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Simulating The Driving and Charging of Electric Minibus Taxis: A Case Study for Stellenbosch

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Abstract

The Global North is increasing the drive for the electrification of the mobility industry. In sub-Saharan Africa, however, the adoption is yet to pick up steam due to various other challenges in the region. The viability of converting the paratransit fleet (which consists mostly of minibus taxis) to electric vehicles (EVs) with current combustion-based operations is investigated by making use of simulation software, and EV-Fleet-Sim. This developed software simulates the driving and charging of operationally tracked taxis in the Stellenbosch area. A charging algorithm, as well as a simple battery model, was included in the simulation to provide a more accurate representation of the scenario. Most of the taxis were found to still complete their required trips with the specified battery size of 70 kWh. However, new methods would need to be found, such as including a mixed fleet with some petrol or diesel taxis, to assure a 100% trip completion rate. The grid impact per vehicle was found with an expected maximum load appearing between the hours of 08h00 and 10h00 of 22 kW per vehicle, which corresponds to the time after the morning peak traffic of getting people to work. Furthermore, a minimum number of chargers can be implemented which will not affect the trip completion rate of the taxis. This was found to be for 4 chargers per 17 taxis. Future work is left to the testing of various parameters to find optimal solutions as well as including home charging and failed trip classification.

Keywords: minibus taxi, electric mobility, grid impact, charging

1. Introduction

The drive for scaled electric mobility in the Global North has increased exponentially in the past decade. However, in sub-Saharan Africa, this adoption has been slow due to the many other challenges the region faces, such as a severely restricted electricity supply. This paper evaluates the viability of converting the paratransit industry (consisting mostly of minibus taxis) to electric vehicles by investigating whether the demand of the taxis can be met with an electric version of it. This is done by simulating the driving and charging of the taxis over a period of a month. Furthermore, this paper aims to investigate the impact that these vehicles will have on the grid, for the case scenario of charging at a centralised taxi rank.

Sub-Saharan Africa's so-called "paratransit" industry differs substantially from the developed countries' paratransit industry in both the vehicle type and operations. In developed countries, it is defined as a point-to-point, demand-responsive and flexible transport. However, in sub-Saharan Africa, this word refers to the mode of mobility for the majority and has subsequently been termed as an informal public transport system (Askari et al., 2021; Behrens et al., 2017; Horni et al., 2016; Ndibatya et al., 2014). Its operation can be characterised as one falling between a private passenger transport system and a conventional public transport system in terms of its scheduling, cost, routes, and quality of service (Horni et al., 2016; Ndibatya et al., 2014). As a result, many depend on this industry for their livelihood (Behrens et al., 2015), and the social and economic development of a country heavily depends on the existing transport sector (Khalid et al., 2019).

The minibus taxis make up most of the vehicles in the paratransit industry, with South Africa having approximately 250 000 taxis (SA Taxi, 2023). These minibus taxis are currently powered by internal combustion engines (ICE) which contribute towards the emission of greenhouse gasses

(GHG) as well as a general decline in air quality within cities (Collett & Hirmer, 2021). The minibus taxi contribution towards the decline in air quality within a city is further aided by the minibus taxis being old (often older than 20 years) and thus fuel inefficient (Amegah & Agyei-Mensah, 2017; Dalal et al., 2011).

The World Health Organisation has linked the exposure to ambient air pollution to the increase in cardiopulmonary and cardiovascular diseases and have thus classified exposure as a major threat to human health (Amegah & Agyei-Mensah, 2017; Khalid et al., 2021). Three of the seventeen United Nations Sustainable Development Goals are clean energy, sustainable cities, and climate action (goals one, eleven and thirteen respectively) (Zinkernagel et al., 2018). Thus, the development of low-carbon transport in cities is crucial to the global agenda, with the electrification of vehicles promoted as the low-carbon transport strategy to slow down climate change and reduce carbon emissions (Khalid et al., 2019).

The transition from ICE vehicles to electric vehicles (EVs) is gaining traction in developing countries (C. J. Abraham et al., 2021; Berckmans et al., 2017; Münzel et al., 2019), with many of the global manufactures planning to stop production of ICE vehicles as early as 2030 (Booysen et al., 2022; Niese et al., 2022). Sub-Saharan Africa has already seen a few isolated cases of electric mobility with the focus on the micro-mobility (tricycles and motorcycles) industry, as well as a small minority investigating buses and cars (C. J. Abraham et al., 2021). Many have called for a total overhaul of the minibus taxi industry (to something akin to that in Europe) as part of this global shift, but it is well entrenched within society. It is unlikely to be phased out as the preferred mode of transport due to its existing dominance in the market as well as its agility in the informal townships (Collett & Hirmer, 2021). The electrification of the paratransit industry is therefore a necessity, but the question still remains regarding the impact that such vehicles will have on an already energy scarce and fragile grid system (Buresh et al., 2020).

1.1 Contributions

This paper aims to quantify the impact that the charging of electric minibus taxis will have on the local infrastructure, or the localised grid. Furthermore, the paper establishes to what extent the electric minibus taxis will be able to complete the trips based off current operations, thereby meeting the demand of passengers, given the limiting nature of the battery size, slow charging and number of chargers. These impacts are assessed using custom software using tracking data of real vehicles driving within the city of Stellenbosch, South Africa.

2. Literature Review

The electrical grid in South Africa is run by the government-owned entity, Eskom, which has an installed capacity of 48 GW. However, the available capacity frequently reduces to 24 GW due to regular breakdowns and maintenance programs. This has resulted in rolling regional blackouts, colloquially known as "loadshedding", being a regular occurrence in the country. (Buresh et al., 2020) The localised grid of Stellenbosch is in question for this paper, which experiences many of the challenges of the national grid.

2.1 Grid Impact of EV Charging

The utility grid, and more specifically the distribution grid, can be negatively affected when private EVs charge either at public charging stations or at home in an unscheduled manner (Dang, 2018; Sundström & Binding, 2012). The same logic can then be applied to the electrification of the minibus taxis. The development of EV charging structures with minimal impact on the existing grid is therefore required for sustainable integration (Khalid et al., 2019). This is further substantiated by Abraham et al., 2021, who states that a substantial burden can be placed on the local electrical grid if a large enough fleet is charging.

Three different charging strategies are currently utilised in industry: charging ports, battery swap stations and fast charging stations (FCS) (Liu, 2012). It has been stated by Giliomee & Booysen

(2023) that the battery swapping method is not a viable solution to the electric taxi fleet, as it would place strain on the OEMs to produce this technology when sufficient other technologies already exist. The charging power for EVs in charging ports and FCSs can be categorised into various classes and power levels (Wang et al., 2021a). The first class is known as slow charging (Wang et al., 2021b), which consists of AC charging at Level 1, ranging from 1.4 to 2.2 kW (Khalid et al., 2019; Meyer & Wang, 2018a; Rajendran et al., 2021a). The second class is known as accelerated charging (Rajendran et al., 2021b), which consists of AC charging at Level 2 and ranges from 19.2 to 22 kW (Khalid et al., 2019; Meyer & Wang, 2018a; Rajendran et al., 2021a). However, AC Level 2 can also range between 4 and 8 kW (YILMAZ & Krein, 2013), depending on the vehicle type. The final class is known as fast charging (Wang et al., 2021b), which consists of DC charging at Level 3, which can range anywhere from 50 to 350 kW (Meyer & Wang, 2018b; Rajendran et al., 2021b; Wang et al., 2021b). DC charging stations require an external power converter while AC charging requires an on-board power converter (Rajendran et al., 2021b; Wang et al., 2021b).

3. Methodology

This section describes the details and functionalities of the software developed to determine the grid impact and completion rates of the electric taxis. Furthermore, the type of input required for the simulation program and EV-Fleet-Sim (the program responsible for simulating the driving of the electric vehicle) is also described. A high-level overview of the simulation setup is shown in Fig. 2. Each of these components are broken down and discussed in further subsections.

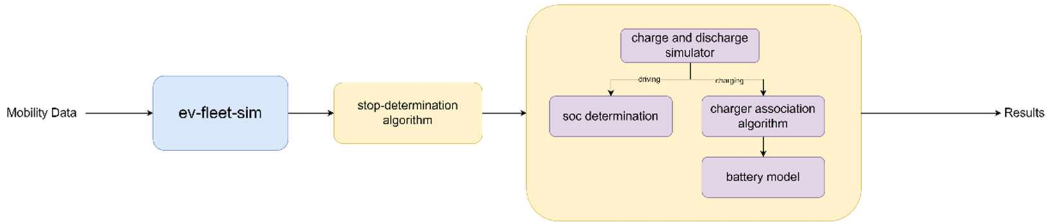


Fig. 2. High-Level Overview of software and EV-Fleet-Sim

3.1EV-Fleet-Sim

EV-Fleet-Sim is a software developed by Abraham et al. (2021) which takes in the mobility data of tracked vehicles, in this case minibus taxis, and calculates the energy requirements of an electric version of the vehicle by using a developed EV-model, and routing simulator. The mobility data used in this study was provided by GoMetro. Seventeen taxis were tracked for a month within the Stellenbosch area. An example of the mobility data provided can be seen in Fig. 3, which shows a heat map of where a taxi drove in the Stellenbosch area. The "hotspots" show how often the taxi was in a specific location in the month. Additionally, one of the outputs of EV-Fleet-Sim is the energy consumed from the EV battery during driving [in Wh/s], which is used in Eq. (1).

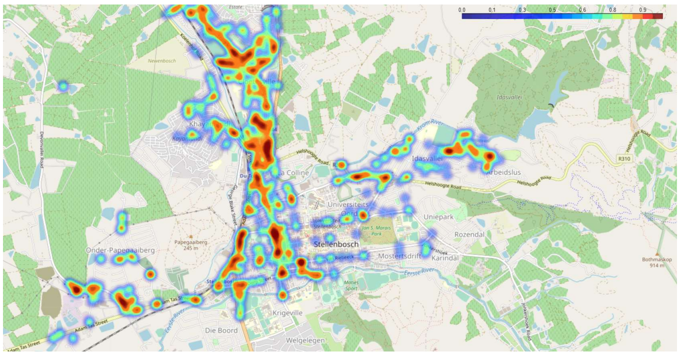
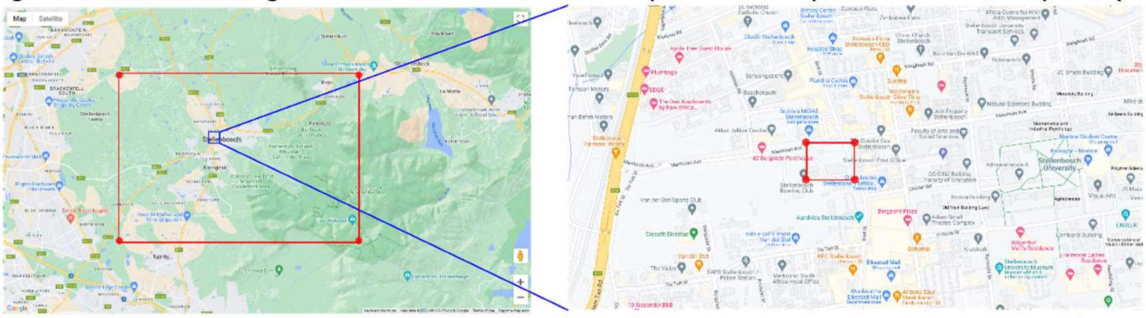


Fig. 3. Example of mobility data

The tracked taxis travelled in and around Stellenbosch. The set boundary can be seen in Fig. 4(a). If a vehicle is found to travel outside this boundary, it is not considered within the data and the vehicle is seen as "not driving" on that day. Furthermore, on weekends, the taxis make long distance trips to the Eastern Cape, and so weekends are also excluded from the dataset. A solution for long distance travelling of electric minibus taxis is presented by Giliomee & Booysen (2023).



(a) (b)

Fig. 4. (a) Stellenbosch Boundary (b) Stellenbosch Taxi Rank - Charging Location

3.2 Stop-determination Algorithm

The data was setup and run according to the steps in the documentation of EV-Fleet-Sim (C. Abraham, 2022). However, even though EV-Fleet-Sim was able to provide the energy requirements for the EV battery, it was unable to determine if the vehicle was stopped and available to charge. Thus, a stop-determination algorithm was developed for this.

The vehicle is considered to be "stopped" based on two conditions: speed within 10 km/h and the new GPS location being within a 25 metre radius of the first stop location. The first stop location is determined by the vehicle speed being below 1 km/h. The algorithm evaluates if the vehicle has stopped and if the vehicle remains stopped based on the conditions stated previously. Once these stop locations are determined, the vehicle must be stopped for a minimum of 20 minutes in order to be considered "Available to Charge". These values are used in subsequent sections.

3.3 Taxi-State Model

The output of EV-Fleet-Sim has datapoints for every second for each day, ranging from 00h00 to 23h59, for a normal day. This data exists as daily information grouped to each vehicle. However, the simulation software requires the day to start at 04h00 and simulate until 03h59 of the next day, instead of the normal day. This more accurately resembles the activity and motion of the taxis, as they start their operations at approximately 04h00 in the morning. Thus, the data must be transformed from the original times to these new times. The simulation software also takes in the data as vehicle information, grouped to each day, and requires further formatting.

The stopping data created in the previous section was used to determine if the vehicle has stopped at the specified charging location or if the vehicle has merely stopped at a traffic light or is in traffic. The charging location was taken as the Stellenbosch Taxi Rank in the centre of town and can be seen in Fig. 4(b). This presents the two states the taxi can be in: driving or charging. Even though the taxi may be stopped in traffic, it is still considered to be "driving". The state-of-charge (SOC) of the vehicle's battery can then be calculated according to Eq. (1) for the driving state, where *i* represents the current time index, *e* is the energy consumed by the vehicle in *Wh* and *B* is the battery capacity of the vehicle in *Wh*. The SOC for the taxi for the case of charging is described in further sections.

$$SOC[i] = SOC[i-1] - \frac{e[i]}{B} \quad (1)$$

3.4 Charger Association Algorithm

A charging algorithm was developed and incorporated into the simulation software to perform the association of available chargers during charging. If the vehicle needs to charge and is available to charge (based on the condition that it is within the bounds of the taxi rank and stopped for more than 20 minutes), and a charger is available, the algorithm assigns the vehicle to that charger. The algorithm can also handle a few conditions and edge cases when simulating. If there are not enough chargers available for the number of vehicles that need to be charged, the algorithm checks if there is a vehicle on charge that has an SOC greater than 80%. It then selects the vehicle with the highest SOC and de-assigns it from the charger and replaces it with a vehicle with a low SOC. If all the vehicles have an SOC greater than 80%, the algorithm keeps the vehicles on charge until they have reached 100% before assigning a new to charger to a vehicle with an SOC greater than 80%.

3.5 Battery Model

The slower charging of the battery as the SOC approaches 100% can be accounted for with the inclusion of a simple battery model within the simulation software. A Constant Power Constant Voltage (CP/CV) charging profile was assumed. The implemented battery model can then be used to determine if the battery of the EV is in Constant Power or Constant Voltage mode. The battery model parameters are highlighted in Table 5, with the calculations and charging mode determination based on the work presented by Qian et al. (2023). The only modification to the equations presented in their work is given by Eq. (2), where V_{OC} is the open circuit voltage, which has been modified from their Eq. 5. Furthermore, the calculation of the SOC during charging is given by Eq. (3), where *g* is the charging power based on the calculations presented by Qian et al. (2023). For the purposes of this simulation, a grid charging power of 22 kW was chosen due to it being able to charge vehicles sufficiently without having the impact that DC chargers would have on the grid. Furthermore, a charging efficiency of 88% (Qian et al., 2023) was incorporated to account for the inefficiencies of real chargers.

$$V_{oc}[i] = a_v(SOC[i] \times E_{nom}) + b_v \quad (2)$$

$$SOC[i] = SOC[i-1] + \frac{g[i]}{B} \quad \mathbf{(3)}$$

Table 5: Battery Model Parameters

Parameters	Description	Values	Parameters	Description	Values
V_{nom}	Nominal cell voltage	3.7 V	M_p	Number of cells in parallel	78
V_{max}	Maximum cell voltage	4.15 V	M_s	Number of cells in series	110
R	Cell impedance	148 mΩ	a_v	Model coefficient per cell	67.92 mV/Wh
Q_{nom}	Nominal cell capacity	2.2 Ah	b_v	Model coefficient per cell	3.592 V
E_{nom}	Nominal cell energy	8.14 Wh			

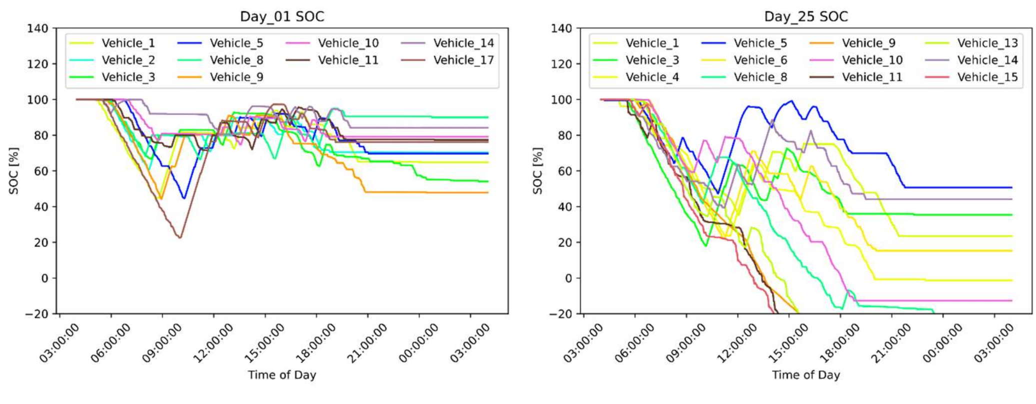
4. Results

This section describes the results obtained from the simulation software. The first section describes the ability of the electric minibus taxis to drive and meet the demand of the passengers, and is followed by the second section, which describes the grid impact with current approaches. The vehicles were simulated for each day of a month. Each vehicle started at 100% SOC at the beginning of each day, and "loadshedding" times were not incorporated in the simulation.

Fig. 5 demonstrates two example days of the month, with Fig. 5(a) being an example of a good day and Fig. 5(b) being an example of a bad day. It is important to note that the vehicles were allowed to "travel" past 0% SOC, as it was assumed that a larger battery capacity would be needed in this case. This was done to test if the vehicle would be able to regain its expended energy if a larger battery capacity was used, without having to re-simulate at different battery capacities. This can be seen in Fig. 5(b). Furthermore, the Charging Allocation Algorithm can be seen in operation in Fig. 5(a), where a total of 2 chargers were used at the taxi rank.

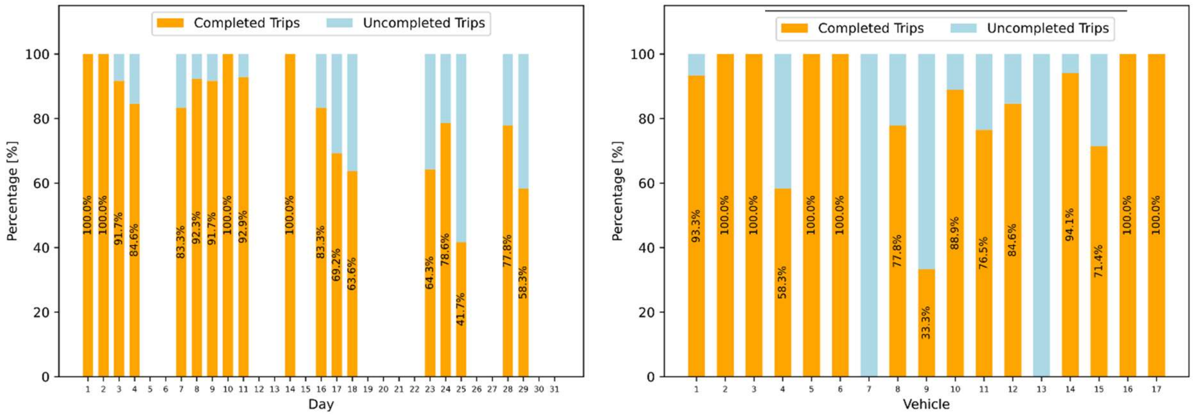
4.1 Trip Completion Rate

Fig. 6 shows the vehicle trip completion rates for the month as well as the trip completion rates for each vehicle. A vehicle is considered to have a successful trip if the SOC remains above 0% for the whole day. Fig. 6(a) answers the question of: "how many vehicles, of those driving on each day, had successful trips?". Furthermore, the weekends were excluded from this figure, as well as days where the vehicles did not drive. Fig. 6(b) answers the question of: "how many days, when the vehicle was driving, were successful trips?".



(a) (b)

Fig. 5. Example Days of Simulation for SOC (a) Good vehicle-day with charger association (b) Bad vehicle-day with energy expenditure



(a) (b)

Fig. 6. Completion Rates: (a) Daily completion rates (b) Vehicle completion rates

As can be seen from Fig. 6, most of the vehicles were able to complete the necessary trips in a day based on the current demand of trips, with a given usable battery capacity of 70 kWh. The battery capacity is based on current on-the-market electric taxis (*Higer H5C EV*, 2020). However, there are certain trips that the vehicle makes which EVs would be unable to match. Further investigation into what specific routes and distances to classify these failed trips is left for future work. It can also be seen in Fig. 5(b) that there are not enough charging opportunities in the day for the vehicle to regain its expended energy, and so bigger batteries may not be the solution. Possible solutions could include increasing charging opportunities by introducing home charging and/or incorporating some petrol or diesel vehicles to the electric fleet.

4.2 Grid Impact

Fig. 7 shows the maximum power for each day for differing number of chargers, where N denotes the number of chargers. As the number of chargers decreases, a limit is reached in the maximum power required from the grid while charging, as can be seen for the case of 4 chargers and lower. It was found that 4 chargers for 17 vehicles was the minimum number of chargers which could be implemented without affecting the trip completion rates of the taxis.

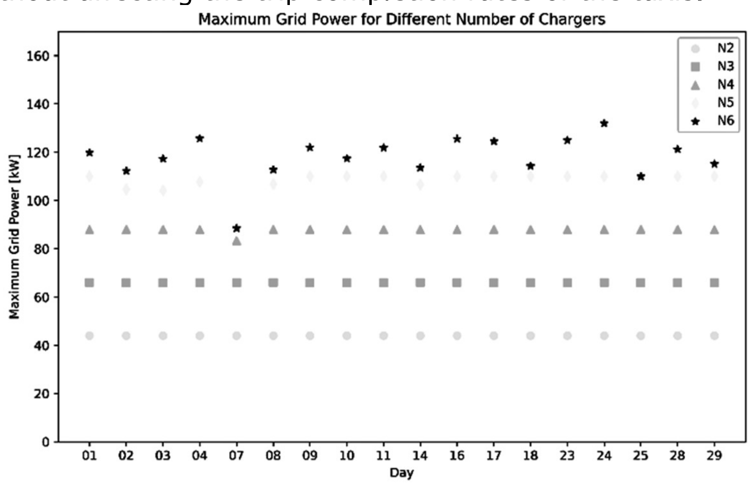


Fig. 7. Maximum Power per Day for Different Number of Chargers

In the case of 6 chargers, the maximum power on the grid is achieved on day 24. As a result, the maximum and minimum power on the grid was taken for the case where the number of chargers being utilised is 6. The minimum and maximum power was determined by finding the average of the power drawn from the grid in an hour over all the days. The maximum and minimum values of these averages would then correspond to the specific day and hour that experienced the minimum and maximum power. These values were then used to build the maximum and minimum power per vehicle that could be drawn from the grid, with the result displayed in Fig. 8. The average power per vehicle is also displayed and given by the blue line.

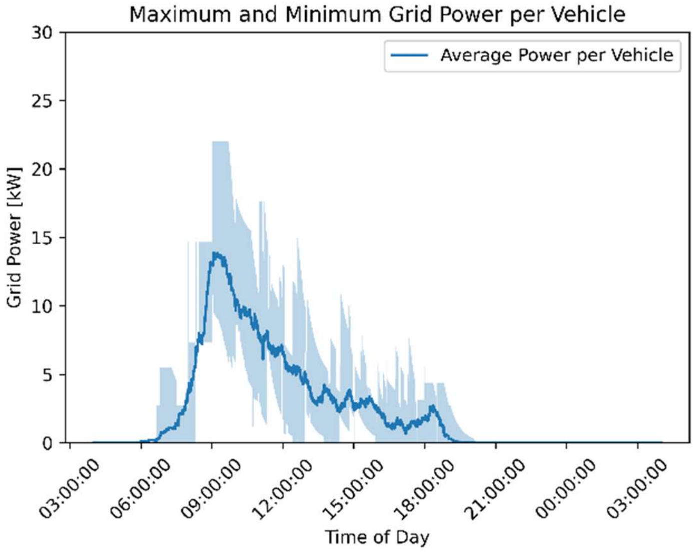


Fig. 8. Maximum and Minimum Power on the Grid for charging at the depot (taxi rank) only

As can be seen in Fig. 8, the peak power for charging occurs between the hours of 08h00 and 12h00 which corresponds to the time after which the minibus taxis have driven the population to their work. Furthermore, given a certain number of operational electrical taxis, the grid power required for charging will fall somewhere between a multiple of the shaded region, and never exceed a maximum of 22 kW per vehicle.

5. Conclusion

A novel tool was developed to simulate the driving and charging of electric minibus taxis within Stellenbosch. This tool was incorporated with an existing and already developed model known as EV-Fleet-Sim. A simplified battery model was also added to the simulation to better simulate charging.

The simulation was run to determine the impact that these electric vehicles would have on the grid, and the ability of the vehicles to complete their trips. It was found that the electric taxis would be able to meet the demand given a 70 kWh usable battery capacity. However, this was not for all the cases and a further investigation is required to determine what these conditions are.

Furthermore, the impact on the grid was determined with the highest peak being experienced with 6 chargers being implemented. This resulted in a maximum power of 22 kW drawn from the grid per vehicle. It was also found that one can implement a minimum number of chargers without affecting the trip completion rate of the taxis. This was found to be 4 chargers for 17 taxis. Future work is left to investigating home charging, changing variable values to find optimal solutions and classifying successful trip completion vehicles.

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