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Empirically Validated Method to Simulate Electric Minibus Taxi Efficiency Using Tracking Data

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Abstract: Simulation is a cornerstone of planning and facilitating the transition towards electric mobility in sub-Saharan Africa's informal public transport. The primary objective of this study is to validate and refine the electro-kinetic model used to simulate electric versions of the sector's minibuses. A systematic simulation methodology is also developed to correct the simulation parameters and improve the high-frequency GPS data used with the model. A retrofitted electric minibus was used to capture high-frequency GPS mobility data and power draw from the battery. The method incorporates key refinements such as corrections for gross vehicle mass, elevation and speed smoothing, radial drag, hill-climb forces, and the calibration of propulsion and regenerative braking parameters. The refined simulation demonstrates improved alignment with measured power draw and trip energy usage, reducing error margins and enhancing model reliability. Factors such as trip characteristics and environmental conditions, including wind resistance, are identified as potential contributors to observed discrepancies. These findings highlight the importance of precise data handling and model calibration for accurate energy simulation and decision making in the transition to electric public transport. This work provides a robust framework for future studies and practical implementations, offering insights into the technical and operational challenges of electrifying informal public transport systems in resource-constrained regions.

Keywords: electric vehicle; electric mobility; paratransit; minibus taxi; mobility modelling; renewable energy; transport data

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1. Introduction

The shift towards electrifying the transport sector is gaining significant traction worldwide. According to the Intergovernmental Panel on Climate Change (IPCC), transportation was responsible for 23% of energy-related greenhouse gas emissions globally in 2014 [1,2]. Efforts to promote low-carbon transport in urban areas are now integral to international strategies aimed at combating climate change according to Odhiambo et al. [3] and are closely tied to three of the United Nations' Sustainable Development Goals [4,5]. In the Global North, sales of electric vehicles (EVs) have risen dramatically with many major car manufacturers pledging to end the production of internal combustion engine vehicles by 2030 [6–8].

As developed countries start to push the change to electric mobility, developing countries are feeling increasing pressure to follow suit [9–11]. The critical questions are whether these advancements genuinely benefit developing countries and whether they can adapt to the significantly different infrastructure demands of these technologies. One major challenge is that many developing countries' struggling electricity utilities are already unable to meet existing energy needs, making it difficult to support the substantial increase in demand that widespread EVs usage would require [12,13]. Research suggests that in some African contexts, transitioning private vehicles to EV technology may be unsustainable for current power grids [14,15] and, in some cases, could even have adverse environmental consequences [16].

In many developing countries, public transport dominates the modal share. Kumar et al. [17] show that in Africa, besides walking, minibus taxis hold the largest modal share (as observed across 14 cities). Given the significance of this sector, prioritising the electrification of public transport over private vehicles seems a logical step.

The transition to EVs presents a unique opportunity to address longstanding issues in African public transport, which is often characterised by ageing and poorly maintained minibuses [17]. However, progress in sub-Saharan Africa (SSA) remains exceedingly slow. Privately owned minibus taxis, which form the backbone of transportation in SSA, are ubiquitous in both urban and rural areas. This sector supports 83% of the so-called "paratransit" or "popular transportation" industry, which serves over 70% of daily commuters in the region. Paratransit refers to an informal, decentralised system of shared public transport operated by small-scale owners. These services lack fixed schedules and routes, adapting dynamically to passenger demand [18]. For this sector to achieve sustainability, transitioning to electric energy sources is essential [14,19–24].

Currently, there is limited knowledge about the energy demands of minibus taxis, particularly considering their distinct and largely undocumented mobility patterns [25,26]. Many factors affect the energy requirements of a transport sector in its particular context [24,27–31]. For a given passenger demand, these factors include the following:

- Properties of the routes and terrains: elevation changes, road surface (pavement) type and its condition, tortuosity, speed restrictions, number of stops, speed restrictions, traffic conditions, distances covered;
- Driver behaviour and driving style: acceleration and deceleration aggressiveness, compliance to speed restrictions, regularity of stopping to collect passengers;
- Vehicle-related properties: weight, occupancy, propulsion power, vehicle range, re-energising (fuelling/charging) rates, vehicle efficiency.

These factors (and the mobility patterns) impact how much (and when) an electric vehicle's battery will deplete. Without the actual deployment of electric vehicles, the impact is simulated using mobility models or mobility data, driver models, electro-kinetic vehicle models, and charging infrastructure models [27,29,32]. For an unscheduled and decentralised transport system, in which charging is not predetermined (as it would be for a scheduled transport system in a developed country or a centralised scheduled bus system), the status of the vehicles' batteries at any given time is key to understanding charging requirements and the impact thereof on the electricity network [33,34]. Therefore, planning for energy provision in the electrification of a transport sector requires a thorough understanding of how these factors will affect the energy depletion of a vehicle's battery to ensure reliable simulation models. This understanding fundamentally concerns the energy expenditure in kWh/km simulated for a given route or terrain, driving style, and vehicle. Simulation models have been validated for specific modes in some regions [35,36]. However, existing studies focusing on this aspect of minibus paratransit rely on theoretical or simulation-based models that have not been validated.

Accurate simulation models are urgently needed to determine the energy requirements of electric taxis, predict grid demand, and conduct technical, economic, and environmental analyses and optimisations. These tools will be crucial in guiding the electrification of the minibus taxi sector effectively and sustainably.

1.1. Limitations of Existing Methodologies

Some research effort has been invested to develop and improve EV taxi simulations [31,35,37–40]. However, the reliability of this research has been hampered by the unavailability of measured data surrounding public transport in developing countries. Additionally, electric vehicle penetration in developing countries has been relatively slow [41,42]. On the one hand, routes, fleet sizes, timetables, etc. are vastly undocumented due to the unregulated nature of public transport [18,43]. On the other hand, data of EV taxis have been hitherto completely unavailable to validate the simulations.

To illustrate this point, the simulated energy usage of taxis has been simulated from 0.93 kWh/km [38] to 0.39 kWh/km [31] to 0.50 kWh/km [40], as shown in Figure 1. Without accurate simulations, it is difficult to reliably forecast the feasibility of and strategise the transition to sustainable public transport [25,44].

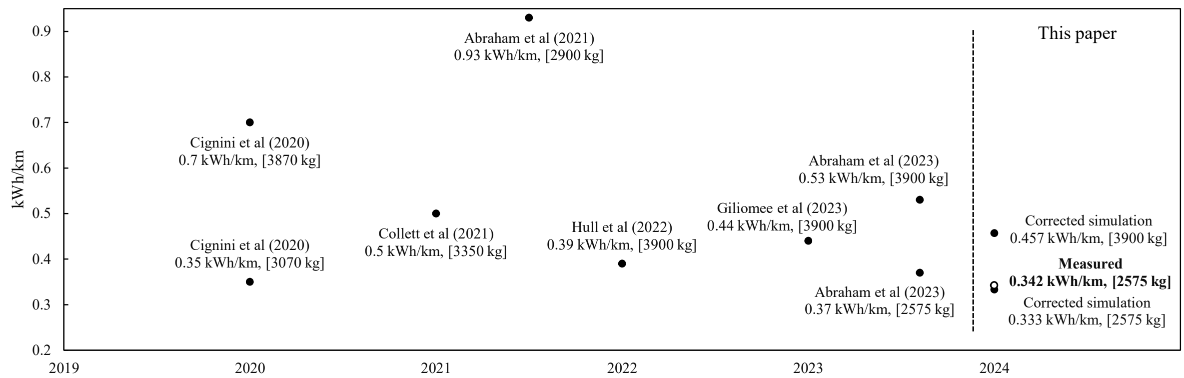


Figure 1. Energy expenditures from recent attempts in the literature compared to that measured in this paper [31,35,37–40]. Care should be taken when comparing these numbers, since different datasets and vehicles with different weights were used. The weights used for each source are reported.

After the initial estimation of minibus taxi energy requirements by Abraham et al. [38], various corrections were suggested by Hull et al. [31], Giliomee et al. [39], and Abraham et al. [40] in order to improve the accuracy of EV taxi simulations. The progression of these models is listed in Table 1.

Table 1. Progression of model improvements from the literature.

Reference	Progressive Steps
Abraham et al. [38] (2021)	Contributes a simulation model, which takes typical low-frequency mobility data, upsamples it using a mobility model, and simulates it with an energy-based simulation model.
Hull et al. [31] (2022)	Suggests the use of high-frequency data.
	Develops and contributes a high-frequency electro-kinetic simulation model.
Giliomee et al. [39] (2023)	Suggests improvements to the mobility model (driver model and mapping) to the model used by Abraham et al. [38].
Abraham et al. [40] (2023)	Implements the suggestions of Giliomee et al. [39]
	Merges the electro-kinetic simulation model of Hull et al. [31] into EV-Fleet-Sim.
	Makes mathematical corrections to the electro-kinetic simulation model of Hull et al. [31].

Although all these publications have made strides to improve these models, they remain theoretical and unvalidated using data from a physical electric minibus taxi.

Therefore, the primary objective of this work presented is to validate and refine the electro-kinetic model of a minibus taxi, using high-frequency GPS mobility data. To achieve this objective, a simulation framework is proposed to improve parameters and refine the tracking data.

1.2. Contribution

The article presents a unique contribution to electric vehicle efficiency simulation by introducing a two-part improvement framework, encompassing advancements in the simulation method and the data processing methodology.

First, an electro-kinetic simulation model and a coupled robust data processing (wrangling) method are developed. This model integrates key physical and environmental parameters to simulate the energy efficiency of an electric minibus taxi using real-world tracking data. The initial methodology establishes a baseline for accurately capturing vehicle dynamics and energy usage patterns.

Second, the data processing method is advanced by refining the treatment of raw GPS-tracking data. These improvements include improved handling of noisy data, detection and handling of outlier data points, and correction of GPS-based elevation profiles. This step ensures the accuracy and reliability of generic input data for simulation and validation purposes.

Third, the simulation model is validated and improved based on the processed data compared to that of actual data. This involves two major enhancements:

1. Parameter updates: Fine-tuning key parameters such as rolling resistance, motor efficiency, and drag coefficients to align the model outputs closely with measured results.
2. Model improvements: Incorporation of corrections for radial drag, heading angle, and hill-climb forces, providing a more realistic representation of aerodynamic and gravitational effects.

Finally, we present a fully validated simulation approach that combines the improved electro-kinetic model with the data processing refinement. This validated methodology accurately predicts the energy efficiency of electric minibus taxis but can also be implemented with generic electric vehicles in other transport systems, making it a practical tool for assessing the feasibility and performance of electric vehicles in real-world scenarios and fleet optimisation.

2. Methodology

This section outlines the method used to validate the theoretical EV simulation model developed in Abraham et al. [40]. The model's output is compared to the measured data obtained from tracking a physical electric minibus taxi, which was developed in Lacock et al. [45].

The process of this methodology is shown in Figure 2. Data are collected using a physical EV (in this case, the retrofitted electric minibus taxi). The obtained data are then analysed for various issues that may affect the simulation. In this step, extraneous data may be removed. With the raw data processed accordingly, the data are used to run an initial simulation, using EV-Fleet-Sim. With the first simulation completed, the simulation output is validated by comparing it to the results of the measured data. As further shown in Figure 2, this is followed by an iterative process of simulating and validating the results, which allows for making various corrections. These corrections are discussed further below.

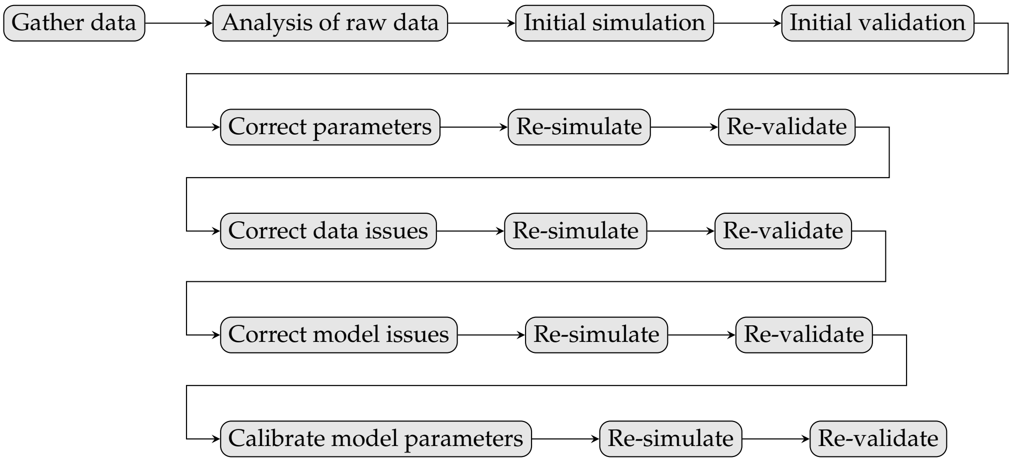


Figure 2. Methodology pipeline.

2.1. Data Collection

The electric taxi was driven a total of 1400 kilometres across a variety of terrains, including urban areas, hilly regions, and intercity routes, as shown in Figure 3. To ensure a comprehensive evaluation, the taxi was tested under different load conditions, using sandbags to simulate full-load scenarios near its gross-vehicle mass (GVM) and instances where the vehicle was empty. The tested vehicle weights ranged from 2060 kg to 3090 kg. Thirty discrete trips were conducted over ten days and analysed to capture the most accurate representation of the vehicle's performance.

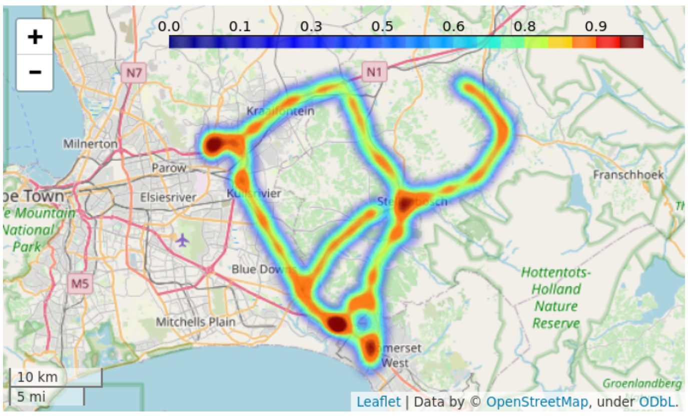


Figure 3. Vehicles routes over 30 trips conducted over 10 days with colour indicating density of samples.

Data collection was facilitated by an onboard telematics system that recorded CAN bus data at a frequency of 0.5 Hz, including key parameters such as power draw or regeneration, vehicle speed, and state of charge. However, the system did not capture GPS coordinates. To address this, a cellular device was used to record GPS coordinates at 1 Hz with speed and altitude. The two datasets were synchronised with curve-fitting methods to align the variables common across the two datasets (e.g., speed), allowing meaningful comparison and analysis. The CAN data was up-sampled to match the 1-second frequency of the GPS data, resulting in a cohesive dataset that could be used to develop and validate energy efficiency models. To further reduce the error in time between the dataset, we use window sampling to reduce the synchronisation error between the common value throughout the methodology.

2.2. Data Analysis

2.2.1. Mobility

The data collected from the various trips were analysed for mobility characteristics. Several metrics were selected, which influence the energy usage by the vehicle. These are listed in Table 2.

Table 2. Mobility metrics used.

Metrics	**Definition**
Trip payload	The weight carried by the vehicle. Heavier loads would require more energy.
Trip route	A number of routes were chosen for the purpose of this experiment. These trips were intra-town (within the same town) and inter-town (between towns). The two types of routes contain different terrains and result in different mobility characteristics, which would cause different energy requirements. Inter-town trips would require more energy due to longer distances and higher average speeds, but they would require less energy per unit distance because of fewer stop–start events compared to intra-town trips.
Trip length	This metric quantifies the exact length travelled by the vehicle. Longer distances would require more energy.
Elevation delta	This metric requires the net elevation difference between the end and beginning of the trip. Ending at a higher elevation than the vehicle started would imply a higher potential energy and thus more energy drawn from the battery.
Sum of upward elevation deltas per unit distance	The net elevation difference is not enough to conclude the effect that elevation has on energy usage. Since energy is not perfectly conserved when climbing and descending hills, hillier terrains would require more energy. Large elevation deltas per unit distance indicate routes with hills and valleys.
Sum of downward elevation deltas per unit distance	See previous metric's description.
Sum of absolute heading angle deltas per unit distance	The tortuousness (windiness) of a trip has a large impact on energy usage. Tortuous trips cause more energy losses due to braking and turning-friction. A larger number of heading angle deltas per unit distance indicate a more tortuous trip.
Mean speed	Trips taken at higher speeds require more energy to traverse due to losses to aerodynamic friction.
Standard deviation of speed	This metric indicates how much the speed varied. A larger standard deviation implies that more acceleration and deceleration took place during the trip.

2.2.2. Energy

The power and energy usage data of each of the trips were analysed. For each trip, the net energy requirement was established by adding the power samples over the trip duration. This was then divided by the distance of the route to find the energy usage rate (kWh/km). Each trip's energy usage rate should correspond to the mobility characteristics encountered in the trip, as determined in the previous steps. This correspondence is checked to verify that the energy usage rates are as expected.

The total energy was then broken down into its propulsion and regeneration components. Once again, this should correspond with the mobility characteristics of the corresponding trips. A high proportion of propulsion energy to regeneration energy indicates that the vehicle had more upward elevation deltas than downward elevation deltas. A high proportion of regenerated energy implies that many there were many opportunities for regenerative breaking, such as downward elevation deltas and aggressive acceleration (high standard deviation in speed). This correspondence was checked.

2.3. Simulation

Once confidence in the measured energy data was established, the mobility data were reformatted into a format suitable for usage by the EV-Fleet-Sim tool developed by Abraham et al. [40]. The tool consists of two electric vehicle models: an energy-based model derived from Kurczveil et al. [46] and a kinetic-based model derived from Hull et al. [31]. In this study, the model of Hull et al. [31] was used due to the flexibility of its implementation. As will be described, numerous aspects of the implementation were tweaked in order to test the effect of various changes to the model on energy usage.

The initial energy results were substantially different from the measured results, as described in Section 3.1. The primary reasons for the discrepancy were identified and corrected. These corrections are listed in Table 3, which are followed by a detailed analysis.

Table 3. Refinements applied in this work to improve the model.

Type of Refinement	Refinement Detail
Vehicle parameter updates	Gross vehicle mass updated
Data corrections	GPS-reported elevation smoothing
	GPS-reported speed profile smoothing
	GPS-reported heading angle correction
Model corrections	Hill-climb force-based model change to energy-based model
Model parameter calibration	Propulsion and regeneration factor calibration

The model parameters were reviewed and adjusted, if necessary, to match the vehicle that was being tested. In this case, the vehicle had a variable weight between 2060 kg (tare weight) and 3090 kg (fully loaded). The simulation model was thus adjusted to read the weight of the trip from a data file before conducting the simulation.

After making this parameter update, the scenario was simulated and the results compared/validated against the measured values. This revealed noisy power profiles, as discussed in Section 3.2. The cause of this was a consequence of three data issues. The first two issues were the presence of high-frequency components in the elevation and speed profiles. Therefore, the first two corrections were to apply Gaussian smoothing to the elevation and speed profiles. Details about this issue and the effect of the two corrections are described in Sections 3.2.1 and 3.2.2.

The third issue was that the heading angle in the data often jumps to zero. This was because the data logger calculated the heading angle from GPS coordinates rather than measuring it using a magnetometer or gyroscope. The GPS coordinates would fail to update when the GPS signal was poor, leading to duplicate GPS coordinates, which resulted in an undefined heading angle, which was recorded as 0°. This was corrected by performing linear interpolation on the heading angle. This interpolation followed the shortest acute angular distance between non-zero heading angles. For example, if the sequence of heading angles was `[10, 0, 0, 0, 350]`, this would interpolate as `[10, 5, 0, 355, 350]` instead of the less likely `[10, 95, 180, 265, 350]`.

After applying these corrections, the power profile still contained noisy "spikes". This was found to be due to an issue with the simulation model. Following the pipeline of Figure 2, this process of correction → simulation → validation was repeated for the simulation model correction. The model used the difference in GPS coordinates to calculate the road inclination, which is used to calculate the power propelled/regenerated while climbing/descending. However, since the difference in GPS coordinates was often zero, the calculated inclination would be an impossible 90 °. To resolve this, the hill climb power was calculated using the following equation:

$$P_{\text{hill}} = \frac{m \cdot g \cdot \Delta h}{\Delta t} \tag{1}$$

After applying all these corrections, the simulation underestimated both the propulsion and regeneration energy compared to the measured data. Consequently, the last correction was to tune the propulsion and regeneration model parameters to match the measured data more closely.

After all of these corrections, the simulated result converged within a satisfactory error margin.

A similar pipeline can be followed in the case of other vehicles and scenarios. However, the exact parameters to be updated, data issues to be corrected, model corrections, and parameters to be calibrated may differ based on the unique characteristics and issues in that scenario.

3. Results

The result section is outlined to present the flow proposed in Figure 2. The measured data and the uncorrected simulation results are compared in Figure 4. On the left hand y-axis, the energy usage (kWh/km) is shown with the column chart as an indicator. On the right hand y-axis, the distance travelled (km) per trip is displayed with the dashed line as an indicator. Note that the x-axis represents each trip travelled with the vehicle in ascending order from the shortest to the longest trip distance. For example, with trip 7, the vehicle travelled 23 km with a total measured energy usage of 3.4 kWh/km.

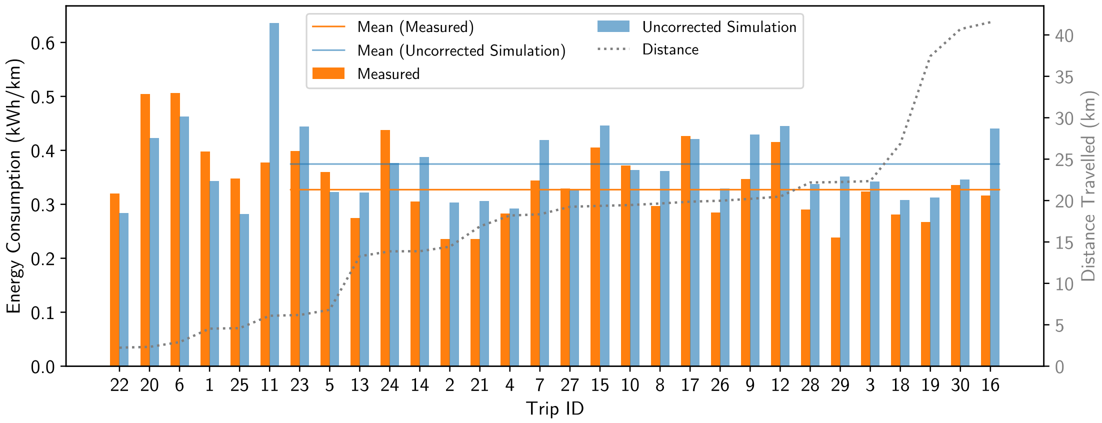


Figure 4. Energy usage rate (kWh/km) recorded for various trips, and simulation results with the uncorrected model (measured mean of all trips = 0.342 kWh/km; measured mean of trips longer than 5 km = 0.327 kWh/km; simulated mean of all trips = 0.372 kWh/km; simulated mean of trips longer than 5 km = 0.375 kWh/km).

3.1. Measured Results

Figure 4 shows that the mean measured energy usage across trips was measured to be 0.342 kWh/km.

Analysing the data captured from the minibus taxi revealed that five trips fell under 5 km in length. These trips are trips 1, 6, 20, 22, and 25.

Short trips such as these proved to be outliers. Firstly, the two trips with the highest energy usage per unit distance both fell under 5 km. This is because for shorter trips, the energy usages of auxiliary components have a greater role. For example, when the vehicle starts, energy is consumed to power auxiliary components such as the brake pressure system, water/oil pumps, air conditioner, etc.

The trip with the largest sum of upward elevation deltas is also present in this subset. Short trips, if driven exclusively uphill or downhill, would not represent typical driving behaviour. The two trips with the highest tortuousness (represented by the absolute heading angles deltas per unit distance) were also encountered in this subset. This is because of the turns required to get out of the parking areas, which skew the overall tortuousness of the trip. The trips in this subset were also characterised by low average speeds. This prompted us to focus only on trips longer than 5 km when validating the results. Taking the average of trips exceeding 5 km yielded an average energy efficiency of 0.331 kWh/km.

After this, the remaining data were observed to identify if they accurately represented the characteristics of the vehicle. Several hypotheses were tested to ensure reliability:

Hypothesis 1. *Trips with larger payloads would require more energy.*

Hypothesis 2. *Trips with more hills would require more energy.*

Hypothesis 3. *More tortuous trips would require more energy.*

Hypothesis 4. *Higher speeds would require more energy.*

Given these hypotheses, the trips appeared to follow all the rules, except for Hypotheses 4, where the correlation was not absolutely clear.

Trips exceeding 5 km (>5 km) with a GVM of around 2.1 tonnes had an energy usage of 0.31 kWh/km. Trips with a GVM of around 3 tonnes had an energy usage of 0.35 kWh/km, which was 13% higher. This confirmed Hypothesis 1.

The top 50% of trips (>5 km) ranked by hilliness (varied elevation as indicated by upward elevation deltas per unit distance) had an energy usage of 0.345 kWh/km, while the bottom 50% had an energy usage of 0.311 kWh/km. The hillier trips therefore used 10% more energy per unit distance. This confirmed Hypothesis 2.

The top 50% of trips (>5 km) ranked by tortuousness (as indicated by the absolute heading angle deltas per unit distance) had an energy usage of 0.335 kWh/km, while the bottom 50% was 0.320 kWh/km. This meant that the more tortuous trips used 5% more energy per unit distance. This confirmed Hypothesis 3.

Investigating Hypothesis 4, trips (>5 km) with higher average speeds had a 1% lower energy usage than trips at lower average speeds. This is likely due to other trip characteristics (stop, start, etc.) weighing more heavily on the energy usage. However, looking at certain trips where other characteristics are more controlled reveals that speed does have an effect. For example, trips 7, 15 and 12 are all intercity trips from Somerset West to Stellenbosch (distance of 18.8 km) and have similar trip characteristics except for their increasing mean speeds of 43, 46, and 50 km/h, respectively. The energy usage (0.34 kWh/km, 0.40 kWh/km and 0.41 kWh/km, respectively) is higher for trips that have higher average speeds. A similar conclusion can be obtained for trips 2, 4, and 26, which are from Stellenbosch to Somerset West (0.24 kWh/km, 0.28 kWh/km and 0.29 kWh/km, respectively), confirming Hypothesis 4.

3.2. Simulated Results with Existing Model

In Abraham et al. [40], the simulation model was refined using various techniques and applied to a large dataset of 10 minibus taxis in and around Stellenbosch, yielding an average energy usage of 0.53 kWh/km. Applying the unmodified model, with the same parameters to trips (>5 km) in this study, yielded an energy usage of 0.530 kWh/km, which is the same as the aforementioned study. The vehicle modelled in Abraham et al. [40] was simulated with a GVM of 3900 kg. The vehicle in this study, however, had a weight which varied between 2060 kg (tare weight) and 3090 kg (fully loaded). When the parameters were accordingly adjusted, the simulation yielded an average energy efficiency of 0.372 kWh/km for trips >5 km, which was significantly closer to the measured value of 0.327 kWh/km. The mean absolute error associated with these trips was 18.1% with a standard deviation of 18.3%. This meant that some trips were substantially underestimated (trips: 22, 20, 6, 1, 25, 5 and 24) and others were substantially overestimated (trips: 11, 23 14, 2, 21 7,15, 9, 28, 29 and 16). This is shown in Figure 4, and the error is shown in Figure 5.

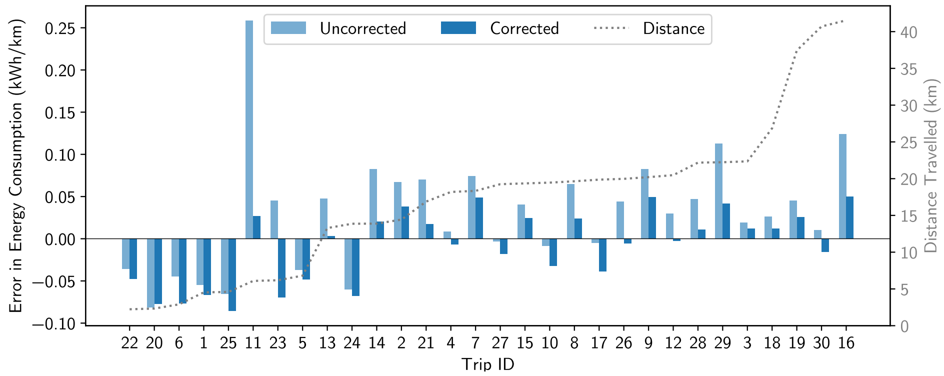


Figure 5. Error in energy usage of each trip simulated before and after data correction.

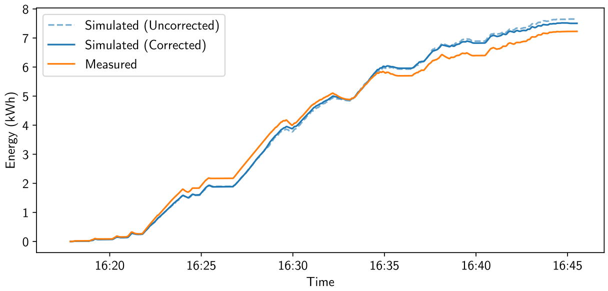
Figure 5 presents energy usage error data sorted by ascending trip distance. The results highlight that simulations for shorter trips are significantly less accurate with energy usage often underestimated. This discrepancy is likely due to the omission of auxiliary components in the model, such as the brake pump and climate control, which consume considerable power during startup.

For the trips that exceed 5 km, Trip 12 exhibited the smallest absolute error, whereas Trip 23 had the largest error. Consequently, these two trips were selected for detailed comparative analysis in subsequent plots. Notably, Trip 23 is an intra-town journey within Somerset West, whereas Trip 12 spans from Somerset West to Stellenbosch (18.8 km). With these extremes, Trip 3 is also shown as a typical trip in Figure 6. The energy profile of Trip 23, for example, shows that the simulated energy (before corrections, indicated by the dashed line) overshoots the measured energy shortly after time 15:56. In Trip 3, the energy is initially underestimated, but from around 16:35, it is overestimated.

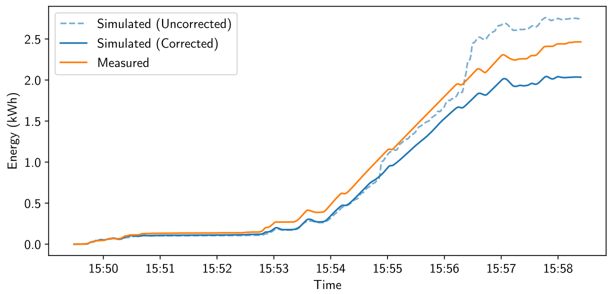
In addition to this, the power profiles shown in Figure 6 are extremely noisy. In Trip 3, the power profile spikes up to 150 kW. This is an obvious overestimation by the simulator since the motor's maximum power is capped to 50 kW and should not have been able to perform mobility that requires power that exceeds this limit. Likewise, in Trip 23 and Trip 12, the power profile spike is frequently above that limit. To analyse this anomaly, the power profile was smoothened using Gaussian smoothing (*sigma* = 10, kernel size = 81) to indicate the average trend underlying the noisy power profile. In Trip 23, the continuously high power between 15:56 and 15:57 indicates the reason for the energy overshoot identified in that period.

The simulated power profile was separated into its various principal components for further inspection. This is shown in Figure 7a. The figure shows that the hill-climb power was especially noisy.

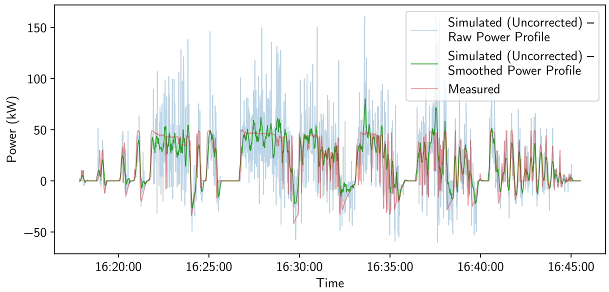
Figures 6 and 7a clearly highlight discrepancies between the simulated and measured data across the 30 trips. In particular, Figure 7a helps identify that the speed and elevation variables, within the tracked data, are responsible for the power component discrepancy, which in turn contributes to the increase in energy usage error across the trips. To address these issues, the following corrections are proposed to enhance the accuracy of both the simulation model and the quality of data collected from the vehicle, ensuring a more accurate representation of vehicle efficiency.



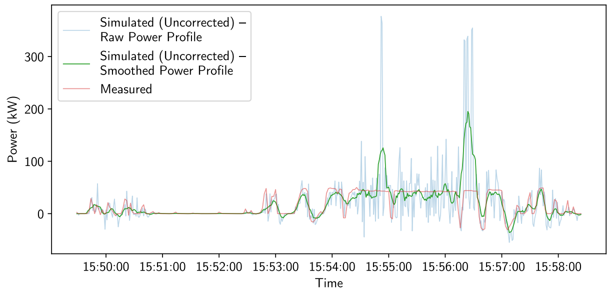
(**a**) Trip 3 Energy Profile.



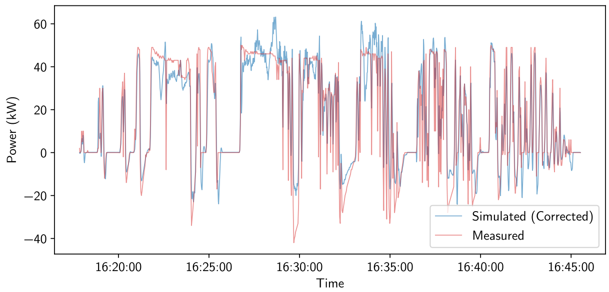
(**b**) Trip 23 Energy Profile.



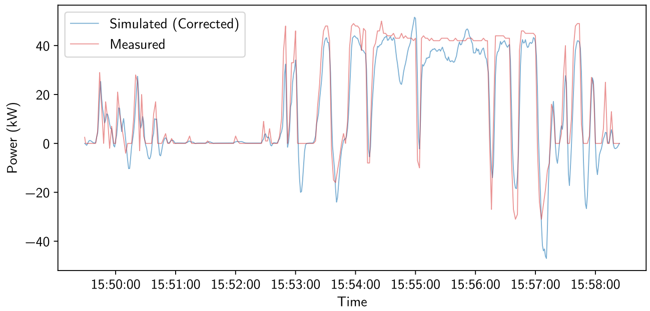
(**c**) Trip 3 Power Profile—Uncorrected.



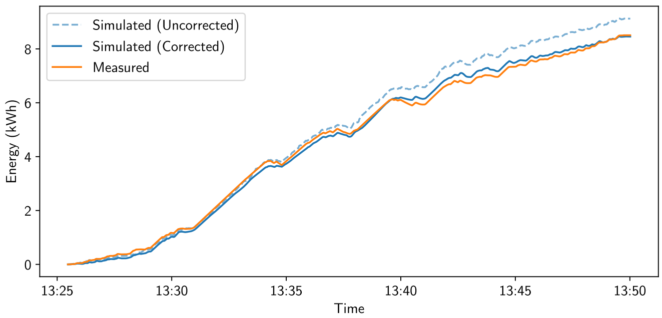
(**d**) Trip 23 Power Profile—Uncorrected.



(**e**) Trip 3 Power Profile—Corrected.

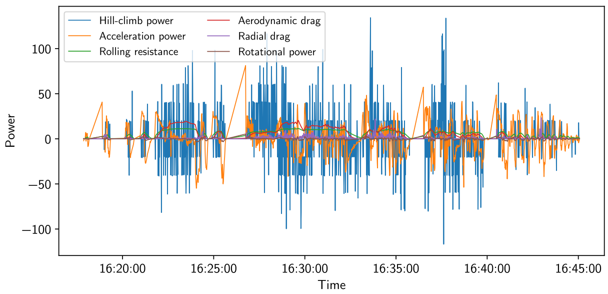


(**f**) Trip 23 Power Profile—Corrected.

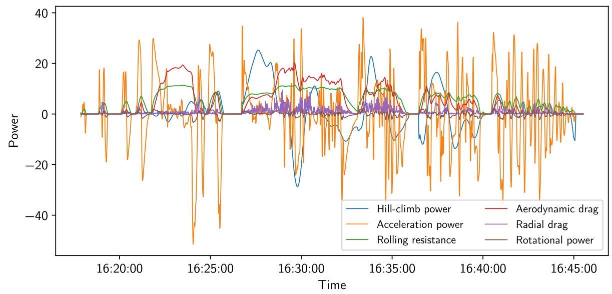


(**g**) Trip 12 Energy Profile.

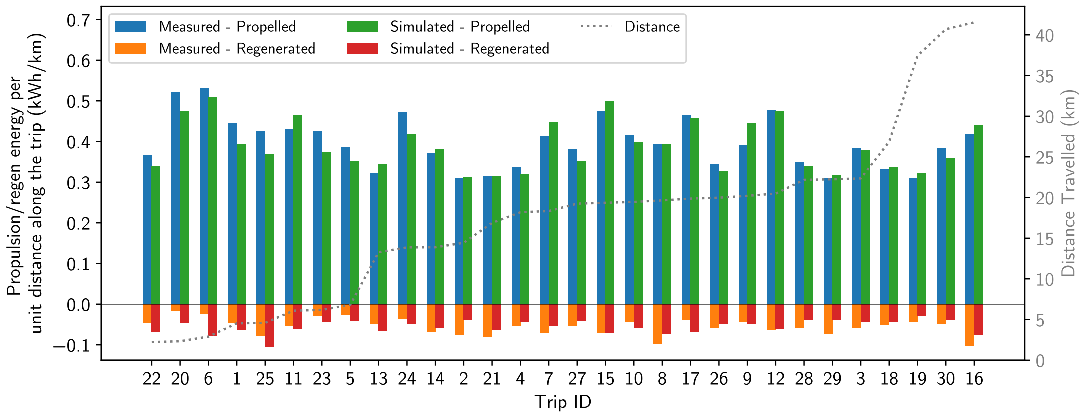
Figure 6. Measured and simulated energy and power profiles for trips before and after corrections were applied to the simulation method. Trip 3 is a normal trip with a typical error between measured and (corrected) simulated profiles. Trip 23 is the trip with the worst-case simulation error, and Trip 12 is the best-case simulation error, both after corrections were applied.



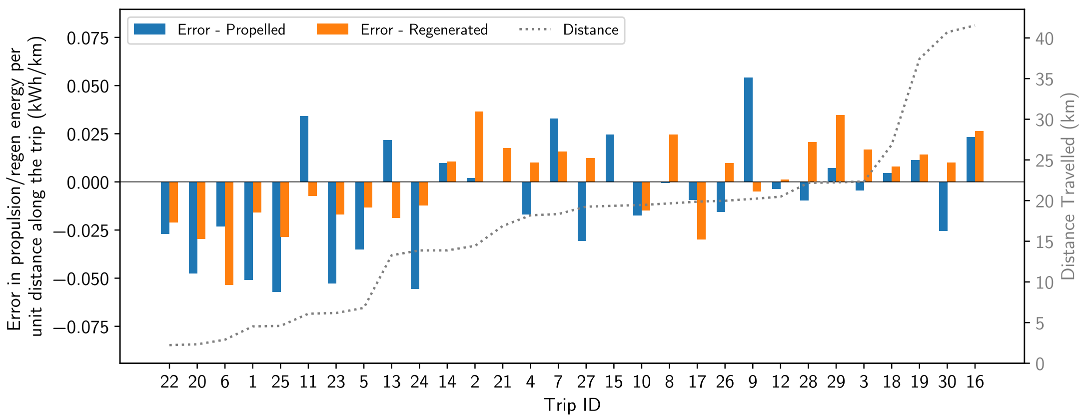
(**a**) Trip 3 before corrections.



(**b**) Trip 3 after corrections.



(**c**) Disaggregated energy in terms of propulsion and regenerative braking per trip.



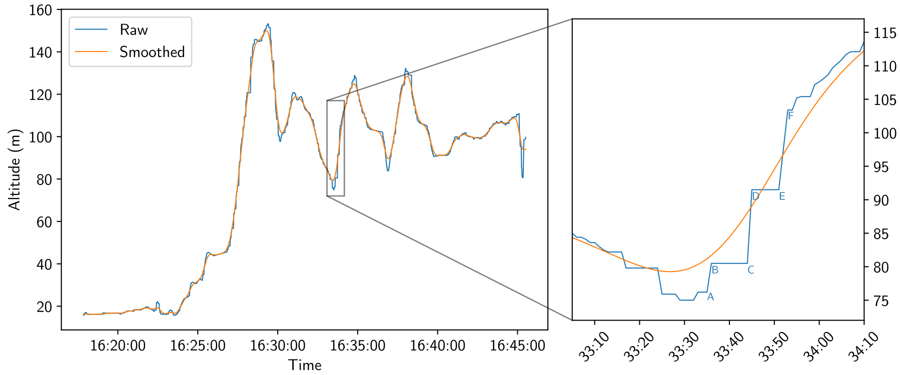
(**d**) Error in simulated energy used for propulsion and regenerative braking per trip.

Figure 7. Disaggregation of power components. Trip 3 (**a**,**b**) shows the disaggreated output for all the components. The simulation before corrections were applied is shown in (**a**,**b**) shows the output from the corrected simulation. Propulsion and regeneration energy components per trip after corrections are shown in (**c**), and the remaining errors are shown in (**d**).

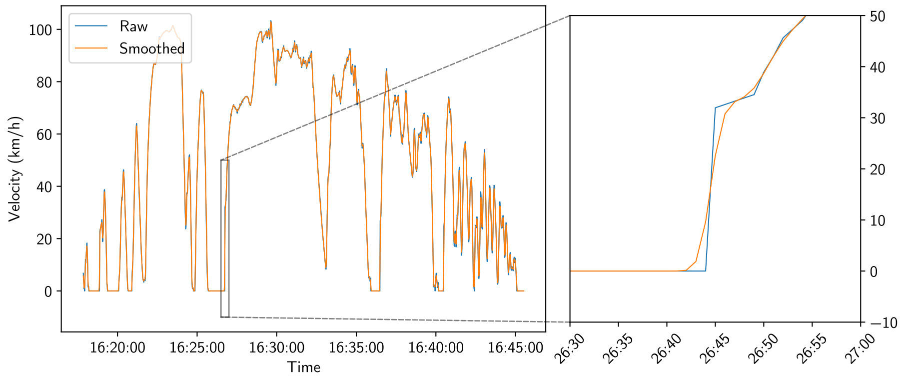
3.2.1. Elevation Profile Correction

Gaussian smoothing was applied to the power profile in order to obtain an understanding of the general power response of the model, which are shown in Figure 6. It is clear that the smoothed power profile (indicated in green) follows the measured power usage (in red). Upon detailed inspection of the GPS data, it was found that the reason for the noisy power profile is due to inaccuracies and aliasing in the measured elevation data. Figure 8a highlights inaccuracies in the elevation data. For example, from point B to C, the altitude (indicated by the blue line) is recorded as a constant 80.5 m for approximately 10 s. However, the altitude immediately jumps to 91.5 m (point D) in 1 s. This implies that the vehicle climbed an elevation of 11 m in 1 s, which would require an unrealistic amount of power. Herein lies the cause of the spikes in Figure 7a. Inspecting the site of this trip segment reveals that the altitude profile should be smooth, and that this jagged profile is inaccurate.

To improve the elevation profile, a Gaussian filter was applied to the measured elevation data to smoothen the transitions. The resultant elevation profile is shown in orange in Figure 8a. This smoothened elevation profile was then used in the corrected energy simulation, the results of which are shown in Section 3.3.



(**a**) Smoothened GPS altitude profile ($\sigma = 10$, kernel size = 81).



(**b**) Smoothened GPS speed profile ($\sigma = 1$, kernel size = 9).

Figure 8. Gaussian smoothing operations on GPS altitude and speed data for Trip 3.

3.2.2. Speed Profile Correction

Detailed inspection of the raw GPS speed data revealed that the noisy profile is caused by inaccuracies and aliasing inherent to GPS signal processing. For instance, rapid and improbable changes in speed were observed over short time intervals, which do not align with realistic vehicle behaviour. These inaccuracies distort the calculated energy usage, as they directly influence the power demand estimations. Gaussian smoothing was therefore applied to the measured speed profile to reduce noise and better reflect the actual vehicle dynamics, as shown in Figure 8b. The smoothed speed profile (shown in orange) follows the measured speed profile (in blue) more closely while eliminating abrupt, unrealistic fluctuations.

A Gaussian filter with $\sigma = 1$ and kernel size = 9 was applied to the speed profile, producing the smoothened curve shown in Figure 8b in orange.

3.2.3. Radial Drag and Heading Angle Correction

The simulated power profile was separated into its various components for inspection, as shown in Figure 7a. This revealed that radial drag was an additional source of power spikes. The reason for this was found by inspecting the raw GPS data, which are shown in Table 4.

Table 4. Raw GPS data where heading angle resets to zero randomly. Highlighted rows indicate rows where the heading angle resets to zero.

GPS ID	Time	Latitude	Longitude	Altitude	Heading	Velocity	Energy
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
21949	2024-04-23 15:27:05	−33.984837	18.834373	135	237.2	85.1	−8.5
21950	2024-04-23 15:27:06	−33.984954	18.834156	135	238.1	84.2	−23
21951	2024-04-23 15:27:07	**−33.985065**	**18.833939**	135	**0**	85.1	−7.5
21952	2024-04-23 15:27:08	−33.985065	18.833939	134	239.5	84.5	8
21953	2024-04-23 15:27:09	−33.985279	18.833502	132	240.7	83.8	7
21954	2024-04-23 15:27:10	−33.985382	18.833281	132	241.5	83.7	6
21955	2024-04-23 15:27:11	**33.985483**	**18.833056**	132	**0**	85.0	−20.5
21956	2024-04-23 15:27:12	−33.985483	18.833056	132	242.5	84.7	−47
21957	2024-04-23 15:27:13	−33.985677	18.832607	132	243.1	84.5	−31
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Highlighted rows indicate that there are instances where the heading angle is erroneously reported zero. The heading angle is calculated by the vehicle tracker using the difference between subsequent coordinates. This makes it apparent why the heading angle reset to zero. Looking at the data point with GPS ID 21951, the following data point (ID 21952) has the exact same coordinates despite the vehicle travelling at a velocity of 85 km/h. The GPS coordinate had not been updated because of a poor GPS signal. Since the difference between the two data points is zero, the heading angle is undefined, causing the system to log a heading angle of zero.

Within the simulation environment, the heading angle is used in the electro-kinetic model to calculate the energy lost to radial friction forces in the tyres when cornering.

The model tries to replicate this apparent rapid change of heading angle from 240 deg to 0 deg by skidding the vehicle's tyres. Since the vehicle maintains the same velocity while performing this apparent behaviour, the simulation model concludes that a large amount of power was used.

To correct this, the heading angle was linearly interpolated to obtain the final energy usage shown in Section 3.3.

3.2.4. Hill-Climb Force Model Correction

In Figure 7a, the hill-climbing power was found to spike at the same time as spikes in the radial drag (which is resolved in Section 3.2.3). It was observed that the spikes of the GPS coordinates affected the hill-climbing power calculation. This power was calculated by multiplying the hill-climbing force by the vehicle's velocity. The hill climbing force was determined using the incline angle of the road, as determined using the arctan of the difference in altitude divided by the distance between GPS coordinates. Since the distance between the GPS coordinates was zero when the GPS signal was poor, it resulted in a 90° incline angle, requiring unrealistically large amounts of power.

To correct the model, the hill-climb power, P_{hill}, was rather calculated using the change in elevation. The hill-climb energy, E_{hill}, is consequently determined as

$$E_{\text{hill}} = m \cdot g \cdot \Delta h, \quad (2)$$

where m is the vehicle mass (kg), g is gravitational acceleration (9.81 m/s^2), and Δh is the elevation change (m). The hill-climb power is then given by

$$P_{\text{hill}} = \frac{m \cdot g \cdot \Delta h}{\Delta t}, \quad (3)$$

where Δt is the time interval between timestamps (s). This modification improves the model's accuracy by accounting for hill-climbing energy and power requirements.

3.2.5. Parameter Tuning

Having implemented these corrections, the propulsion and regeneration factors were tuned to match the measured values by running the simulation models with many combinations of propulsion and regeneration factors. It was found that the factors were mutually exclusive in their effect. In other words, a change in propulsion factor did not have any change in the regeneration energy error and vice versa. The error in the propulsion/regeneration energy calculation for various propulsion/regeneration factors is shown in Figure 9. This figure shows that the optimum propulsion and regeneration factors are 0.9 and 0.65, respectively. However, these are the same values used in the original simulation (as determined in Abraham et al. [40]).

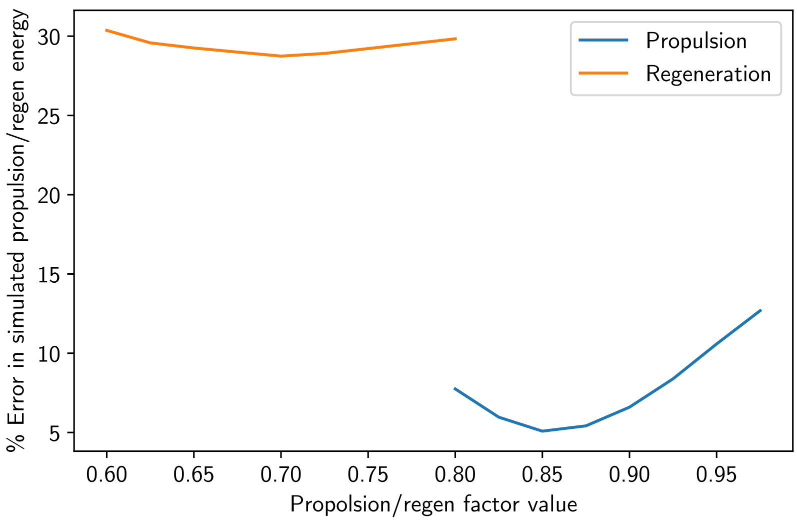


Figure 9. Error in propulsion and regeneration energies for various propulsion and regeneration factors.

3.3. Corrected Simulation Result

The final energy usage results are shown in Figure 10 after the changes described in Section 3.2 were implemented into the data and simulation model. The average energy usage reduced to 0.331 kWh/km for the longer trips (>5 km), which was significantly closer to the measured value of 0.327 kWh/km. This leads to an average error of 8.61%, with a standard deviation of 10.1%, which is substantially better than the initial error of 18.1% and standard deviation of 18.3%.

Abraham et al. [40] used a vehicle weight of 3900 km and found a result of 0.530 kWh/km. The corrected simulator was run using their weight and the data from this paper. The resulting usage was 0.457 kWh/km, which is 14% lower than with the uncorrected model.

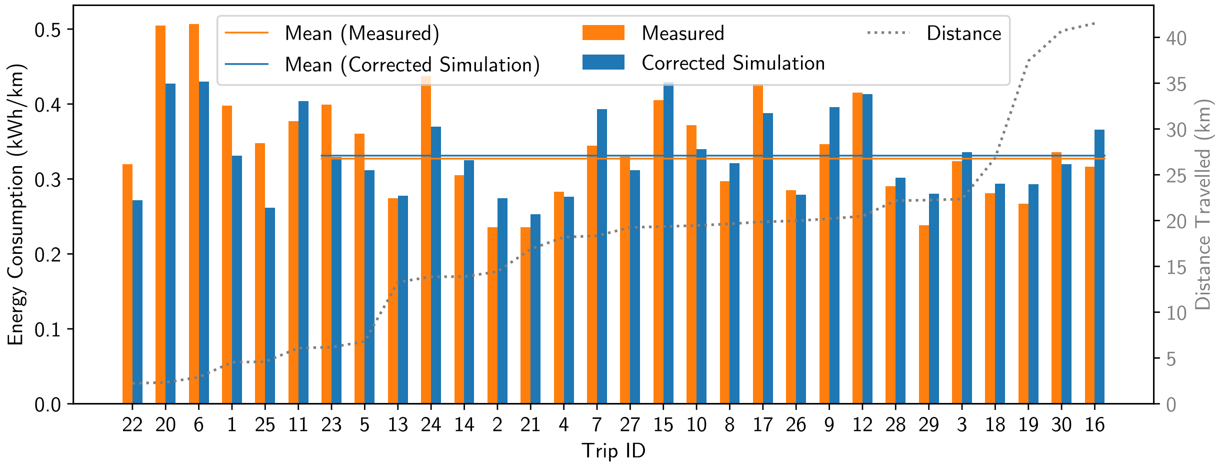


Figure 10. Final propulsion and regeneration energy usage (measured mean of all trips = 0.342 kWh/km; measured mean of trips longer than 5 km = 0.327 kWh/km; simulated mean of all trips = 0.333 kWh/km; simulated mean of trips longer than 5 km = 0.331 kWh/km). The errors are shown in Figure 5.

The energy usage for each trip was also broken into propulsion and regeneration components. These are shown in Figure 7c. For both the propulsion and regeneration components, the simulated energy is sometimes overestimated and sometimes underestimated compared to the measured values. This is likely due to aspects not included in the model.

The corrected model results, as shown in Figure 1, are more accurate than those found in the literature. It is evident that the consumption values reported in existing studies often overestimate energy consumption, while the actual consumption is much more efficient. The results produced by this model demonstrate the accuracy of the proposed methodology.

Analysing the power profile in Figure 6f reveals a substantial reduction in noise compared to the original profile shown in Figure 6, which exhibited numerous spikes. The corrected profile displays minimal discrepancies, though occasional power spikes exceeding 50 kW are observed in some trips. These spikes can be attributed to the simulation not being strictly constrained to a 50 kW limit. Additionally, the simulation may overestimate the required power due to its omission of environmental factors, such as headwinds or tailwinds, which can contribute to the discrepancies observed in the graph.

A tabular summary of the key corrections and their connection with simulation accuracy is provided in Table 5.

Table 5. Summary of key corrections and their impact on simulation accuracy.

Correction	Description	Difference in Energy Consumption (%)	Impact on Simulation Accuracy
Original simulation	Original simulation before corrections with model parameters of Abraham et al. [40]: **0.530 kWh/km**	–	–
Parameter update	The mass of the model was updated to match the physical vehicle. The mass, which was a fixed 3900 kg, was updated to a value between 2100 kg to 3000 kg, depending on how heavily the vehicle was loaded in the given trip.	−29	Depends on the parameter being adjusted. In this case, it had a high impact on energy consumption, as mass is a highly sensitive parameter, as highlighted by Abraham et al. [40].

Table 5. *Cont.*

Correction	Description	Difference in Energy Consumption (%)	Impact on Simulation Accuracy
Elevation smoothing	Gaussian smoothing was applied to GPS elevation data.	−3	Small, negative impact on energy consumption. High impact on power profile, as frequent power spikes due the hill-climbing are removed.
Speed profile smoothing	Gaussian smoothing was applied to GPS speed data.	−5	Medium/low, negative impact on energy consumption. Medium impact on power profile, as power spikes due to acceleration are removed.
Heading angle correction	Heading angles that were falsely reset to zero by the GPS sensor were interpolated from other non-zero heading angles in order to more accurately predict the radial drag power loss.	−6	Medium/low, negative impact on energy consumption. Medium/low impact on power profile, as power spikes due to radial drag are removed. However, these spikes are not very significant, as radial drag is a small component of the total power.
Hill-climb power model correction	The hill-climb power was calculated from the change in altitude rather than from the road gradient, which was sometimes inaccurate.	−7	Medium, negative impact on energy consumption. High impact on power profile, as frequent power spikes due the hill-climbing are removed.
Parameter tuning	Propulsion and regen coefficients were tuned until the simulation accuracy was optimised. Propulsion coeff. changed from 0.90 to 0.855 and regen coeff. changed from 0.65 to 0.70	+9	Medium impact on energy consumption. Impact depends on how accurate the initial guess was and what parameters are tuned.
Final simulation	Final simulation after all corrections were applied: **0.331 kWh/km**	–	–

4. Conclusions

With this research, a systematic methodology (see Figure 2) is proposed to refine and validate an energy usage model for an electric vehicle for the model developed by Abraham et al. [40]. Therefore, the work presented here serves as a guideline for other researchers to use the available energy usage model to further their own research, given their own unique datasets.

The methodology pipeline included multiple stages: parameter correction (GVM), data corrections (elevation smoothing and speed profile smoothing), model corrections (radial drag, heading angle, and hill-climb force models), and calibration of key parameters such as propulsion and regeneration factors. This approach led to a final simulation that closely approximated real-world performance, achieving an average simulated energy usage of 0.327 kWh/km for trips longer than 5 km. Although the measured data showed an average usage of 0.331, the discrepancy between the measured and simulated values (approximately 1.2% lower for simulated results) is within an acceptable range, considering the complexity of factors involved.

The energy efficiency achieved, despite the simulation's inherent simplifications and assumptions, suggests that this efficiency (0.327 kWh/km) is promising and concludes that the model was accurately validated through the proposed methodology.

Significant improvements were made through the corrections of the elevation and speed profiles. The elevation smoothing helped remove inaccuracies and aliasing from the GPS data, while the speed profile smoothing addressed discrepancies due to noise and abrupt speed changes. Furthermore, model corrections, such as the radial drag and heading angle adjustments, along with the hill-climb force model correction, provided more realistic power usage estimates, particularly on hilly terrain or winding routes.

Moreover, the calibration of propulsion and regeneration factors was essential in refining the energy model. This calibration ensured that the simulation accurately accounted for the energy recaptured during braking and the actual power required for propulsion under different conditions.

The study also validated several key hypotheses, such as the influence of payload, varied elevations (hilliness), tortuousness, and vehicle speed on energy usage. Payload had a clear positive correlation with energy use with heavier trips consuming more energy. Similarly, hillier routes and more tortuous driving patterns led to higher energy usage, confirming the expected trends. However, the relationship with speed was less straightforward: while higher speeds generally led to higher energy usage, this effect was modulated by other trip characteristics like terrain and route complexity.

Some of the discrepancies in the mobility data can be due to environmental factors, particularly wind conditions, which can have a significant impact on energy usage. Headwinds or tailwinds could lead to variations in the required energy, which was not fully captured by the model. This suggests that incorporating environmental data, such as wind speed and direction, will be valuable to further improve the model's accuracy for real-world applications. Additionally, radial drag estimations can be improved by measuring the heading angle using a Gyroscope or Magnetometer rather than deriving this measurement from GPS coordinates.

This paper contributes a pipeline of iterative corrections and calibrations that can be used for accurate EV modelling. This pipeline is applied to electric taxis but can be applied to a variety of other vehicles and scenarios.

From a policy perspective, the results show the importance of using data-driven and validated models in contextually representative simulation environments when planning for the electrification of informal transport. Unlike scheduled and centralised transport sectors, the mobility patterns, route and terrain properties, driver behaviour, and vehicle properties play an essential role in paratransit's eventual electrical energy requirements. This impacts the expected energy required (kWh) and the expected temporal load (kW). Accordingly, the inaccurate modelling of these factors will directly impact the extent to which electrification appears viable and beneficial given the region's energy challenges.

Although applied to minibus taxis in this paper, the method and approach extend to other informal modes of transport, including boda-bodas (motorbikes used as taxis), jeepneys, tuk-tuks, midibuses, chapas, etc.

In conclusion, the iterative corrections and calibrations applied throughout this study led to a reliable energy usage model with a realistic efficiency range for the vehicle in typical conditions. The methodology and insights from this research are instrumental in enhancing the performance and feasibility of electric vehicles in urban and inter-town contexts.

Limitations and Future Work

Despite the contributions of this study, several limitations are acknowledged, whose resolution is reserved as future work.

Firstly, the energy consumption was measured from only one electric minibus. Additionally, this electric minibus was a retrofitted vehicle, which may have manufacturing defects which make it less efficient than a new electric minibus. Using a fleet of electric minibuses in the validation could help to account for manufacturing variations which affect the results.

Secondly, the data were collected from an electric minibus which travelled across a variety of terrains under a variety of conditions. This made it difficult to isolate the cause of trips with an unexpectedly high/low energy consumption. It is therefore envisaged to collect data in more controlled experiments, such that only one mobility metric is varied, while attempting to keep other mobility metrics fixed. For example, several trips could be conducted which vary the speed of the vehicle between trips while keeping the road elevation, trip length, vehicle payload, etc. constant between those trips.

Environmental effects were not accounted for in this study. In some trips, the simulated power exceeded the vehicle's power limit of 50 kW, which was possibly because the simulation did not account for tailwinds, which would have caused the vehicle to travel faster than would be possible with a 50 kW motor.

Although a 1 Hz data sampling has been regarded as the ideal sampling rate in previous research publication, this is not necessarily the case for model calibration. From this work, it has been shown that a high sampling rate of 1 Hz is valuable but also comes with unique data issues. Fortunately, data processing techniques, such as Gaussian smoothing, can rectify data issues related to high sampling rates. However, the errors caused by this estimation should be quantified. Both GPS and CAN bus data would need to be captured at high frequencies.

In this paper, the model was calibrated using high-frequency data. However, the improvement of using the calibrated model on typical low-frequency data was not quantified.

The study employed two different devices to collect data, allowing for the synchronisation of the vehicle's power consumption with its GPS coordinates. Future work will involve installing a CAN device that integrates GPS tracking, enabling real-time data synchronisation instead of relying on post-processing.

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Conflicts of Interest: The funders had no role in the design of the study, in the collection, analyses, or interpretation of data, or in the writing of the manuscript. The funders were given the opportunity to comment on the paper before publication.

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