. Booysen, C. J. Abraham, A. J. Rix, and I. Ndibatya. Walking on sunshine: Pairing electric vehicles with solar energy for sustainable informal public transport in Uganda, in press. *Energy Research and Social Science*, 2022. doi: 10.1016/j.erss.2021.102403.