

## Article

# A Validated Physics-Based Powertrain Model for an Electric Motorcycle in Sub-Saharan Africa

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## Abstract

Reliable prediction of energy consumption for electric motorcycles in sub-Saharan Africa requires models that reflect local riding conditions and measured component behaviour. This paper presents a validated, physics-based simulator for the Roam Air electric motorcycle that combines longitudinal dynamics with empirically derived motor and inverter efficiency maps obtained from dynamometer testing. The model ingests measured drive cycles and elevation-derived gradients to compute tractive effort and battery power flow and is validated against six real-world city and highway trips in Nairobi. The simulator reproduces temporal battery-power profiles with strong correlations between 0.87 and 0.91 and predicts energy per distance with small positive bias, achieving errors between 0.4% and 11.3%, where the measured energy consumption per distance ranges between 30.2 and 51.7 Wh/km. A sensitivity analysis quantifies the influence of key design parameters, and a scenario analysis assesses the impact of representative African driving conditions, including terrain, posture, payload, and surface type. The resulting framework is compact, transparent, and potentially adaptable to a wide range of electric two-wheelers, supporting design optimisation and electrification planning in the region.

**Keywords:** electric motorcycle; powertrain model; validation; energy consumption; two-wheeler; simulation



Academic Editor: Vladimir Katic

Received: 21 January 2026

Revised: 5 February 2026

Accepted: 6 February 2026

Published: 10 February 2026

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## 1. Introduction

Transport accounts for about 24% of global CO<sub>2</sub> emissions [1]. Although sub-Saharan Africa (SSA) contributed only 2.3% of global emissions in 2018, transport in the region accounted for 12% of that total and continues to grow rapidly, with an 84% increase between 2010 and 2016 driven by population growth and urbanisation [2]. Motorcycles are central to mobility and livelihoods in SSA: registrations rose from 5 million in 2010 to 27 million in 2022, and approximately 80% are used for transport or delivery services [3].

Electrifying motorcycles offers a pathway to lower operating costs and reduce urban pollution. With Kenya's relatively low-carbon grid, electric motorcycles emit approximately 7.8 gCO<sub>2</sub>/km, compared with 50.5 gCO<sub>2</sub>/km for internal combustion engine (ICE) motorcycles [4]. Even on South Africa's more carbon-intensive grid, emissions around 22.46 gCO<sub>2</sub>/km are achievable [4,5]. Electric motorcycles also eliminate tailpipe particulate emissions, improving air quality relative to ICE motorcycles, which emit an estimated 4.5 mg/km [4].

An electric motorcycle comprises a battery, inverter, motor, drivetrain (typically a chain and sprocket system), and auxiliary components, with bidirectional energy flow enabled through regenerative braking (as shown in Figure 1). Inverters incur conduction and switching losses that depend on device current, voltage, and power factor [6]. Motors incur copper, core, and mechanical losses that vary with operating region [7]. Drivetrain losses arise from chain-drive behaviour, which depends on transmission speed, load, and lateral sprocket alignment [8]. Regenerative braking converts an electric vehicle's kinetic energy into electrical energy which is charged to the battery. Generally, the intensity of regenerative braking depends on the battery's State of Charge (SoC), ambient temperature, and charging rate, as well as the power, speed, and torque of the electric motor [9].

Planning for vehicle electrification in SSA requires models that reflect local operating conditions. Simulations enable rapid design assessment and reduce prototyping effort, while supporting tasks such as energy minimisation, range prediction, and charging-infrastructure siting [6]. Roam has donated two Roam Air motorcycles to Stellenbosch University for research, enabling direct characterisation under real-world African conditions. This work develops and validates a physics-based simulator that predicts energy consumption from measured drive cycles and elevation data and evaluates sensitivity to key design parameters and riding conditions relevant to SSA.

*Goal and Objectives:* The goal was to model energy flow between the drive wheel and battery terminals for the Roam Air and to validate the model against real-world trips. The objectives were to

1. Characterise motor and inverter efficiencies from dynamometer tests to form empirical efficiency maps;
2. Develop a validated physics-based simulator for measured drive cycles;
3. Quantify sensitivity to modelled design parameters;
4. Assess the impact of representative drive-cycle conditions.

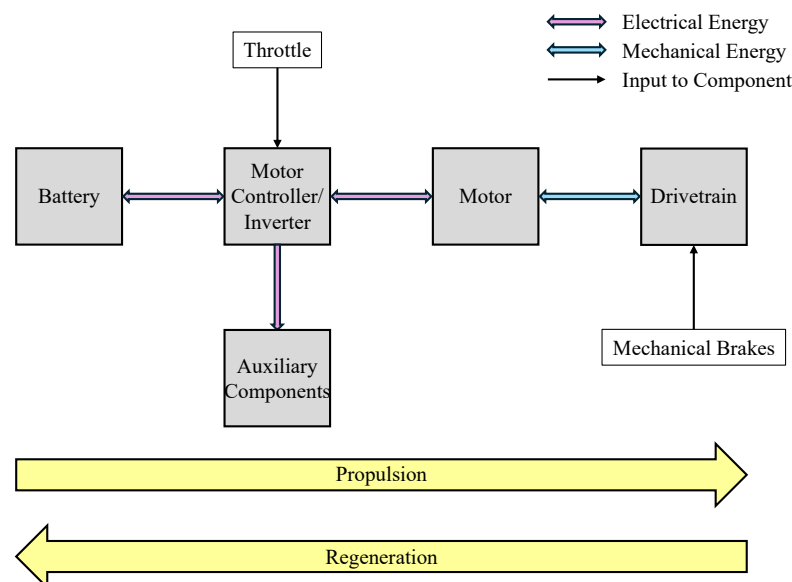


**Figure 1.** Block diagram of an electric motorcycle powertrain.

*Motivation and Scope:* SSA's operating environments differ from those in high-income regions due to mixed road surfaces, varied terrain, and diverse rider behaviours [2]. Existing tools, such as ADVISOR and VTB, rely on detailed component sub-models or proprietary efficiency maps [10], limiting their applicability in this context. A tailored simulator that ingests measured SSA ride data is therefore required. While the present

model targets the Roam Air platform, the approach can potentially generalise to other electric motorcycles given sufficient parameter availability. Battery electrochemistry and thermal effects on the powertrain's components are beyond the scope of this work and are part of future work. Behavioural scenarios are considered at a high level owing to limited rider-profile data.

## 2. Related Work

### 2.1. Electric Minibus Taxi Models

*Energy-based models:* Abraham et al. developed an electric minibus taxi (eMBT) model using a pipeline in SUMO (Simulation of Urban Mobility) that inferred 1 Hz mobility from sparse tracking data and estimated propulsion energy from kinetic and potential changes, aerodynamic and radial drag, and rolling resistance [2,11,12]. That approach was sensitive to assumptions about the inferred mobility and the underlying road network. Subsequent refinements incorporated elevation data, removed artificial stops, tuned speed limits and driver parameters, and aligned vehicle parameters with improved sources [2].

*Force-based models:* Hull et al. applied a force-balance model driven by measured 1 Hz mobility for 62 trips, estimating the tractive force required to reproduce observed velocity traces and accounting for aerodynamic drag, rolling resistance, and gradient forces. Identified limitations included omission of rotary inertia and radial drag, as well as an error in the tractive-force formulation highlighted in later work [12].

Final eMBT energy estimates, after synthesising the modelling lines, converge to approximately 0.49–0.52 kWh/km depending on input data [12]. These eMBT models use measured tracking data as their inputs, in which data processing techniques are required to counter GPS error. This aspect of the eMBT models, as well as the longitudinal dynamic force equations, are applicable to this work.

### 2.2. Electric Two-Wheeler Models

Kumar et al. incrementally developed a powertrain model to select a motor and battery for a retrofitted electric two-wheeler. The vehicle's longitudinal dynamics model was described, where only flat-road riding was considered. The motor was selected based off the calculated peak power of the Indian drive cycle. A Gaussian Process Regression-based model was applied to determine the motor's efficiency for different torque–speed combinations. Kumar et al. then mathematically modelled the battery current and used the results of the Indian drive cycle to ultimately design the battery [13].

Yuniarto et al. presented a backward-facing model for an electric scooter which incorporated force-based longitudinal dynamics, assumed a constant-efficiency powertrain, and included a simplified battery model. The model was validated against dynamometer and road test data, demonstrating energy per distance errors of −8.63% and −4.7% respectively [14].

Lakshmanan et al. modelled scooter-scale dynamics using a force-based approach and validated energy per distance within 5.4% against a comparable electric scooter [15,16].

### 2.3. Simplified EV Powertrain Model

The simplified EV powertrain (SEVP) framework couples longitudinal vehicle dynamics with reduced-order inverter and motor loss models, computing battery power as the sum of mechanical output, motor and inverter losses, and auxiliary loads [6]. The SEVP model was validated against dynamometer test data ( $\theta = 0$ ) and demonstrated energy per distance errors within 4.5% for a passenger vehicle, performing comparably to ADVISOR and FASTSim.

### 3. Methodology

#### 3.1. Selection of Modelling Approach

Trade-offs in model development include: (1) the number of assumptions versus model setup time and (2) the model's detail versus model run time [10]. Experimental look-up maps require less computations whilst accurately representing the modelled component.

Force-based models are more popular in Section 2 and have demonstrated good accuracies through validation. Furthermore, the studies by [6,15] show that incorporating operating-point-dependent component efficiencies improves accuracy relative to purely mechanical models.

Therefore, a compact force-based simulator was pursued, using measured mobility, elevation-derived grade, and empirically derived inverter and motor efficiency maps for the Roam Air in Nairobi, Kenya.

#### 3.2. Data Inputs and Pre-Processing

The developed simulator predicts the Roam Air's energy consumption using time-stamped GPS coordinates and motor speed and is validated against the motorcycle's measured energy consumption (as shown in Figure 2). The distance between each GPS coordinate is computed using the Haversine formula, which is used in conjunction with the ALOS World 3D 30 m 3.1 elevation dataset to estimate the road's gradient. This is an approximation since the elevation dataset contains errors and the GPS data jitters occasionally. Data are down-sampled to 1 Hz and Gaussian smoothing is subsequently applied to speed, per-second distance, and elevation differences. Outlier slope angles are identified as any slope angle exceeding the maximum possible slope range of  $[-19^\circ; 19^\circ]$  [17] and are handled by forcing them to zero when no change in consecutive GPS coordinates occurs.

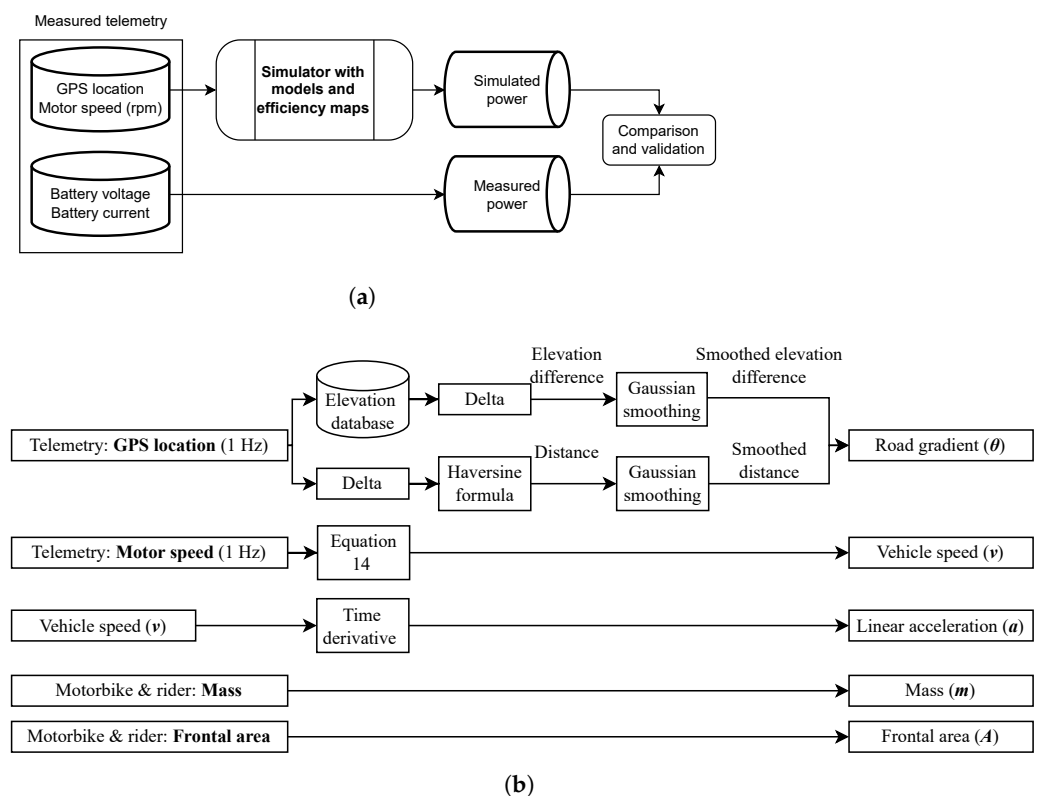


Figure 2. Cont.

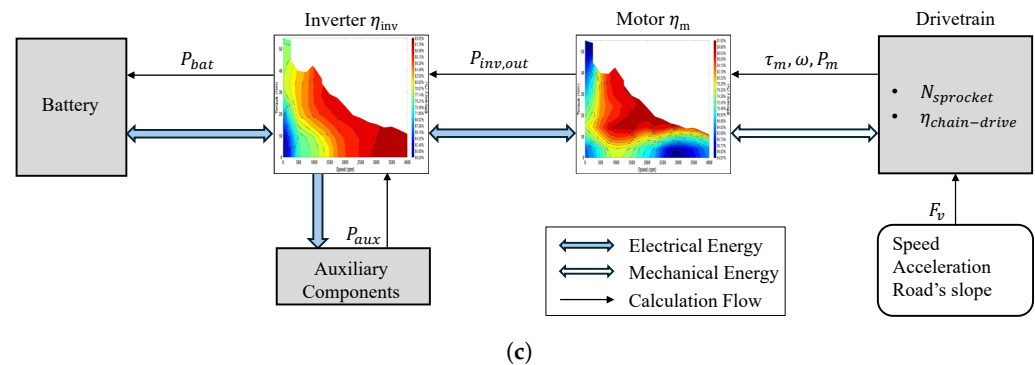


**Figure 2.** Simulation setup. (a) High-level simulator overview: inputs and outputs. (b) Pipeline for estimating road slope. (c) Energy flows and calculation flows. The efficiency maps are indicative in this figure and shown in detail in Figure 6.

### 3.3. Vehicle Dynamics and Power Flow

Let  $m$  be total mass,  $v$  speed,  $a$  acceleration,  $\theta$  road slope,  $\rho$  air density,  $A$  frontal area,  $C_d$  drag coefficient and  $C_{rr}$  rolling resistance coefficient. Tractive force is given by (as visualised in Figure 3)

$$F_v[n] = F_{\text{slope}}[n] + F_{\text{aero}}[n] + F_{\text{roll}}[n] + F_{\text{acc}}[n], \quad (1)$$

where

$$F_{\text{slope}}[n] = mg \sin(\theta[n]), \quad (2)$$

$$F_{\text{aero}}[n] = \frac{1}{2} \rho C_d A (v[n])^2, \quad (3)$$

$$F_{\text{roll}}[n] = mg C_{rr} \cos(\theta[n]), \quad (4)$$

$$F_{\text{acc}}[n] = m(v[n] - v[n-1]) / (\Delta t). \quad (5)$$

Wheel torque is given by

$$\tau_w = F_v r_w \quad (6)$$

Motor torque and speed follow from the final-drive ratio  $N_{\text{sprocket}}$  and efficiency  $\eta_{\text{chain-drive}}$  where

$$\tau_m = \frac{\tau_w}{N_{\text{sprocket}} \eta_{\text{chain-drive}}}, \quad (7)$$

$$\omega = \frac{v}{r_w} N_{\text{sprocket}}. \quad (8)$$

Motor mechanical power is given by

$$P_m = \tau_m \omega. \quad (9)$$

Power losses follow from empirical motor and inverter efficiency maps  $\eta_m$  and  $\eta_{\text{inv}}$ :

$$P_{m,\text{loss}} = \frac{(1 - \eta_m) |P_m|}{\eta_m}, \quad (10)$$

$$P_{\text{inv},\text{out}} = P_m + P_{m,\text{loss}}, \quad (11)$$

$$P_{\text{inv},\text{loss}} = \frac{(1 - \eta_{\text{inv}}) |P_{\text{inv},\text{out}}|}{\eta_{\text{inv}}}, \quad (12)$$

$$P_{\text{bat}} = P_{\text{inv},\text{out}} + P_{\text{inv},\text{loss}} + P_{\text{aux}}. \quad (13)$$

Net energy per distance (Wh/km) is the integral of  $P_{\text{bat}}$  over trip distance. Regeneration is treated through the same flow when  $F_v < 0$ , with the added influence of mechanical braking.

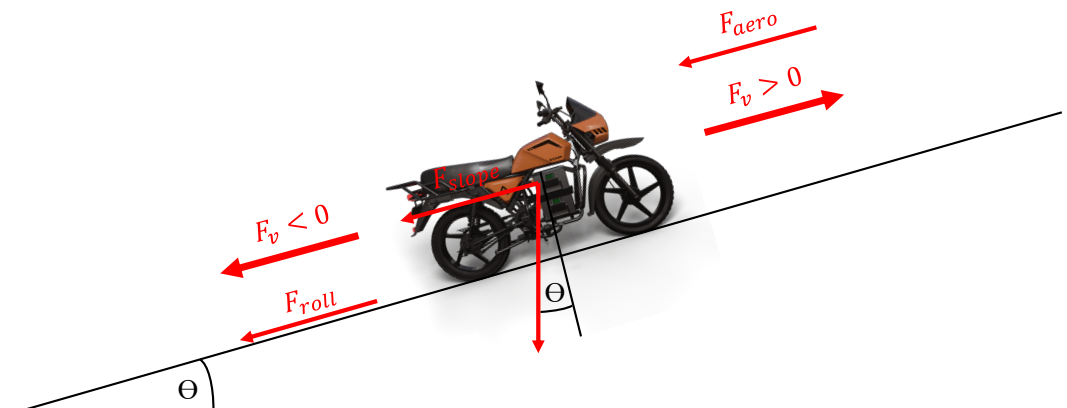


**Figure 3.** Free-body diagram of the motorcycle showing external forces and tractive effort.

### 3.4. Speed and Grade

Vehicle speed is calculated from motor speed,  $\omega_{(\text{rpm})}$ , using

$$v = \frac{\pi r_w}{30 N_{\text{sprocket}}} \omega_{(\text{rpm})}. \quad (14)$$

The road's gradient is determined from elevation difference ( $h[n] - h[n - 1]$ ) and path length ( $x[n] - x[n - 1]$ ) by

$$\theta[n] = \arctan\left(\frac{h[n] - h[n - 1]}{x[n] - x[n - 1]}\right). \quad (15)$$

### 3.5. Model Parameters

Table 1 lists the fixed parameters used in the simulator. When direct measurements were unavailable, values were selected based on manufacturer communication, calibration studies, and the literature, as indicated.

**Table 1.** Fixed parameters used in the simulator.

| Parameter                      |                             | Value                    | Source/Notes                    |
|--------------------------------|-----------------------------|--------------------------|---------------------------------|
| Frontal area                   | $A$                         | 0.773 m <sup>2</sup>     | Measured (ImageJ Version 1.54p) |
| Drag coefficient               | $C_d$                       | 0.5                      | 0.5–0.9 (manufacturer), tuned   |
| Gross vehicle mass             | $m$                         | 234–369 kg               | From trips' metadata            |
| Chain-drive efficiency         | $\eta_{\text{chain-drive}}$ | 0.931                    | [8]                             |
| Sprocket ratio                 | $N_{\text{sprocket}}$       | 56/11                    | Manufacturer                    |
| Wheel radius                   | $r_w$                       | 0.2859 m                 | Manufacturer, tuned             |
| Air density                    | $\rho$                      | 0.9896 kg/m <sup>3</sup> | [18]                            |
| Rolling resistance coefficient | $C_{rr}$                    | 0.01                     | [19], good asphalt              |
| Auxiliary power                | $P_{\text{aux}}$            | 35 W                     | Manufacturer                    |

**Drag Coefficient Tuning:** A subset of driving cycle data (where acceleration and grade approximate zero) was selected. The acceleration and grade variables in the simulator were forced to zero, and the drag coefficient was subsequently tuned (within the specified range) to obtain the smallest RMSE between the simulated and measured power values.

**Wheel Radius Tuning:** Two wheel circumference values for a different drive wheel were obtained through: (i) measurement without a payload and (ii) tuning from the measured value (with a payload) to align display speed and GPS speed. The ratio of the tuned

and measured circumference values was applied to the specified Roam Air wheel radius. The reduced RMSE between the calculated vehicle speed and recorded display speed values validated the approach.

### 3.6. Mechanical Brakes Modelling

For the Roam Air, the motor's regenerative braking torque limit is demonstrated in Figure 4, where mechanical brakes manage the additional braking torque outside this limit. The speed threshold ( $\omega_{\text{regen,max}}$ ) was determined by the minimum speed value at which the peak negative DC bus current was measured. Subsequently, the maximum torque limit ( $\tau_{\text{regen,max}}$ ) was set to the motor's maximum torque at  $\omega_{\text{regen,max}}$ . The experimental efficiency maps for propulsion were used inversely to determine the motor and inverter power losses during regeneration. This implementation assumed optimal battery parameters throughout the motorcycle's trip.

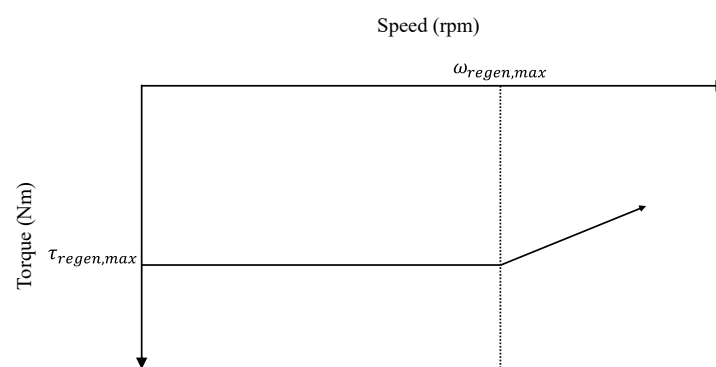


**Figure 4.** Simple representation of the regenerative braking torque limit.

### 3.7. Component Characterisation

Motor and inverter efficiency maps were produced on an eddy current dynamometer over a grid of 5 Nm by 250 rpm up to 55 Nm and 4000 rpm. Figure 5 shows the experimental setup used to perform the characterisation tests.

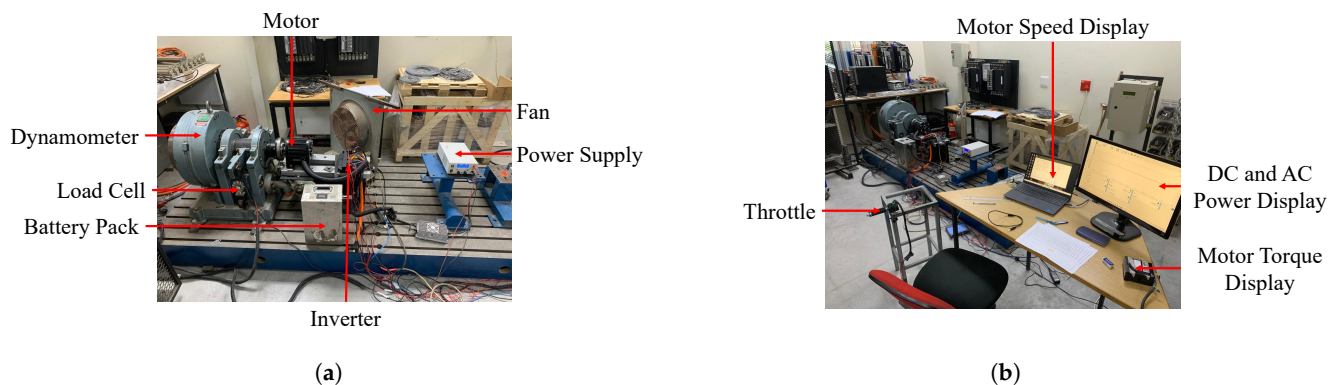


**Figure 5.** Experimental setup to measure motor and inverter efficiency maps. (a) shows the dynamometer and (b) shows the data-capturing setup.

The dynamometer allowed torques to be set, which were measured by the load cell. The throttle enabled speed modulation, which was measured by the motor's internal sensor and displayed through the motor controller's software. DC battery voltage and current, AC line-to-line voltage, and AC phase current were measured and recorded on PicoScope 7. A phase-angle correction was applied to obtain power factor from line-to-line voltage and phase current. Efficiencies were calculated as output to input ratios and lightly smoothed.

## 4. Results

This section reports the measured motor and inverter efficiency maps, evaluates the simulator against six real trips, and then uses the simulator to analyse motorbike energy efficiency for different (i) component parameters and (ii) riding conditions.

### 4.1. Motor and Inverter Efficiency Maps

The efficiency maps in Figure 6 were generated from dynamometer test data. Unmeasured low-torque/low-speed points (0–5 Nm, 0–250 rpm) were assumed equal to the nearest measured points. Gaussian smoothing (Table 2) was increased in 0.1 sigma steps until smooth, concentric regions emerged (kernel sizes from Equation (16)).

$$\text{Kernel size} = 6\sigma + 1. \quad (16)$$

Some efficiency points are missing at the boundaries because of the battery-limited system setup, which can be resolved by testing with a constant voltage supply. This approach does limit the overall range of the efficiency map, but identical batteries were used on the measured trips. Figure 7 shows the operating point profiles of each trip, where undefined points are assigned the efficiency value of their nearest neighbour.

**Table 2.** Parameters for Gaussian smoothing.

| Variable/Map            | Sigma (Samples) | Kernel Size (Samples) |
|-------------------------|-----------------|-----------------------|
| Vehicle speed           | 1               | 7                     |
| Per-second distance     | 4               | 25                    |
| Elevation difference    | 10              | 61                    |
| Motor efficiency map    | 0.7             | $6 \times 6$          |
| Inverter efficiency map | 0.1             | $2 \times 2$          |

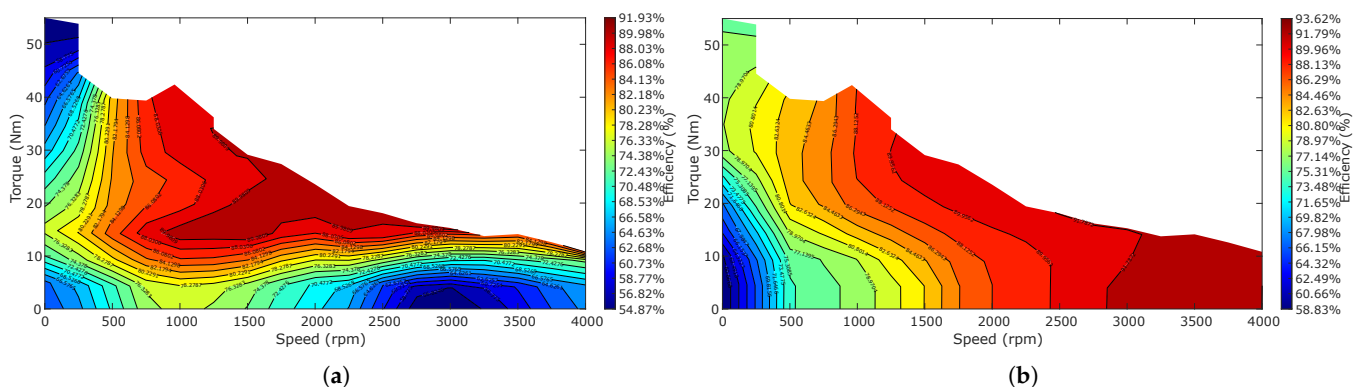


**Figure 6.** Efficiency maps from dynamometer tests. (a) Motor; (b) inverter.

### 4.2. Simulator Validation

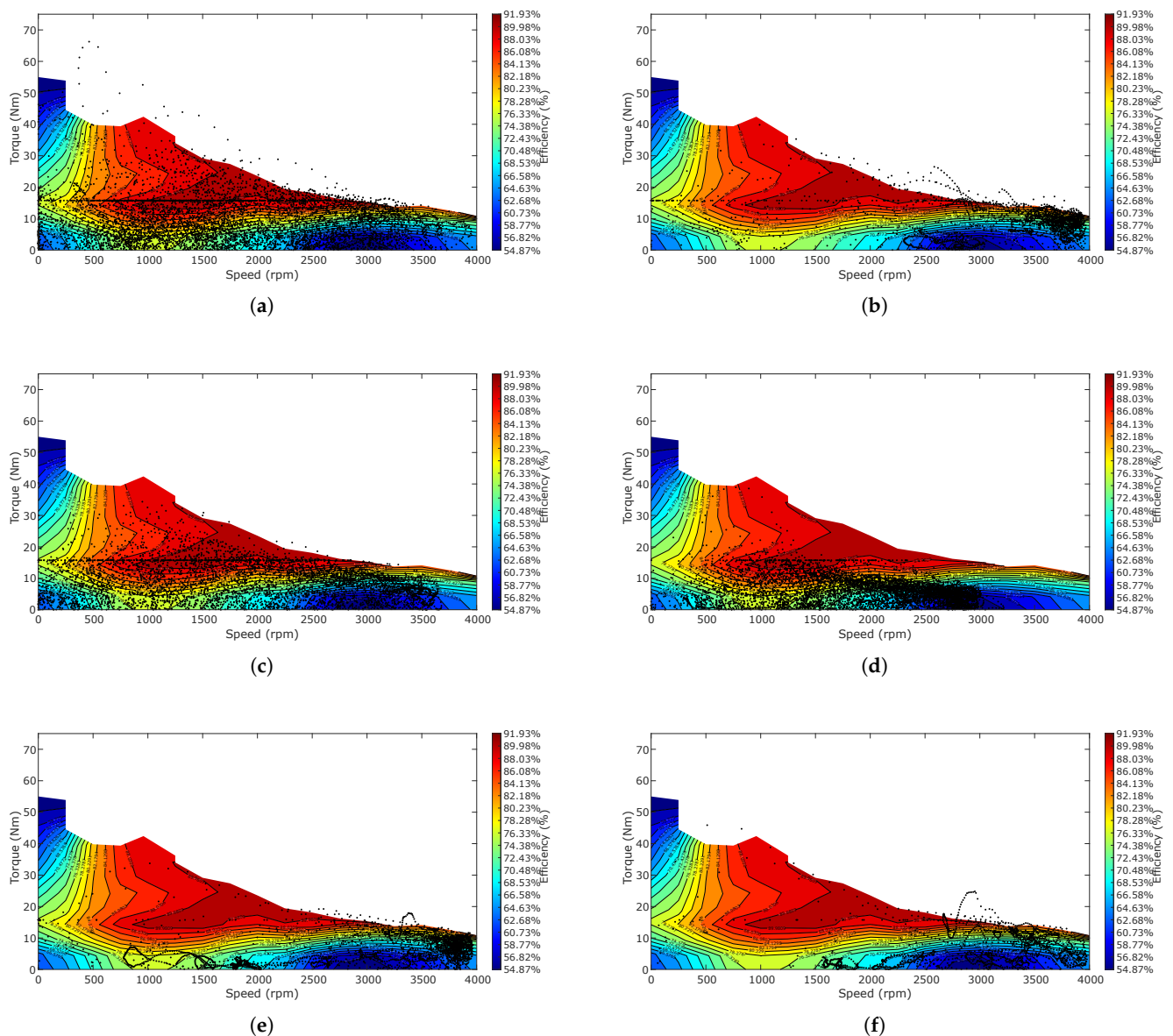
The movement data from six measured trips taken in and around Nairobi were simulated. Figure 8 shows the simulated and measured battery power profiles of each trip, and Tables 3 and 4 show the validation results.

**Table 3.** Similarity metrics for battery power profiles.

| Trip | Scenario | MAE [W] | RMSE [W] | NRMSE  | r      | p |
|------|----------|---------|----------|--------|--------|---|
| 1    | City     | 585.2   | 948.2    | 0.1017 | 0.9052 | 0 |
| 2    | Highway  | 756.6   | 1104.5   | 0.1185 | 0.9105 | 0 |
| 3    | City     | 605.2   | 896.9    | 0.1167 | 0.9074 | 0 |
| 4    | City     | 500.3   | 683.6    | 0.0948 | 0.8730 | 0 |
| 5    | Highway  | 663.0   | 930.4    | 0.0993 | 0.9097 | 0 |
| 6    | Highway  | 811.1   | 1095.3   | 0.1253 | 0.8964 | 0 |

**Table 4.** Trip summary and energy per distance (simulated vs. measured).

| Trip | Scenario | Duration [hh:mm:ss] | Distance [km] | Avg Spd [km/h] | Simulated [Wh/km] | Measured [Wh/km] | Err [%] |
|------|----------|---------------------|---------------|----------------|-------------------|------------------|---------|
| 1    | City     | 1:55:19             | 61.7          | 32.6           | 41.8              | 41.5             | 0.7     |
| 2    | Highway  | 0:44:57             | 44.8          | 60.5           | 55.4              | 51.7             | 7.2     |
| 3    | City     | 1:30:35             | 56.5          | 37.2           | 40.3              | 38.4             | 4.9     |
| 4    | City     | 1:57:11             | 75.5          | 39.1           | 33.6              | 30.2             | 11.3    |
| 5    | Highway  | 0:50:37             | 52.9          | 62.1           | 45.7              | 44.6             | 2.5     |
| 6    | Highway  | 0:28:30             | 28.9          | 62.8           | 45.9              | 45.7             | 0.4     |

**Figure 7.** Distribution of operating points on the motor efficiency map for each trip. (a) Trip 1 (city); (b) Trip 2 (highway); (c) Trip 3 (city); (d) Trip 4 (city); (e) Trip 5 (highway); (f) Trip 6 (highway).

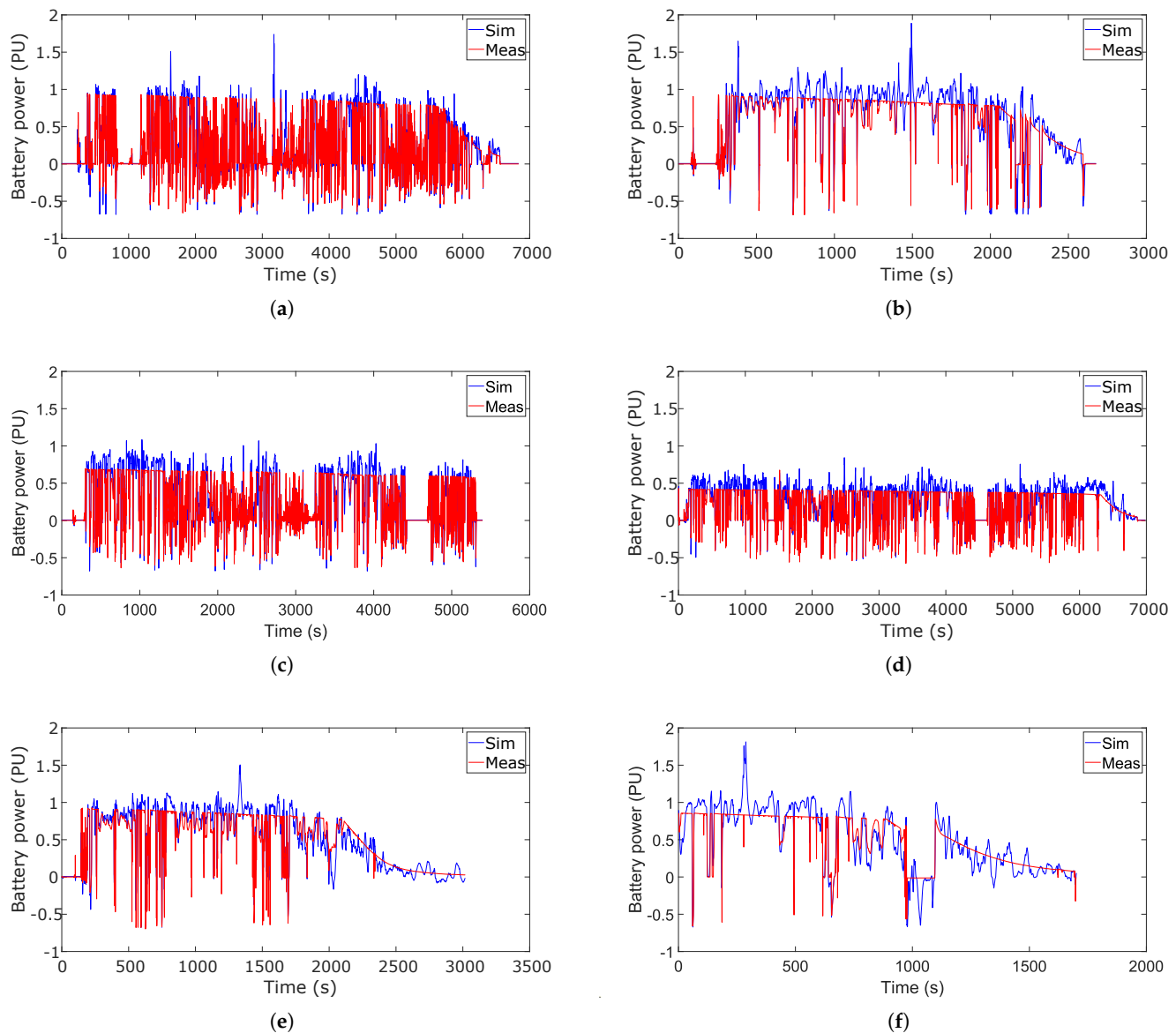


**Figure 8.** Simulated (blue) vs. measured (red) battery power (full trips). *Note: the labels on the axes have been normalised to protect the commercial confidentiality of the industry partner.* (a) Trip 1 (city); (b) Trip 2 (highway); (c) Trip 3 (city); (d) Trip 4 (city); (e) Trip 5 (highway); (f) Trip 6 (highway).

Energy-per-distance outcomes are visualised in Figure 9; the model slightly overestimates propulsion magnitudes and closely approximates regeneration magnitudes.

#### Discussion of Results

Strong correlations ( $r = 0.87\text{--}0.91$ ) indicate that the temporal dynamics are captured. The larger RMSE than MAE suggests the presence of error spikes. The NRMSE indicates that the maximum average error across the trips is 12.51% of the measured power range. The energy per distance results exhibits a moderate maximum error of 11.3%, which is slightly higher than other applicable models found in [6,15], demonstrating maximum errors of 4.5% and 5.4% respectively. However, ref. [6] does not model road slope since validation is against dynamometer test data, and ref. [15] is superficially validated by comparing its results to another similar vehicle's measured results.

Since vehicle mobility was measured and the simulation parameters were reasonably determined, slope angle estimation is likely the principal source of bias. The ALOS World

3D 30 m 3.1 dataset performs well according to an elevation validation study ([20]); however, that study was located in Armenia and elevation dataset accuracy is region-specific [20]. Therefore, further investigations into elevation data may improve the simulator's results.

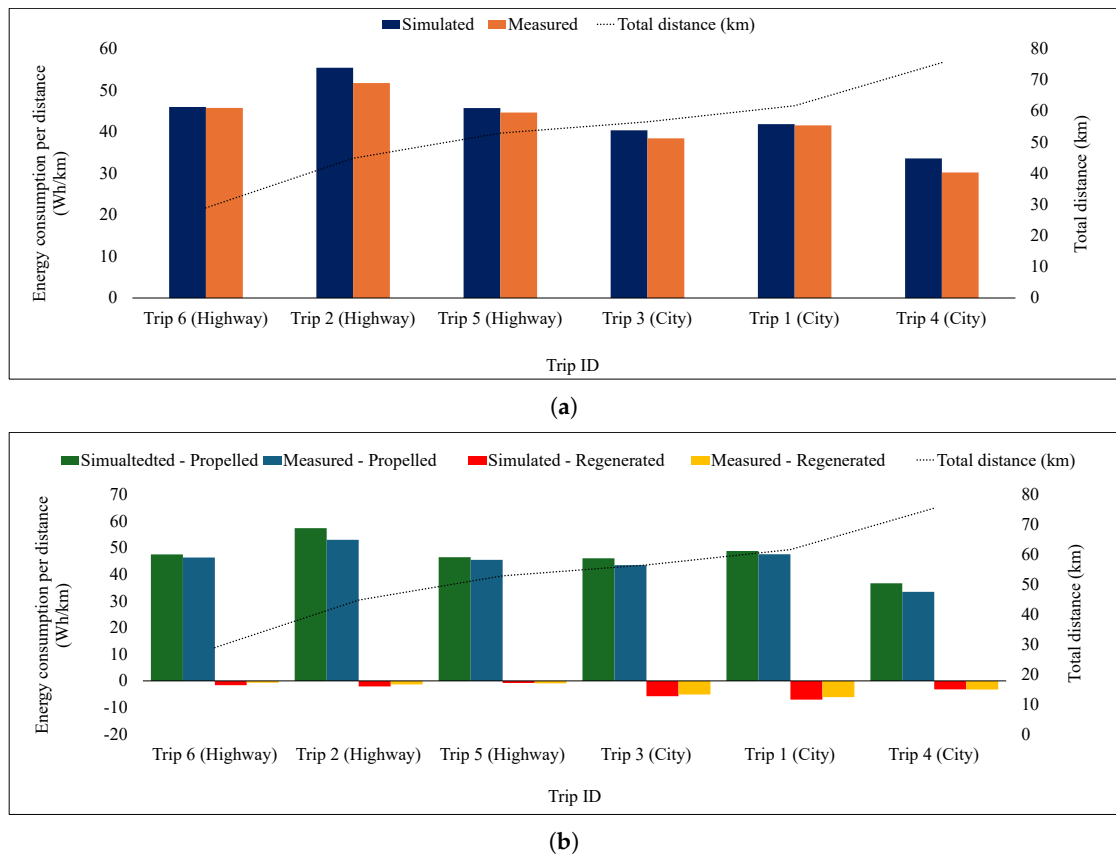


**Figure 9.** Net energy, and propulsion and regeneration components per distance (simulated vs. measured). (a) Net energy per trip. (b) Propulsive vs. regenerative energy.

#### 4.3. Experimental Analyses

##### 4.3.1. Component Parameter Sensitivity

Trip 1 was used for the component parameter sensitivity analysis, with  $\pm 10\%$  one-at-a-time perturbations. Inputs for the component sensitivities are listed in Table 5.

The results are shown in Figure 10 and Table 6. The results show that energy per distance is inversely related to sprocket ratio, with a higher ratio decreasing consumption and increasing efficiency, and a lower ratio increasing consumption and decreasing efficiency.

**Table 5.** Simulation parameter values and conditions used for the sensitivity analysis.

| Parameter                   | Low    | Baseline                           | High                  |
|-----------------------------|--------|------------------------------------|-----------------------|
| Sprocket ratio              | 4.582  | 5.091 (56/11)                      | 5.6                   |
| Wheel radius [m]            | 0.2573 | 0.2859                             | 0.3144                |
| Drag coefficient $C_d$      | 0.45   | 0.50                               | 0.55                  |
| Efficiency map scaling      | Low    | Baseline                           | High                  |
| Inverter map scale          | 0.8182 | 0.9091 (1/1.1)                     | 1.0000                |
| Motor map scale             | 0.8182 | 0.9091 (1/1.1)                     | 1.0000                |
| Driving conditions          |        | Baseline                           | Change                |
| Hilly terrain (up and down) | –      | $\theta = 0^\circ$                 | $\pm 5^\circ$         |
| Passenger                   | –      | $m_{\text{rider}} = 85 \text{ kg}$ | 160 kg                |
| Low drag posture            | –      | $C_d A = 0.3865 \text{ m}^2$       | 0.1824 m <sup>2</sup> |
| Rural/gravel terrain        | –      | $C_{rr} = 0.01$                    | 0.03                  |

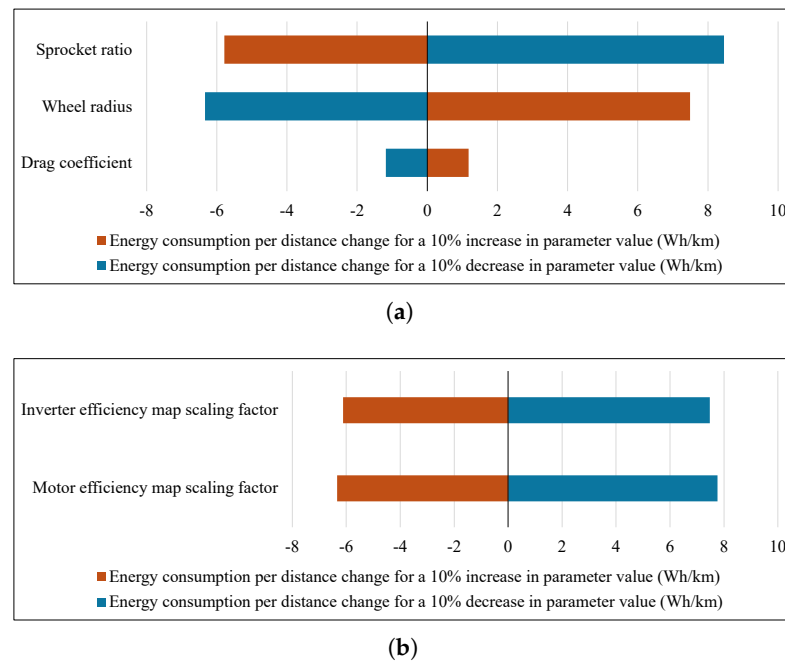


**Figure 10.** Parameter sensitivity: (a) sprocket ratio, wheel radius,  $C_d$ ; (b) inverter and motor efficiency scales (Trip 1).

Meanwhile, an increase in wheel radius results in a consumption increase (efficiency decrease), compared with a consumption decrease (efficiency increase) for an equivalent reduction in wheel radius.

An increase in drag coefficient results in an expected consumption increase, while a decrease results in a consumption reduction.

The increase in inverter efficiency by 10% results in a reduced consumption (efficiency increase of 13%), while a 10% decrease results in an increased consumption (efficiency decrease of 12%).

The 10% increase in motor efficiency results in a reduced consumption (efficiency increase of 13%), while a 10% decrease results in an increased consumption (efficiency decrease of 13%).

**Table 6.** Impact of parameter variation, efficiency map scaling, and driving conditions on energy consumption and efficiency relative to baseline.

|                             | $\Delta$ Cons.<br>[Wh/km] | $\Delta$ Eff.<br>[km/kWh] (%) | $\Delta$ Cons.<br>[Wh/km] | $\Delta$ Eff.<br>[km/kWh] (%) |
|-----------------------------|---------------------------|-------------------------------|---------------------------|-------------------------------|
| Parameter                   | Low                       |                               | High                      |                               |
| Sprocket ratio              | +8.458                    | −4.02 (−17%)                  | −5.782                    | +3.834 (+16%)                 |
| Wheel radius [m]            | −6.338                    | +4.268 (+18%)                 | +7.492                    | −3.631 (−15%)                 |
| Drag coefficient $C_d$      | −1.179                    | +0.693 (+3%)                  | +1.176                    | −0.653 (−3%)                  |
| Efficiency map scaling      | Low                       |                               | High                      |                               |
| Inverter map scale          | +7.474                    | −2.254 (−12%)                 | −6.115                    | +2.368 (+13%)                 |
| Motor map scale             | +7.763                    | −2.33 (−13%)                  | −6.341                    | +2.467 (+13%)                 |
| Driving conditions          | City (Trip 1)             |                               | Highway (Trip 6)          |                               |
| Hilly terrain (up and down) | +7.126                    | −4.881 (−17%)                 | +6.068                    | −2.742 (−12%)                 |
| Passenger                   | +4.141                    | −3.054 (−11%)                 | +2.681                    | −1.299 (−6%)                  |
| Low drag posture            | −7.022                    | +7.259 (+25%)                 | −15.335                   | +12.085 (+53%)                |
| Rural/gravel terrain        | +15.992                   | −9.042 (−31%)                 | +17.350                   | −6.401 (−28%)                 |

#### 4.3.2. Impact of Different Riding Conditions

The baseline driving conditions for city (Trip 1) and highway (Trip 6) are given in Table 5, along with the updated values for each assessment. To assess the impact of driving conditions on energy consumption, the slope, payload, rider posture, surface, and constant-speed scenarios were varied. The results are shown in Figures 11 and 12 and Table 6.

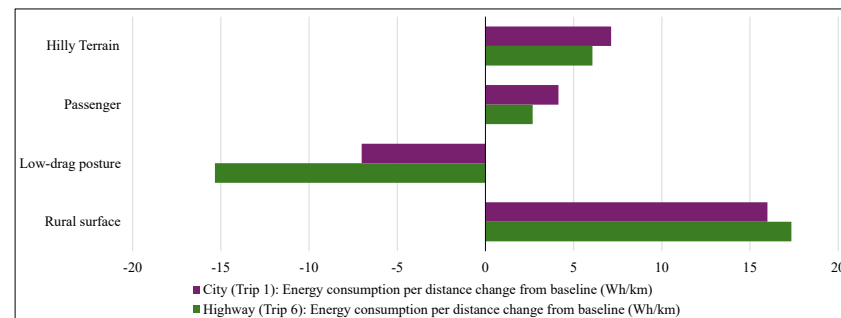


**Figure 11.** Impact of driving conditions on energy per distance: change from baseline.

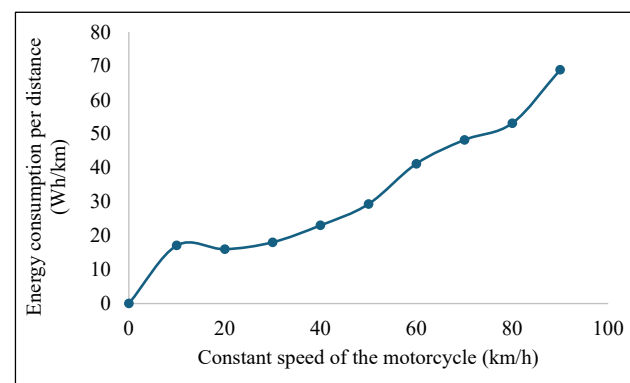


**Figure 12.** Energy per distance at constant speed (baseline settings).

Downhill and low-drag posture markedly reduce energy consumption due to regeneration and reduced aerodynamic load, respectively; the low-drag posture effect is much larger on highways where drag dominates. In the city environment, low-drag posture decreases consumption by 7.022 Wh/km (increasing efficiency by 7.259 km/kWh or 25%). In the highway environment, low-drag posture decreases consumption by 15.335 Wh/km (increasing efficiency by 12.085 km/kWh or 53%).

Hilly terrain, rural rolling resistance, and passenger mass increase energy use; the passenger impact is stronger in city operation due to frequent accelerations.

Constant-speed sweeps (Figure 12) show rising energy with speed (due to drag and mechanical power); a slight dip from 10–20 km/h is consistent with low-efficiency regions in the motor and inverter efficiency maps. Between 10 and 20 km/h, the operating point changes from (472.4 rpm; 1.5 Nm) to (944.8 rpm; 1.7 Nm), which corresponds to motor and inverter efficiency increases of 7.8% and 4.4% respectively.

## 5. Conclusions

This paper presented a compact, physics-based simulator for predicting the energy consumption of the Roam Air electric motorcycle under real operating conditions in sub-Saharan Africa. The model integrated measured drive cycles, elevation-derived gradients, and empirically characterised motor and inverter efficiency maps obtained from dynamometer testing. Validation against six real-world city and highway trips in Nairobi showed strong temporal agreement between simulated and measured battery power, with

correlations between 0.87 and 0.91 and energy-per-distance errors between 0.4% and 11.3%. The simulator consistently exhibited a small positive bias, which is favourable for planning tasks.

Using the validated framework, a sensitivity analysis quantified the influence of key component parameters on efficiency. Sprocket ratio, wheel radius, drag coefficient, and motor and inverter efficiency maps all showed predictable impacts on energy consumption, highlighting the parameters that should receive priority during design optimisation. An assessment of representative driving conditions demonstrated the substantial effects of road gradient, rider mass, posture, and surface type. City operation is particularly sensitive to payload and terrain, while highway consumption is dominated by aerodynamic effects.

The model provides a transparent and computationally light tool tailored for the varied conditions of African two-wheeler operation. Future work will focus on improving elevation estimation and extending the simulator to include battery thermal and electrochemical models. The framework can potentially be adapted to other electric two-wheelers where measured component data are available, supporting planning, design, and policy decisions for sustainable transport in the region. Future work will include in-depth battery modelling to estimate total energy consumed from charging.

**Author Contributions:** Conceptualization, M.J.B.; methodology, H.A., S.B. and M.J.B.; software, H.A.; validation, S.B. and M.J.B.; formal analysis, H.A., S.B. and M.J.B.; investigation, H.A., S.B. and M.J.B.; resources, S.B. and M.J.B.; data curation, H.A.; writing—original draft preparation, H.A.; writing—review and editing, S.B. and M.J.B.; visualization, H.A. and M.J.B.; supervision, S.B. and M.J.B.; project administration, M.J.B.; funding acquisition, M.J.B. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received financial support from the Western Cape Government Motorised Transport (WC GMT), contract number S009285, and Catalytic Finance through the Subnational Climate Fund, contract number S010624.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author.

**Acknowledgments:** Acknowledgement and appreciation are extended to Roam for providing their motorcycle and data, and to colleagues in the Electric Mobility Lab at Stellenbosch University for their experimental support.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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