Ray of hope for electric paratransit: solar PV charging of sub-Saharan Africa's urban minibus taxis

C.J. Abraham [a], A.J. Rix [a], I. Ndibatya [a,b], M.J. Booysen[a,*]

[a] *Department of E&E Engineering, Stellenbosch University, South Africa*
[b] *College of Computing and Information Sciences, Makerere University, Uganda*

Abstract

Minibus taxi public transport is a seemingly chaotic phenomenon in the developing cities of the Global South with unique mobility and operational characteristics. Eventually this ubiquitous fleet of minibus taxis will have to transition to electric vehicles. This paper examines the impact of this inevitable evolution. We present a generic simulation environment to assess the grid impact and charging opportunities, given the unique paratransit mobility patterns. We used floating car data to assess the energy requirements of electric minibus taxis, which will have a knock-on effect on Africa's already fragile electrical grids. We used spatio-temporal and solar photovoltaic analyses to assess the informal and formal stops that would be needed for the taxis to recharge from solar PV in the region's abundant sunshine. The results showed energy demand from a median of 215 kWh/d to a maximum of 490 kWh/d, with a median charging potential (stationary time) across taxis of 7.7 h/d to 10.6 h/d. The potential for charging from solar PV was 0.38 kWh/m^2 to 0.90 kWh/m^2. Our simulator and results will allow traffic planners and grid operators to assess and plan for looming electric vehicle roll-outs, and could lead to a new funding model for transport in Africa.

Keywords: Electric vehicle; paratransit; Minibus taxi; Demand management; Renewable energy

1. Introduction

Paratransit plays a vital role as the primary form of transport in sub-Saharan Africa's public transit system. It transports more than 70% of the daily commuters and is a source of livelihood for many families (Behrens et al., 2015a). Paratransit in the region takes various forms, such as minibus taxis, motorcycle taxis and bicycle taxis (Ehebrecht et al., 2018), with minibus taxis carrying the largest daily share of passengers (Behrens et al., 2017). Powered by internal combustion engines, the taxis contribute to the emission of greenhouse gases and a general decline of air quality in African cities (Collett and Hirmer, 2021).

Paratransit in Africa's developing countries differs substantially from that of developed countries, from its inception to its vehicle types to its operations. In developed countries, paratransit usually means a point-to-point flexible demand-responsive transport service customised with special requirements for the elderly and the disabled (Behrens et al., 2017; Askari et al., 2021). The Americans with Disabilities Act of 1990, for example, requires paratransit drivers to be trained and paratransit vehicles to be equipped with specialised lifts, doors, seating, a global positioning system (GPS) and dispatch systems (ADA, 1990). For Africa's developing countries, paratransit means an organically evolved, informal, market-oriented, self-organising urban transport service that operates somewhere between private passenger transport and conventional public transport in terms of cost, scheduling, routes and quality of service (Ndibatya and Booysen, 2021; Neumann and Joubert, 2016). Here the paratransit system consists of shared-ride, demand-responsive privately owned vehicles, such as the minibus taxis in Lagos, Johannesburg, Nairobi and Kampala, or the single-passenger motorcycle taxis ("boda bodas") in Kampala, or the tricycle taxis ("tuk-tuks") in Nairobi (Mutiso and Behrens, 2011; Booysen et al., 2013; Diaz Olvera et al., 2019). Travel by paratransit accounts for approximately 70%, 90%, 91%, and 98% of the road-based public trips in Johannesburg, Lagos, Kampala and Dar es Salaam,

*Corresponding author
Email address: mjbooysen@sun.ac.za (M.J. Booysen)

respectively (Behrens et al., 2015b; Evans et al., 2018). Of these paratransit passenger trips, 83% are by minibus taxi (Dorothy et al., 2016; KCCA, 2016; Evans et al., 2018).

1.1. The revolution in sub-Saharan Africa's paratransit

In sub-Saharan Africa, the public transport industry experienced two fundamental organic changes in the last quarter of the nineteenth century. The first was the shift of transport services proprietorship, from public to private, most often sole proprietorship, as a result of the World Bank's structural adjustment policies of the 1990s that restricted financing to state-owned entities, leading to their eventual collapse (Kumar, 2011; Ajay Mahaputra Kumar et al., 2008; Cervero and Golub, 2007). The second was the gradual introduction of low-capacity (five- to twenty-seater) passenger-carrying vehicles to fill the public transport vacuum (Diaz Olvera et al., 2019; Mutiso and Behrens, 2011; Behrens et al., 2015a; Jennings and Behrens, 2017). From the five seater Anglia (Ford cars of the 1970s), to the 10-seater Peugeot 204 (1980s), to the current 16-seater Toyota HiAce, paratransit service vehicles have been of many types in many countries. Since the 1990s, the fourth and fifth generations (H100 1989-model and H200 2004-model) of the Japanese Toyota HiAce have dominated the paratransit market in Africa. The Toyota HiAce trades under several names depending on the country of assembly, such as Toyota Quantum in South Africa and Toyota Ventury in Thailand. Originating simply as a complementary transport service, the minibus taxis have become a way of life for the urban poor in several African cities.

Two competing views have broadly shaped discourse on the minibus taxis as part of the paratransit system in Africa. The predominant view is that minibus taxis and paratransit in general are the most extreme example of public transport failure in the developing world (Lucas et al., 2019). To support this view, terms such as "chaotic", "unsustainable", "unsafe" and "pollutants" are common in the literature in reference to the minibus taxis (Venter et al., 2019; Pojani and Stead, 2017, 2018; Agbiboa, 2016). In fact, the contribution of minibus taxis to urban air pollution is significant, partly because they are old (often older than 20 years) and they stand idling their engines for long hours, thus hugely contributing to greenhouse gas emissions and the deteriorating air quality in African cities. The World Health Organisation classifies exposure to ambient air pollution (AAP) as a major threat to human health in sub-Saharan Africa, linking it to the increase in cardiovascular and cardiopulmonary diseases and lung cancer and respiratory infections (Dalal et al., 2011; Amegah and Agyei-Mensah, 2017). Consequently, proponents of this view advocate for a total overhaul of the minibus taxi industry and its replacement with the western idea of orderly transport, the bus rapid transit (BRT) system.

Proponents of the second view advocate for a hybrid future, with paratransit complementary to the scheduled BRT. However, the adoption of this view is very slow and facing much resistance from the paratransit operators. Although several benefits would accrue to them (such as job security for the drivers, proper regulation, and government subsidies) they would lose their autonomy and the elements of self-organisation that formed the core of the original paratransit in Africa.

An alternative third view is emerging, which imagines Africa's paratransit system as a complex adaptive system, composed of many interdependent components that interact non-linearly, often operating between "chaotic" and semi-orderly states (Behrens et al., 2015b; Goodfellow, 2017). This view acknowledges the coping mechanisms and innovative forms of self-organisation exhibited by paratransit and how the system adapts to serve the population's mobility needs with little or no centralised control. Actually paratransit "chaos" reveals to some degree the hidden order described by Hecht as the "invisible governance ... that maintains competing agendas and aspirations in some kind of functional and parallel existence" (Hecht, 2007).

The minibus taxi paratransit came into being to suit the mobile lifestyle of the urban poor in sub-Saharan Africa. It is unlikely that the minibus taxis will be phased out of Africa's cities any time soon. They are ubiquitous and will continue for many reasons: their schedule flexibility, the urban sprawl, the irregular commuter movement patterns in urban spaces due to informal employment and the socio-cultural lifestyles of the urban poor in developing cities. However, the environmental cost of running these old internal combustion engine vehicles is worrying. It has triggered discussions about the possibility of transitioning to electric minibus taxis as part of the global electrification and sustainability agenda (Collett and Hirmer, 2021).

1.2. The transition to electric vehicles and the electric minibus taxi

The development of low-carbon transport in cities is crucial to the global agenda to combat climate change's various effects sustainably. The Intergovernmental Panel on Climate Change (IPCC) estimates that the transport sector generates 23% of the global energy-related greenhouse emissions. In sub-Saharan Africa the deteriorating air quality resulting from ambient air pollution and a high concentration of particulate matter ($PM_{2.5}$) is partly attributed to vehicle emissions (Lozano Gracia et al., 2021; Singh et al., 2020; Rajé et al., 2018). The WHO estimated that 712,000 deaths in Africa in 2012 were due to air pollution, though the figure may be higher than reported because air pollution epidemiological data is limited (Cohen Aaron J et al., 2017). Akumu estimates the cost of air pollution in African cities to be as high as 2.7% of GDP (Akumu, 2014). Three of the seventeen United Nations Sustainable Development Goals, one, eleven and thirteen, are clean energy, sustainable cities and climate action (Zinkernagel et al., 2018).

Consequently, electrification is promoted as a low-carbon transport strategy to reduce combustion emissions and slow down the possibly damaging effects of climate change. In the same spirit, the transition to electric vehicles is gradually picking up in developing countries to the extent that some vehicle manufacturers are planning to phase out internal combustion engines. Sub-Saharan Africa is seeing a few isolated pilot electric vehicle projects, mainly focusing on micro-mobility (as motorcycles and tricycles), as well as buses and private cars (Black et al., 2018). At present, there is no known electric vehicle transition initiative targeting the paratransit industry, let alone the minibus taxis that are responsible for more than 80% of the public transport trips in the region.

This paper builds a foundation for evaluating the eventual impact of the transition to electric minibus taxis on cities' electrical grids, localised pollution, carbon footprint and taxi owners' profitability. Specific attention is given to the energy requirements of these vehicles, the potential distribution of charging stations and the potential electricity generation capacity from renewable sources.

1.3. Overview of earlier studies and approaches

Initiatives to achieve sustainable urban mobility often follow a three-pronged transport decarbonisation approach, the "Avoid-Shift-Improve" paradigm (Galuszka et al., 2021; Lah, 2017). This approach aims to reduce trips, shift towards public transport and non-motorised modes and improve vehicle efficiency coupled with electrification (Le and Trinh, 2016; Osei et al., 2021). In sub-Saharan Africa, the avoid and shift approaches have not been intensively studied (Krüger et al., 2021). The focus has been primarily on improvements: urban traffic management strategies such as widening roads, optimising road signalling and encouraging multi-modal transport (developing mass transit systems such as BRT and promoting walking and cycling) (Sietchiping et al., 2012; Shams and Zlatkovic, 2020; Krüger et al., 2021; Venter et al., 2018). Ironically, evidence from other world cities suggests that building freeways and roads around cities only increases car dependence and thus intensifies congestion and pollution (Sietchiping et al., 2012). Improving vehicle efficiency, particularly by introducing electric vehicles in public transport and paratransit, is an approach that has been neglected. The literature on paratransit in sub-Saharan Africa focuses on aspects of sector governance (Goodfellow, 2017) and regulation and reforms (Jennings and Behrens, 2017; Lucas et al., 2019), but seldom on operations (Ndibatya and Booysen, 2020), mobility characteristics (Ndibatya and Booysen, 2021) and the prospects of electric mobility integration (Galuszka et al., 2021).

Research from outside the region shows that electric vehicles are three times more efficient than internal combustion engine vehicles and twice as efficient as hybrid vehicles (Du et al., 2017; Weiss et al., 2020). This efficiency is achieved partly by the efficient braking systems and elimination of idling losses and the consequent saving of energy for the vehicle's actual movement (Weiss et al., 2020). Although debate continues on the economic and environmental trade-offs associated with electric vehicles (Li et al., 2016), there is evidence of sustainable electric vehicle deployment. Some researchers argue that deploying electric vehicles shifts gasoline usage to coal-fired power generation, which exacerbates CO_2 emissions by the power systems (Li et al., 2016). However, electric vehicle proponents counter-argue that, on a macro-scale, these vehicles' impact in terms of CO_2 emissions depends mainly on the charging strategy and that the emissions can be reduced by optimising the use of renewable energy sources such as solar power (Schücking et al., 2017; Buresh et al., 2020). In one of the scarce and isolated publications on electric vehicles in sub-Saharan Africa, Buresh et al. (2020) note that South Africa (like many countries in the region) has high levels of insolation (the measure of solar energy at a place over a specified time), from between 4.5 and 6.5 kWh/m^2 per day, with annual sunshine averaging more than 2500 hours. This implies that the region has an excellent chance of harnessing this renewable energy source to power electric vehicles. Indeed, projects researching alternative renewable energy have taken shape in the region (Jadhav et al., 2017), though not targeting electric vehicles for public transport services.

Two main research gaps remain in the literature on sub-Saharan Africa's transition to electric minibus taxis. One is the mobility characteristics of minibus taxis. As Quirós-Tortós et al. (2018) observe, to estimate the charging requirements and vehicle performance of an electric vehicle we need to know its mobility patterns, such as distance, travelling time and idle time (or stopping time and duration). In other words, the vehicle's mobility has spatio-temporal dimensions. Apart from the findings of isolated studies on minibus taxi mobility, such as those by Ndibatya and Booysen (2021), the general mobility dynamics of paratransit in sub-Saharan Africa are unknown. The other is the region's potential for renewable energy from different sources such as solar PV, wind and bio-fuel as part of this transition (Sawadogo et al., 2020; Jadhav et al., 2017; Soares et al., 2019).

From the sparseness of the work, it is clear that we lack information on the mobility of minibus taxis in sub-Saharan Africa and specifically the requirements of these minibus taxi fleets if they are converted to electric vehicles (Collett and Hirmer, 2021). Our reproducible method for determining their mobility and analysing the generated data will fill the gap and help city planners as well as fleet owners to improve their future operations.

1.4. Contribution

This paper explores the energy requirements of electric minibus taxis in an urban paratransit system, on journeys within and between towns and cities. Over a year's worth of floating car data was analysed to assess the energy demand of minibus taxis. The paper explores the potential charging opportunities at the formal and informal organically formed taxi stops during the daytime when charging with solar PV is feasible. Our method is applied to a case study in an urban scenario near Cape Town in South Africa, and we contribute our integration and stop extraction software, which can be used to perform similar evaluations. Finally, we assess the impact on the struggling South African grid of converting all the minibus taxis in South Africa to electric vehicles, with and without solar augmentation.

2. Method

This section describes the dataset and the three models used for the research: the minibus taxi (MBT) mobility model, the photovoltaic (PV) model and the electric minibus taxi (eMBT) electric vehicle (EV) model. It describes the pre-experimental collection and analysis of the floating car data from a fleet of nine internal combustion engine minibus taxis. Inter-town MBT mobility modelling involved spatial clustering of floating car data to identify stopping events and generate routes between stops in preparation for PV and eMBT modelling. We present two model simulation setups for the EV and PV models and discuss their application to our urban paratransit context. The PV model was based on the System Advisor Model (SAM) developed by the National Renewable Energy Laboratory (Blair et al., 2014). We ran the PV and the EV models independently in a micro-transport simulator (SUMO) (Lopez et al., 2018; Kurczveil et al., 2014), then recorded and analysed the eMBT energy and PV requirements for each simulated context.

2.1. Mobility

The dataset consisted of floating car data obtained by tracking urban minibus taxis operating on bi-directional routes connecting Stellenbosch, Brackenfell and Somerset West in the Western Cape Province of South Africa. The area under study is defined by coordinates are (34.229224, 18.656884) and (-33.786222, 18.969438) as shown in Figure 1a. The data obtained from Mix Telematics (a local fleet management service provider), consisted of timestamped geo-locations (latitude and longitude), speed and direction, logged at a frequency of one minute from onboard tracking devices for over two years. After cleaning, filtering and performing pre-data loading preparations, we had an average of 201 days' worth of floating car data per minibus taxi for use in EV and PV modelling.

2.1.1. Spatial clustering and analysis

An overlay heatmap showing the intensity variation of minibus taxi activity (based on the count of GPS data points) was plotted as shown in Figure 1a. Three high-intensity areas were visible in the heatmap: Stellenbosch, Brackenfell (west of Stellenbosch) and Somerset West (south of Stellenbosch). We interpreted these three areas as the epicentres of minibus taxi activity, a view that closely matches that of Ebot Eno Akpa et al. (2016).

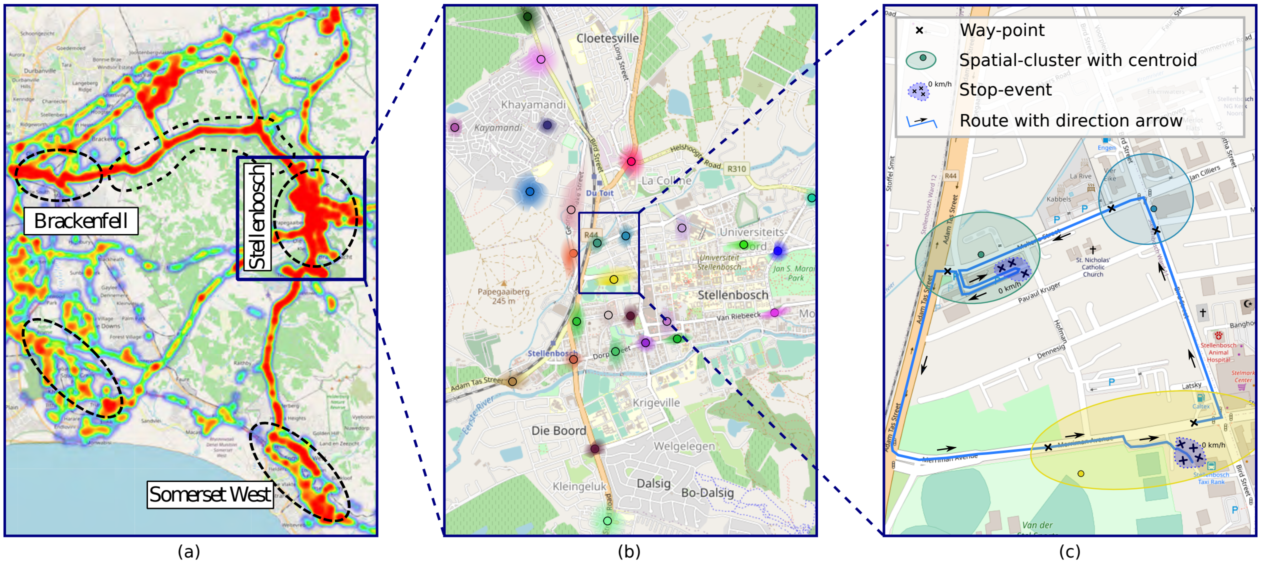


Figure 1: (a) Heat map showing the variation (by density) of floating car data; (b) Distribution of spatial-clusters in Stellenbosch as determined by the clustering process; (c) Illustration of *way points*, *stop events* and route generation process.

We used the density-based spatial clustering of applications with noise (DBSCAN) 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 the DBSCAN algorithm because of its robustness to outlier detection, its ability to discover clusters with uneven densities and arbitrary shapes, and the fact that it does not need prior knowledge of the number of clusters (Liu et al., 2012; Renjith et al., 2020). For cluster analysis we used a Python implementation of the DBSCAN algorithm from the Scikit-Learn package (Pedregosa et al., 2011). The minimum cluster size (min_samples) was 70, and the maximum distance between neighbouring points in a cluster (max_eps) was 0.0002 °(Ndibatya et al., 2014). Figure 1b shows the spatial distribution of cluster centroids overlaid on OpenStreetMap.

2.1.2. Identifying minibus taxi stops

To generate the mobility patterns and establish the potential for charging at stops, it was necessary to identify the spatial clusters with stopping events. Additional temporal analysis was required to determine the stop times and stop durations. We therefore further analysed 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* in our work is closely related to a "stay point" as defined by Zheng et al. (2009) and Damiani et al. (2014) and refers to a series of consecutive GPS locations within a cluster's spatial extent, with a taxi velocity below a threshold of 1 km/h. The arrival time of the stop event is the time of the first GPS location in the series, and the duration of the stop-event is the difference between the timestamps of the first and last GPS locations in the series as illustrated in Figure 1c. The *movement events* (or waypoints) represented by all the cluster data points that do not belong to the 'stop event' category were preserved for use during minibus taxi route generation in the EV model.

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 from these. The statistical summary helped to identify the spatia clusters with the most stop events and their typical time and duration. We were thus able to identify spatial clusters with many stop events as formal taxi stops (terminuses). Spatial clusters with lower counts could be identified as intersections where the taxis pause for traffic, or informal stops made en route to pick up passengers. Clustering the stop events temporally also helped to identify the times when these stops typically occurred.

2.1.3. Generating routes

To simulate the mobility of MBTs between the three towns and subsequently study their energy requirements, we generated the routes linking the identified stops. A *route* in this context is a series of edges connecting two or more stop events, often starting and ending in different clusters (or cluster centroids). A simulated MBT follows pre-selected routes as part of its daily route plan within the simulation boundary.

We used the stop events' cluster centroids, the waypoints (GPS data representing moving events), the roads network, and SUMO's shortest path Djikstra algorithm to generate the routes. The underlying road network was based on OpenStreetMaps (OSM) (OpenStreetMap contributors, 2017), which included the roads, intersections, speed limits, and traffic lights information. All the GPS data points (including cluster centroids and waypoints) were snapped to the OpenStreetMap's road network, and the shortest path between the origin and destination points of interest was computed using SUMO's implementation of the Djikstra algorithm (Lopez et al., 2018). This algorithm searches for the route with the least *cost* (Lewis, 2020), where the *cost* can be the distance, time, or electricity consumption of the simulated EV. In this study, we defined the cost as the *distance* (we omitted speed due to simulation performance considerations). For each simulated day we generated a route, and from these routes we computed extra information that affects an EV's (or eMBT's) energy usage, such as the total distance, the road inclination and the road curvature.

2.2. The eMBT EV model

We set up a simulation model using a custom SUMO electric vehicle simulation model, SUMO EV, to measure the temporal variation of power and energy usage and the relationships between power consumption and eMBT speed. The model's parameters were specified to match the prevailing MBT used in South Africa, the Toyota Quantum. The weight and front surface area used for a synthetic eMBT were measured from one of the Toyota Quantum minibus taxis operating in Stellenbosch. We approximated the rest of the parameters according to the recommendations by Fridlund and Wilen (2020). These parameters include: height 2.3 m, width 1.9 m, front-facing surface area 4 m^2, weight 2900 kg, 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 simulation program initialised the eMBT model for each date that was simulated. The eMBT model was applied to the generated routes. For every second of simulation time, the simulator logged the energy consumption and speed of the eMBT as it progressed along its route.

With an average of 201 routes per taxi, the volume of output data from the model was huge. Our goal was to obtain useful metrics that would summarise this data. The first metric we considered was the average power usage profile of the whole eMBT fleet. Such a profile would indicate how much power the eMBTs used at various points in time. This profile would be indispensable, for example, for testing the hypothesis that there would be a good charging opportunity at midday. It would also show what order of magnitude the motor size should be. We calculated the profile by obtaining the power-vs-time profile for each day, averaging this across all days for each eMBT, and then averaging that across all eMBTs in the fleet. The profile was plotted with respect to time.

2.3. PV model simulation setup

We set up the SAM-based PV model to calculate the energy available from photovoltaic sources and to study the daily charging potential for each eMBT in a synthetic fleet of nine eMBTs. The model generates the plane-of-array solar irradiance profile based on radiometric data, solar azimuth angle, and photovoltaic panel tilt angle. We used radiometric data for a year sampled every 15 minutes from the National Solar Radiation Database (Sengupta et al., 2018). The azimuth and tilt angles were set at 0 °(North) and 20 °, respectively, a common configuration which maximises energy yield in South Africa (Le Roux, 2016).

To get the output power profile of the PV array, a 16 % system efficiency was applied to the irradiance profile, i.e., 20 % and 80 % were used for the solar panel and balance of the system (including the inverter), respectively. We used the stop event analysis from Section 2.1.2 to further analyse the battery charging potential from solar PV by evaluating the times at which the stop events occurred and their durations. We first applied thresholds to filter out stop events with durations above 8 hours or below 20 minutes. This was to ensure that stop events irrelevant to our study did not skew the statistics. These stop events were grouped according to the spatial cluster in which they occurred, and temporal clustering was done within each spatial cluster to obtain spatio-temporal clusters.

Based on the stop events detected during the spatio-temporal clustering, we computed the potential energy sourced from PV per day. For each eMBT stop event, the PV output-power-profile was integrated from the beginning to the end of the stop event in order to calculate the total energy that could be charged from PV during that stop event. The PV energy of each stop event was summed to get the total energy that could be charged from PV for that day as a function of the area of the PV array. These “daily PV charging potentials” were aggregated for each taxi and plotted as box plots. This metric allowed us to approximate the size of the PV array required to provide a certain percentage of an eMBT’s energy demands.

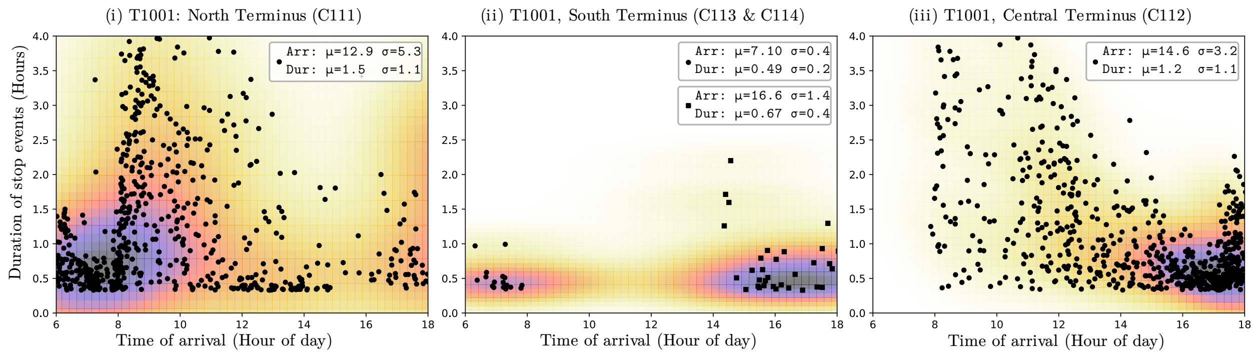
3. Results and discussion

This section describes the results obtained from applying our three models to the floating car data from Stellenbosch and its surrounds. The results obtained refer specifically to the MBT mobility, the eMBT’s power requirements and the potential charging opportunities. The charging opportunities are separated into stop times for the purpose of source-ambivalent charging, and potential charging from PV.

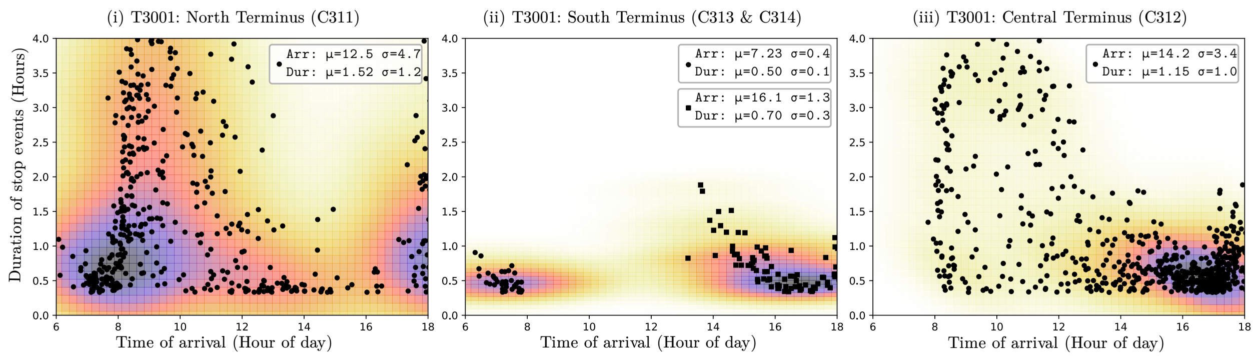
The inter-town MBT mobility modelling provides spatial clustering of the identified stop events that serve as input to the PV modelling while generating routes used to determine the power requirements of the individual eMBT and the fleet of eMBTs.

Table 1: Summary of the MBT stop events identified during the cluster analysis. The clusters are grouped by vehicle ID and sorted by duration in descending order. The vehicles with boldfaced IDs were plotted in Figure 2. (Note: μ = Mean, σ = Standard deviation)

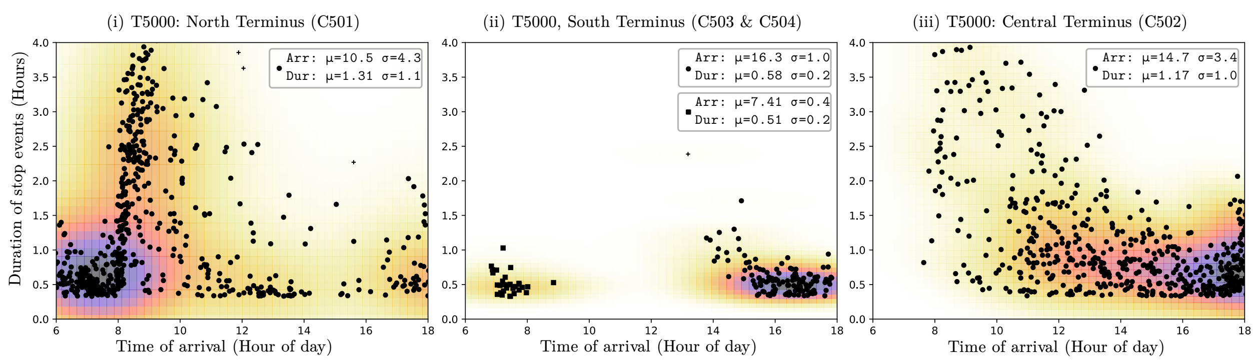
Minibus Taxi ID	Spatio-temporal Cluster ID	Stop events count	Arrival (h)		Duration (h)		Terminus Name
			μ	σ	μ	σ	
T1000	C101	302	12.0	4.8	**1.5**	1.2	North
	C102	309	14.1	3.1	**1.4**	1.2	Central
	C104	15	17.4	1.3	0.7	0.3	South
	C103	18	7.1	0.4	0.5	0.2	South
T1001	C111	1074	12.9	5.3	**1.5**	1.1	North
	C112	782	14.6	3.2	**1.2**	1.1	Central
	C114	41	16.6	1.4	0.7	0.4	South
	C113	17	7.1	0.4	0.5	0.2	South
T3001	C311	686	12.5	4.7	**1.5**	1.2	North
	C312	689	14.2	3.4	**1.2**	1.0	Central
	C314	87	16.1	1.3	0.7	0.3	South
	C313	37	7.2	0.4	0.5	0.1	South
T4000	C402	495	14.2	3.4	**1.5**	1.4	Central
	C401	406	11.8	4.5	**1.3**	1.0	North
	C404	42	16.4	1.0	0.6	0.2	South
	C403	29	7.0	0.4	0.5	0.1	South
T5000	C501	787	10.5	4.3	**1.3**	1.1	North
	C502	709	14.7	3.4	**1.2**	1.0	Central
	C503	139	16.3	1.0	0.6	0.2	South
	C504	30	7.4	0.4	0.5	0.2	South
T6000	C601	34	8.5	0.4	**5.9**	1.0	North
	C602	82	16.6	1.1	**1.1**	0.8	North
	C603	52	7.1	1.0	**1.0**	0.6	North
T6001	C611	403	12.4	4.7	**1.4**	1.1	North
	C612	359	14.1	3.3	**1.3**	1.2	Central
	C613	11	7.2	0.5	0.5	0.2	South
	C614	8	17.6	1.0	0.5	0.2	South
T7000	C702	904	14.3	3.2	**1.3**	1.1	Central
	C701	765	10.7	4.1	**1.3**	1.1	North
	C704	30	16.5	1.5	0.6	0.3	South
	C703	33	7.0	0.4	0.5	0.2	South
T7001	C712	430	15.0	3.7	**1.4**	1.1	Central
	C711	272	12.0	4.9	**1.1**	0.9	North



(a)



(b)



(c)

Figure 2: Spatio-temporal clustering of arrival time and duration of stops at significant spatial-clusters for three MBTs: (a) T1001; (b) T3001; (c) T5000.*North, South and Central termini refer to the spatial-clusters situated near termini found in Kayamandi in Stellenbosch, Somerset West, and Stellenbosch Central, respectively.*

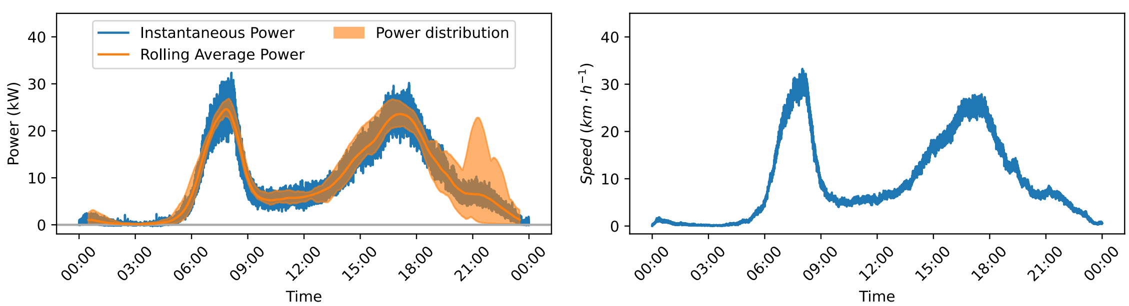
3.1. *Mobility analysis*

Figure 2 shows the results of the spatio-temporal clustering of data from three minibus taxis to determine the stops. Despite the seemingly chaotic patterns, the clustering analysis identified spatio-temporal clusters of stops. The figure shows how each minibus taxi has a vertically distributed (i.e. varying duration) morning cluster at around 8:00 am, and a horizontally distributed (i.e. varying arrival time) cluster in the evening. For example, the spatio-temporal clusters in the South Terminus indicate that those spatial clusters were visited in the morning and in the evening.

The spatio-temporal clusters were primarily used in SUMO to generate the traffic simulator's mobility patterns and then analyse the charging potential during stationary periods. A statistical summary of all the identified stop clusters, showing the stationary periods during daylight hours grouped by taxi, is provided in Table 1. Although the standard deviation is substantial, the mean stop durations of the clusters were more than one hour for at least two stops per taxi. The arrival times of the longer stops were all between 10:30 am and 3:00 pm except for one outlier taxi T6000, which exhibited wildly different clustering results. Accordingly, the clusters indicate that there should be substantial potential for charging from solar power.

3.2. *Energy analysis*

The output of the EV simulation is shown in Figure 3. The mean instantaneous power demand versus time of a working weekday is shown in Figures 3a. A clear typical temporal profile is apparent for the minibus taxis, closely matching the peak traffic hours. There is a sharp peak demand period from 6:00 am to 9:00 am, with a peak value of 32 kW. A diminished demand with a mean of 6 kW is observed from 9:00 am to 1:00 pm, constituting a period of substantially reduced activity, further demonstrating the potential for solar charging. This is followed by a gradual increase to a less pronounced peak value of 30 kW between 5:00 pm and 6:00 pm. This flatter evening demand profile slowly declines to return to the trough of 7 kW by 9:00 pm. Complete inactivity is observed from 11:30 pm to 4:30 am. Not only is this 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 9:00 pm, which results from the long-distance journeys over weekends (departing at 9:00 pm on Friday evenings) and holidays, as reported by Ebot Eno Akpa et al. (2016).



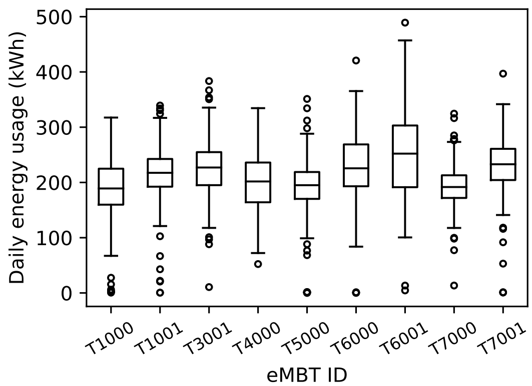
(a) (b)

Figure 3: Summary of electrical for all the simulated eMBTs (a) Daily power (instantaneous and rolling average) sampled per second; (b) Speed vs time

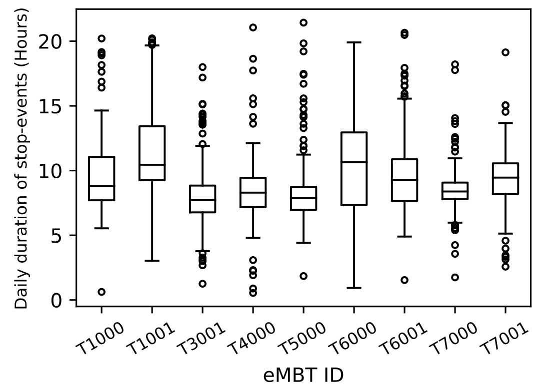
This profile indicates the energy demand profile requirements of the eMBTs, and already hints at substantial charging potential during the evening – probably from grid power – and during the middle of the day – preferably from solar power.

Figure 3b shows the MBT's speed versus time of the day, the similarity of which highlights the substantial impact of speed on power draw. The energy required was close to linearly proportional to the distance travelled, which demonstrates that a simpler distance-based model would have provided good estimations and required substantially less processing power. The mean energy required per day is 212 kWh.

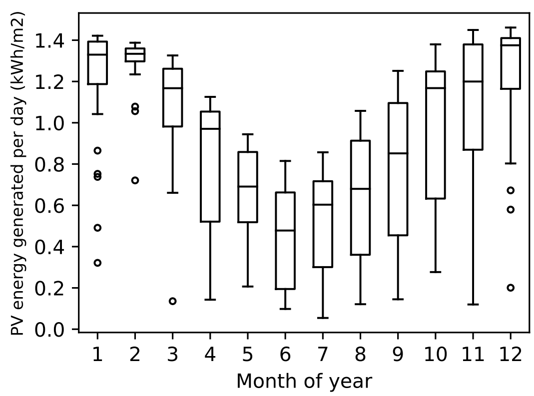
The distribution of energy usage per taxi per day, is shown in Figure 4a for the nine taxis. The taxis' energy usage is similar, with the median energy per taxi per day across all taxis ranging from 189 kWh to 252 kWh, with the mean of the medians equal to 215 kWh. For any given taxi, on 75 % of the days less than



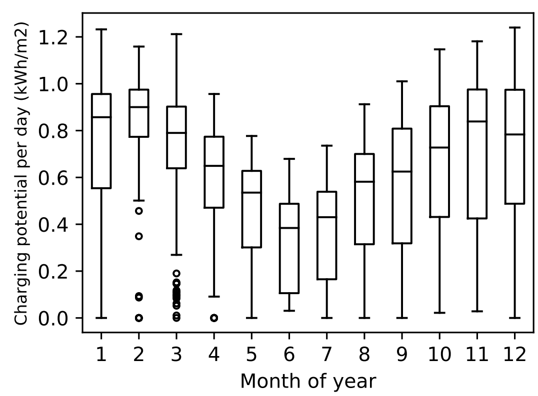
(a) Energy used per eMBT.



(b) Durations of stop events per eMBT.



(c) PV generation per m^2 per month.



(d) PV charging potential per eMBT per m^2 per month.

Figure 4: Summary of mobility, energy requirements, and charging potentials.

303 kWh is used. Eight of the nine taxis, on all days, use less than 420 kWh, while the other taxi uses up to 490 kWh.

The results show that a maximum usable battery capacity of approximately 500 kWh should 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.

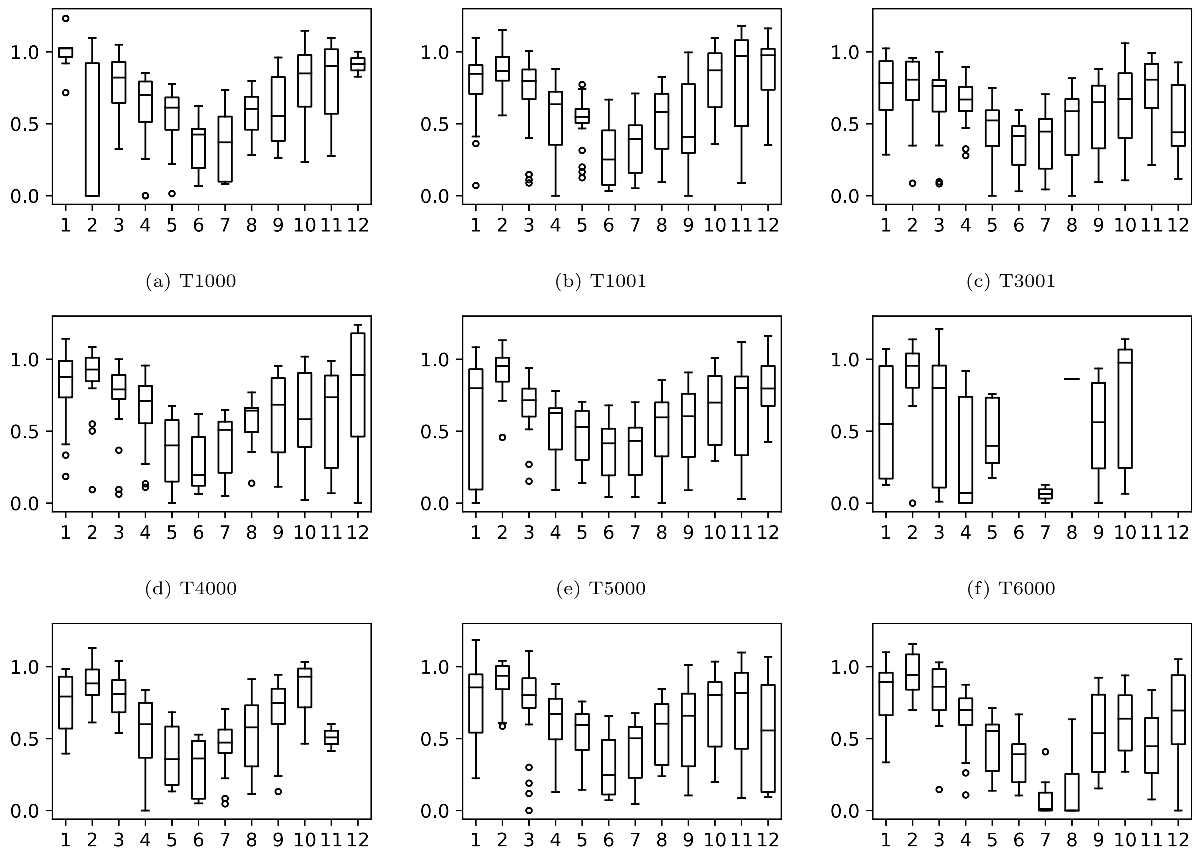
3.3. Charging potential

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 utility could cause infrastructure and electrical supply problems, so we investigated the opportunities for charging these vehicles from solar PV 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 utility. We applied a minimum stop duration of 20 minutes and a maximum stop duration of 8 hours 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 not stop for longer than that on a week day.

3.3.1. Charging from the grid

Figure 4b shows the distribution of stop events across days, with the minimum and maximum stop duration thresholds applied. The figure shows that the MBTs' stop duration times vary considerably, with the median duration per day ranging from a minimum of 7.7 hours for taxi T3001 to a maximum of 10.7 hours for taxi T6000.

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 averages of the 75^{th} percentile of the energy usage (Figure 4a) and the 25th percentile of the 24-hour stop duration times (Figure 4b) as 247 kWh and 7.65 hours respectively to calculate a charger capacity of 32.3 kW. This assumes a constant charging profile and charging only from the local electrical grid.



(a) T1000 (b) T1001 (c) T3001

(d) T4000 (e) T5000 (f) T6000

(g) T6001 (h) T7000 (i) T7001

Figure 5: Disaggregated charging potential (in kWh/m^2) per eMBT for each month of the year.

3.3.2. Charging from solar PV

We evaluated the potential for charging the eMBTs from solar PV, both to reduce the load on the electrical grid and to reduce the size of the battery installed in the eMBT. The energy generated per surface area is shown in Figure 4c for each month of the year, representing an upper bound of charging potential during stationary periods.

The aggregate charging potential per square metre of solar panel, for the fleet, is shown in Figure 4d, indicating that a large amount of the generated energy could be used during stops. The desegregated distribution of charging potential for each taxi, per square metre of solar panel, is shown in Figure 5. The variation of charging potential between taxis is low, indicating that the taxis follow similar patterns during the daylight hours, and that they would require similar charging infrastructure. Assuming that the PV installations were sized to exploit the median stop potential per taxi, the potential would vary from a minimum of 0.38 kWh/m^2 to a maximum of 0.90 kWh/m^2 during the year. The results show that a solar installation of approximately 140 m^2 would be required per taxi to ensure that at least 25 % of the taxi's daily energy requirements are met by solar supply.

Given the estimated 285,000 taxis in South Africa, our analysis indicates that to charge all the minibus taxis from the national grid will require 9.72% (61.27 GWh/d) of the current daily national energy generation. The average taxi would be able to directly utilise between 57% and 80% of installed PV generation capacity during normal stops.

4. Conclusion

Concern about the possible effects of climate change has driven an energy revolution from internal combustion engines to electric vehicles in the Global North. Pushed by market forces and supplier preferences from beyond its own borders, this wave will eventually break over the Global South and its organically evolved and notoriously chaotic paratransit systems and fragile electrical grids. Sub-Saharan Africa has many specific characteristics, challenges, and opportunities that will eventually determine its response. This paper focuses on paratransit in the region, which transports more than 70% of the region's commuters. One of the unanswered questions is how the dissimilar mobility characteristics of the minibus taxis, the mainstay of the region's paratransit system, will translate into electrical requirements. Since these taxis park spontaneously at tacitly known stops of the drivers' choosing, for durations determined by passenger demand, the charging potential at these stops is unknown. Further, the extent to which these charging stations can be powered by the region's abundant sunshine remains unclear. This paper therefore investigated these three unknowns for minibus taxis in an urban scenario in South Africa's Western Cape Province. The results showed that for the taxis we studied would mostly have a similar energy demand with a nominal 250 kWh required per median day if no additional charging capacity was provided. This would increase to 420 kWh when accommodating all days, except for one taxi, which required 490 kWh. Evaluating the charging potential showed that the median stops per day ranged from 7.7 h to 10.6 h.

As expected, the taxis with the shorter stop periods, and hence less time for charging, are also the ones that would need more energy because they are more mobile. Nevertheless, a nominal 32 kWh charger will suffice if charging only from a fully operational grid. Evaluating the solar irradiation for the stop times and durations, showed that the mean charging potential per median day ranged from 0.38 kWh/m^2 to 0.90 kWh/m^2.

References

ADA, 1990. Americans with Disabilities Act (ADA), 1990. URL: https://www.ada.gov/pubs/adastatute08.htm#12143.

Agbiboa, D.E., 2016. 'No Condition Is Permanent': Informal Transport Workers and Labour Precarity in Africa's Largest City. International Journal of Urban and Regional Research 40, 936–957. doi:https://doi.org/10.1111/1468-2427.12440.

Ajay Mahaputra Kumar, Vivien Foster, Fanny Barrett, 2008. Stuck in traffic : urban transport in Africa. Technical Report. Washington, DC: World Bank. URL: http://siteresources.worldbank.org/EXTAFRSUBSAHTRA/Resources/Stuck-in-Traffic.pdf.

Akumu, J., 2014. Improving air quality in African cities. UN Environment, Nairobi .

Amegah, A.K., Agyei-Mensah, S., 2017. Urban air pollution in Sub-Saharan Africa: Time for action. Environmental Pollution 220, 738–743. doi:https://doi.org/10.1016/j.envpol.2016.09.042.

Askari, S., Peiravian, F., Tilahun, N., Yousefi Baseri, M., 2021. Determinants of users' perceived taxi service quality in the context of a developing country. Transportation Letters 13, 125–137. doi:10.1080/19427867.2020.1714844.

Behrens, R., McCormick, D., Mfinanga, D., 2015a. Paratransit in African cities: Operations, regulation and reform. URL: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84960441349&doi=10.4324%2F9781315849515&partnerID=40&md5=0398412121b7de08334b5bfd8cfae5b0, doi:10.4324/9781315849515.

Behrens, R., McCormick, D., Mfinanga, D., 2015b. Paratransit in African cities: Operations, regulation and reform. 1 ed., Routledge, London. doi:10.4324/9781315849515.

Behrens, R., McCormick, D., Orero, R., Ommeh, M., 2017. Improving paratransit service: Lessons from inter-city matatu cooperatives in Kenya. Transport Policy 53, 79–88. doi:https://doi.org/10.1016/j.tranpol.2016.09.003.

Black, A., Barnes, J., Makundi, B., Ritter, T., 2018. Electric two-wheelers in Africa? Markets, production and policy Conference on Green Transformation and Competitive Advantage Evidence from developing countries.

Blair, N., Dobos, A.P., Freeman, J., Neises, T., Wagner, M., Ferguson, T., Gilman, P., Janzou, S., 2014. System Advisor Model, SAM 2014.1.14: General Description URL: https://www.osti.gov/biblio/1126294, doi:10.2172/1126294.

Booysen, M.J., Andersen, S.J., Zeeman, A.S., 2013. Informal public transport in Sub-Saharan Africa as a vessel for novel Intelligent Transport Systems, in: 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013), pp. 767–772. doi:10.1109/ITSC.2013.6728324.

Buresh, K.M., Apperley, M.D., Booysen, M.J., 2020. Three shades of green: Perspectives on at-work charging of electric vehicles using photovoltaic carports. Energy for Sustainable Development 57, 132–140. doi:https://doi.org/10.1016/j.esd.2020.05.007.

Cervero, R., Golub, A., 2007. Informal transport: A global perspective. Transport Policy 14, 445–457. doi:10.1016/J.TRANPOL.2007.04.011.

Cohen Aaron J, D., Brauer Michael, P., Burnett Richard, P., Anderson H Ross, P., Frostad Joseph, M.P.H., Estep Kara, M.P.A., Balakrishnan Kalpana, P., Brunekreef Bert, P., Dandona Lalit, P., Dandona Rakhi, P., Feigin Valery, P., Freedman Greg, M.P.H., Hubbell Bryan, P., Jobling Amelia, P., Kan Haidong, P., Knibbs Luke, P., Liu Yang, P., Martin Randall, P., Morawska Lidia, P., Pope C Arden, P., Shin Hwashin, P., Straif Kurt, P., Shaddick Gavin, P., Thomas Matthew, P., van Dingenen Rita, P., van Donkelaar Aaron, P., Vos Theo, P., Murray Christopher J L, P., Forouzanfar Mohammad H, P., 2017. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. The Lancet (British edition) 389, 1907–1918.

Collett, K.A., Hirmer, S.A., 2021. Data needed to decarbonize paratransit in Sub-Saharan Africa. Nature Sustainability doi:10.1038/s41893-021-00721-7.

Dalal, S., Beunza, J.J., Volmink, J., Adebamowo, C., Bajunirwe, F., Njelekela, M., Mozaffarian, D., Fawzi, W., Willett, W., Adami, H.O., Holmes, M.D., 2011. Non-communicable diseases in sub-Saharan Africa: what we know now. International Journal of Epidemiology 40, 885–901. doi:https://doi.org/10.1093/ije/dyr050.

Damiani, M.L., Issa, H., Cagnacci, F., 2014. Extracting Stay Regions with Uncertain Boundaries from GPS Trajectories: A Case Study in Animal Ecology, in: Proceedings of the 22nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, Association for Computing Machinery, New York, NY, USA. pp. 253–262. doi:10.1145/2666310.2666417.

Diaz Olvera, L., Plat, D., Pochet, P., 2019. Looking for the obvious: Motorcycle taxi services in Sub-Saharan African cities. Journal of Transport Geography , 102476doi:10.1016/J.JTRANGEO.2019.102476.

Dorothy, M., Herrie, S., David, M., 2016. The nature of paratransit operations, in: Roger, B., Dorothy, M., David, M. (Eds.), Paratransit in African Cities: Operations, Regulation and Reform. 1 ed.. Routledge, New York. chapter 3, pp. 59–78.

Du, J., Ouyang, M., Chen, J., 2017. Prospects for Chinese electric vehicle technologies in 2016–2020: Ambition and rationality. Energy 120, 584–596. doi:https://doi.org/10.1016/j.energy.2016.11.114.

Ebot Eno Akpa, N.A., Booysen, M.J., Sinclair, M., 2016. A comparative evaluation of the impact of average speed enforcement (ASE) on passenger and minibus taxi vehicle drivers on the R61 in South Africa. Journal of the South African Institution of Civil Engineering 58, 2 – 10. URL: http://dx.doi.org/10.17159/2309-8775/2016/v58n4a1.

Ehebrecht, D., Heinrichs, D., Lenz, B., 2018. 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. doi:https://doi.org/10.1016/j.jtrangeo.2018.05.006.

Evans, J., O'Brien, J., Ch Ng, B., 2018. Towards a geography of informal transport: Mobility, infrastructure and urban sustainability from the back of a motorbike. Transactions of the Institute of British Geographers 43, 674–688. doi:10.1111/tran.12239.

Fridlund, J., Wilen, O., 2020. Parameter Guidelines for Electric Vehicle Route Planning.

Galuszka, J., Martin, E., Nkurunziza, A., Achieng' Oginga, J., Senyagwa, J., Teko, E., Lah, O., 2021. East Africa's Policy and Stakeholder Integration of Informal Operators in Electric Mobility Transitions—Kigali, Nairobi, Kisumu and Dar es Salaam. Sustainability 13. doi:10.3390/su13041703.

Goodfellow, T., 2017. 'Double Capture' and De-Democratisation: Interest Group Politics and Uganda's 'Transport Mafia'. The Journal of Development Studies 53, 1568–1583. doi:10.1080/00220388.2016.1214722.

Hecht, D., 2007. Invisible Governance: The Art of African Micropolitics . Autonomedia, New Yoork.

Jadhav, A.S., Chembe, D.K., Strauss, J.M., Van Niekerk, J.L., 2017. Status of Solar Technology Implementation in the Southern African Developing Community (SADC) Region. Renewable and Sustainable Energy Reviews 73, 622–631. doi:https://doi.org/10.1016/j.rser.2017.01.113.

Jennings, G., Behrens, R., 2017. The Case for Investing in Paratransit: Strategies for regulation and reform.

KCCA, 2016. Multimodal Urban Transport Master Plan for Greater Kampala Metropolitan Area. Technical Report. Kampala Capital City Authority (KCCA). Kampala.

Krüger, F., Titz, A., Arndt, R., Groß, F., Mehrbach, F., Pajung, V., Suda, L., Wadenstorfer, M., Wimmer, L., 2021. The Bus Rapid Transit (BRT) in Dar es Salaam: A Pilot Study on Critical Infrastructure, Sustainable Urban Development and Livelihoods. Sustainability 13. doi:10.3390/su13031058.

Kumar, A.M., 2011. Understanding the emerging role of motorcycles in African cities : a political economy perspective. Technical Report 13. Washington, DC: World Bank. Washington, DC.

Kurczveil, T., López, P.Á., Schnieder, E., 2014. Implementation of an Energy Model and a Charging Infrastructure in SUMO, in: Behrisch, M., Krajzewicz, D., Weber, M. (Eds.), Simulation of Urban Mobility, Springer Berlin Heidelberg, Berlin, Heidelberg. pp. 33–43.

Lah, O., 2017. Decarbonizing the transportation sector: policy options, synergies, and institutions to deliver on a low-carbon stabilization pathway. WIREs Energy and Environment 6, e257. doi:https://doi.org/10.1002/wene.257.

Le, T.P.L., Trinh, T.A., 2016. Encouraging Public Transport Use to Reduce Traffic Congestion and Air Pollutant: A Case Study of Ho Chi Minh City, Vietnam. Procedia Engineering 142, 236–243. doi:https://doi.org/10.1016/j.proeng.2016.02.037.

Le Roux, W.G., 2016. Optimum tilt and azimuth angles for fixed solar collectors in South Africa using measured data. Renewable Energy 96, 603–612. doi:https://doi.org/10.1016/j.renene.2016.05.003.

Lewis, R., 2020. Algorithms for Finding Shortest Paths in Networks with Vertex Transfer Penalties. Algorithms 13. doi:10.3390/a13110269.

Li, Y., Davis, C., Lukszo, Z., Weijnen, M., 2016. Electric vehicle charging in China's power system: Energy, economic and environmental trade-offs and policy implications. Applied Energy 173, 535–554. doi:https://doi.org/10.1016/j.apenergy.2016.04.040.

Liu, Q., Deng, M., Shi, Y., Wang, J., 2012. A density-based spatial clustering algorithm considering both spatial proximity and attribute similarity. Computers & Geosciences 46, 296–309. doi:https://doi.org/10.1016/j.cageo.2011.12.017.

Lopez, P.A., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flötteröd, Y.P., Hilbrich, R., Lücken, L., Rummel, J., Wagner, P., Wießner, E., 2018. Microscopic Traffic Simulation using SUMO, in: 2019 IEEE Intelligent Transportation Systems Conference (ITSC), IEEE. pp. 2575–2582. URL: https://elib.dlr.de/127994/.

Lozano Gracia, N., Bainomugisha, E., Soppelsa, M.E., Okure, D., 2021. Characterization of Ambient Air Quality in Selected Urban Areas in Uganda : A Low-Cost Approach. Technical Report 9512. URL: https://ideas.repec.org/p/wbk/wbrwps/9512.html.

Lucas, K., Jennings, G., Zuidgeest, M., Behrens, R., Venter, C., Mitullah, W., Thornton, B., 2019. Transport Social Exclusion in Five African Cities. Technical Report. International Network for Transport and Accessibility in Low Income Communities. Leeds,UK. URL: http://www.vref.se/download/18.45182a5f16a84e95fac8b2b5/1561370471910/Transport%20and%20Social%20Exclusion%20in%20five%20African%20Cities%20-%20June%202019.pdf.

Mutiso, W., Behrens, R., 2011. 'Boda Boda' bicycle taxis and their role in urban transport systems: case studies of Kisumu and Nakura, Kenya, in: 30th Annual Southern African Transport Conference 11-14 July 2011 "Africa on the Move", CSIR International Convention Centre, Pretoria, South Africa. pp. 430–444. URL: http://hdl.handle.net/2263/17308.

Ndibatya, I., Booysen, M.J., 2020. Minibus taxis in Kampala's paratransit system: Operations, economics and efficiency. Journal of Transport Geography 88. doi:10.1016/j.jtrangeo.2020.102853.

Ndibatya, I., Booysen, M.J., 2021. Characterizing the movement patterns of minibus taxis in Kampala's paratransit system. Journal of Transport Geography 92, 103001. doi:https://doi.org/10.1016/j.jtrangeo.2021.103001.

Ndibatya, I., Booysen, M.J., Quinn, J., 2014. An adaptive transportation prediction model for the informal public transport sector in Africa, in: 17th International IEEE Conference on Intelligent Transportation Systems (ITSC), pp. 2572–2577.

Neumann, A., Joubert, J.W., 2016. The "Minibus" Contribution, in: Andreas Horni, Kai Nagel, Kay W Axhausen (Eds.), The Multi-Agent Transport Simulation MATSim. Ubiquity Press, London. doi:10.5334/baw.17.

OpenStreetMap contributors, 2017. Planet dump retrieved from https://planet.osm.org . https://www.openstreetmap.org.

Osei, L.K., Ghaffarpasand, O., Pope, F.D., 2021. Real-World Contribution of Electrification and Replacement Scenarios to the Fleet Emissions in West Midland Boroughs, UK. Atmosphere 12. doi:10.3390/atmos12030332.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., 2011. Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research 12, 2825–2830.

Pojani, D., Stead, D., 2017. The Urban Transport Crisis in Emerging Economies: An Introduction, in: Pojani, D., Stead, D. (Eds.), The Urban Transport Crisis in Emerging Economies. Springer International Publishing, Cham, pp. 1–10. doi:10.1007/978-3-319-43851-1_1.

Pojani, D., Stead, D., 2018. Policy design for sustainable urban transport in the global south. Policy Design and Practice 1, 90–102. doi:10.1080/25741292.2018.1454291.

Quirós-Tortós, J., Espinosa, A.N., Ochoa, L.F., Butler, T., 2018. Statistical Representation of EV Charging: Real Data Analysis and Applications, in: 2018 Power Systems Computation Conference (PSCC), pp. 1–7. doi:10.23919/PSCC.2018.8442988.

Rajé, F., Tight, M., Pope, F.D., 2018. Traffic pollution: A search for solutions for a city like Nairobi. Cities 82, 100–107. doi:https://doi.org/10.1016/j.cities.2018.05.008.

Renjith, S., Sreekumar, A., Jathavedan, M., 2020. Performance evaluation of clustering algorithms for varying cardinality and dimensionality of data sets. Materials Today: Proceedings 27, 627–633. doi:https://doi.org/10.1016/j.matpr.2020.01.110.

Sawadogo, W., Reboita, M.S., Faye, A., da Rocha, R.P., Odoulami, R.C., Olusegun, C.F., Adeniyi, M.O., Abiodun, B.J., Sylla, M.B., Diallo, I., Coppola, E., Giorgi, F., 2020. Current and future potential of solar and wind energy over Africa using the RegCM4 CORDEX-CORE ensemble. Climate Dynamics doi:10.1007/s00382-020-05377-1.

Schücking, M., Jochem, P., Fichtner, W., Wollersheim, O., Stella, K., 2017. Charging strategies for economic operations of electric vehicles in commercial applications. Transportation Research Part D: Transport and Environment 51, 173–189. doi:https://doi.org/10.1016/j.trd.2016.11.032.

Sengupta, M., Xie, Y., Lopez, A., Habte, A., Maclaurin, G., Shelby, J., 2018. The National Solar Radiation Data Base (NSRDB). Renewable and Sustainable Energy Reviews 89, 51–60. doi:https://doi.org/10.1016/j.rser.2018.03.003.

Shams, A., Zlatkovic, M., 2020. Effects of capacity and transit improvements on traffic and transit operations. Transportation Planning and Technology 43, 602–619. doi:10.1080/03081060.2020.1780710.

Sietchiping, R., Permezel, M.J., Ngomsi, C., 2012. Transport and mobility in sub-Saharan African cities: An overview of practices, lessons and options for improvements. Cities 29, 183–189. doi:https://doi.org/10.1016/j.cities.2011.11.005.

Singh, A., Avis, W.R., Pope, F.D., 2020. Visibility as a proxy for air quality in East Africa. Environmental Research Letters 15, 84002. doi:10.1088/1748-9326/ab8b12.

Soares, P.M.M., Brito, M.C., Careto, J.A.M., 2019. Persistence of the high solar potential in Africa in a changing climate. Environmental Research Letters 14, 124036. doi:10.1088/1748-9326/ab51a1.

Venter, C., Jennings, G., Hidalgo, D., Pineda, A.F.V., 2018. The equity impacts of bus rapid transit: A review of the evidence and implications for sustainable transport. International Journal of Sustainable Transportation 12, 140–152. doi:10.1080/15568318.2017.1340528.

Venter, C., Mahendra, A., Hidalgo, D., 2019. From Mobility to Access for All: Expanding Urban Transportation Choices in the Global South. Technical Report. World Resources Institute.

Weiss, M., Cloos, K.C., Helmers, E., 2020. Energy efficiency trade-offs in small to large electric vehicles. Environmental Sciences Europe 32, 46. doi:10.1186/s12302-020-00307-8.

Zheng, Y., Zhang, L., Xie, X., Ma, W.Y., 2009. Mining Interesting Locations and Travel Sequences from GPS Trajectories, in: Proceedings of the 18th International Conference on World Wide Web, Association for Computing Machinery, New York, NY, USA. pp. 791–800. doi:10.1145/1526709.1526816.

Zinkernagel, R., Evans, J., Neij, L., 2018. Applying the SDGs to Cities: Business as Usual or a New Dawn? Sustainability 10. doi:10.3390/su10093201.