Article

Electric Two-Wheeler Vehicle Integration into Rural Off-Grid Photovoltaic System in Kenya

Aminu Bugaje *, Mathias Ehrenwirth, Christoph Trinkl and Wilfried Zörner

Institute of New Energy Systems, Technische Hochschule Ingolstadt, 85049 Ingolstadt, Germany; mathias.ehrenwirth@thi.de (M.E.); christoph.trinkl@thi.de (C.T.); wilfried.zoerner@thi.de (W.Z.)

* Correspondence: aminu.iliasubugaje@thi.de

Abstract: In both rural and urban areas, two-wheeler vehicles are the most common means of transportation, contributing to local air pollution and greenhouse gas emissions (GHG). Transitioning to electric two-wheeler vehicles can help reduce GHG emissions while also increasing the socioeconomic status of people in rural Kenya. Renewable energy systems can play a significant role in charging electric two-wheeled vehicles, resulting in lower carbon emissions and increased renewable energy penetration in rural Kenya. As a result, using the Conventional and Renewable Energy Optimization (CARNOT) Toolbox in the MATLAB/Simulink environment, this paper focuses on integrating and modeling electric two-wheeled vehicles (e-bikes) into an off-grid photovoltaic Water-Energy Hub located in the Lake Victoria Region of Western Kenya. Electricity demand data obtained from the Water-Energy Hub was investigated and analyzed. Potential solar energy surplus was identified and the surplus was used to incorporate the electric two-wheeler vehicles. The energy consumption of the electric two-wheeler vehicles was also measured in the field based on the rider's driving behavior. The modeling results revealed an annual power consumption of 27,267 kWh, a photovoltaic (PV) electricity production of 37,785 kWh, and an electricity deficit of 370 kWh. The annual results show that PV generation exceeds power consumption, implying that there should be no electricity deficit. The results, however, do not represent the results in hourly resolution, ignoring the impact of weather fluctuation on PV production. As a result, in order to comprehend the electricity deficit, hourly resolution results are shown. A load optimization method was designed to efficiently integrate the electric 2-wheeler vehicle into the Water-Energy Hub in order to alleviate the electricity deficit. The yearly electricity deficit was decreased to 1 kWh and the annual electricity consumption was raised by 11% (i.e., 30,767 kWh), which is enough to charge four more electric two-wheeler batteries daily using the load optimization technique.

Citation: Bugaje, A.; Ehrenwirth, M.; Trinkl, C.; Zörner, W. Electric Two-Wheeler Vehicle Integration into Rural Off-Grid Photovoltaic System in Kenya. *Energies* **2021**, *14*, 7956. <https://doi.org/10.3390/en14237956>

Academic Editor: Spyros Voutetakis

Received: 24 October 2021

Accepted: 23 November 2021

Published: 29 November 2021

Keywords: Lake Victoria; photovoltaic; off-grid; model; electric two-wheeled vehicle; Water-Energy Hub; CARNOT

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

A worldwide leapfrog to electric cars is already underway in nations such as Norway, China, and others to cut carbon dioxide emissions. Transportation emits nearly a quarter of all CO₂ produced by energy use [1]. By 2050, when the global number of passenger cars is predicted to more than double, it is expected to account for one-third of all vehicles on the road. This increase is expected to be most pronounced in low-income nations, where automobile emission rules are rarely implemented [1].

Electric vehicles (EVs) have an efficiency of 80–95% [2], making them a superior option than conventional cars (CVs), which have less than 20% efficiency [3]. EVs are an important part of modern transportation since they incorporate a variety of cutting-edge industrial technology (e.g., an electric motor, a battery, and a charging facility). Electric vehicle adoption, on the other hand, is not advancing as swiftly as anticipated. Electric cars' limited range and long recharge times are frequently cited as the most important

barriers to their adoption [4,5]. Electric vehicles, despite their expensive initial price, offer low maintenance costs and utilize significantly less energy than traditional vehicles [6].

As the demand for power and electricity by EVs was rising rapidly, numerous research centers and energy supply businesses started seriously thinking about decreasing pressure on local electricity networks due to the increasing number of charging outlets for electric vehicles. The most efficient way of addressing this deficiency in the face of local electricity grids is to supply the EV charging infrastructure [7] with renewable energy sources (RES), like wind and solar.

RES can considerably contribute to the reduction of carbon emissions and the expansion of renewable energy penetration. However, the challenges of implementing RES are in its variabilities such as seasonal changes to wind and sunlight, and daily cloud randomness in solar power panel coverage [8]. As a result, effective solar PV system design is critical to avoid oversizing or undersizing the system, which can result in high capital expenditures or insufficient solar power production [9].

Therefore, this paper presents the results of a modeled off-grid photovoltaic Water-Energy Hub (*WeTu Hub*) that is implemented by *Siemens Foundation* through *WeTu Ltd.* (i.e., its implementation partner) [10] around *Lake Victoria*. The *WeTu Hub* is used to provide reliable and clean electricity for charging fishing lanterns, other electric appliances, and batteries for electric two-wheelers (e-bikes) for water and local transportation.

2. Motivation

More than 90% of Africa's commodities and services are transported by road, resulting in a high reliance on fossil fuels and contributing to greenhouse gas (GHG) emissions. Due to their heavy reliance on imported fuels, African governments are under pressure to aggressively subsidize fuels in order to shield consumers from rising oil costs. Despite this, customers and vehicle drivers are sometimes confronted with high costs, as well as gasoline shortages that result in long queues for fuel [11,12].

Moreover, SLoCaT [13] reports that global transport emissions had grown by 31% from 2000 to 2016 and Asia had the highest transport emission growth of 92% followed by Africa (84%), then Latin America (49%) while they have been falling in Europe and North America. From 2000 to 2016, transport emissions in Sub-Saharan Africa (SSA) grew by 75% to 156 million tonnes (Mt) CO₂, mostly due to increasing passenger and freight transportation activities. Algeria has seen a 161% increase in CO₂ transport emissions, whereas Ghana has seen a 153% increase, Kenya has seen a 123% increase, Egypt has seen a 73% increase, and South Africa has seen a 40% increase. Figure 1 represents the regional growth in CO₂ transport emissions between 2000 and 2016.

Figure 1. Regional share of CO₂ transport emissions growth between 2000 and 2016 [13].

In the year 2015, total domestic transport sector emissions in Kenya amounted to 11.25 MtCO₂ e (see Figure 2). Kenya has set a target to reduce its transport sector emissions to 3.46 MtCO₂ e by 2030. Therefore, to achieve the set target, the annual emissions must not increase by more than 0.4 MtCO₂ e per year. However, the average annual emissions increased by 0.6 MtCO₂ e between 2010 and 2015, thereby putting the sector off track towards meeting its 2030 target [14].

Figure 2. Trend of transport sector emissions (MtCO₂ e), excluding waterborne navigation (data according to [14]).

Mbita was chosen for this study because it fits well to the criteria set for the selection of case study location (i.e., opportunities for short-range electrical vehicles). *Mbita* is situated on the shorelines of *Lake Victoria* in Homa Bay County, one of 47 counties in Kenya (see Figure 3). It is mostly a rural area found latitudes 0°21' and 0°32' south and longitudes 34°04' and 34°24' east [15]. The transport business in *Mbita* is very vibrant and a significant source of income for the residents of *Mbita*. The motorcycle is the most important mode of transport in *Mbita* and is used to transport goods and people within short distances and to the town of Kisumu, which is the largest urban center in the region [15].

Motorcycle transportation, on the other hand, has evident drawbacks in terms of negative externalities such as pervasive noise, increased local air pollution, and greenhouse gas emissions from a public welfare standpoint [16]. Consequently, given that gasoline-powered motorcycles present huge economic and environmental challenges, the transition to electric motorcycles can make a significant contribution to improving the socio-economic lives of people living in *Mbita* and around *Lake Victoria* by reducing fuel costs, CO₂ emissions.

Therefore, this paper intends to optimally integrate e-bikes into an off-grid solar-powered Water-Energy Hub (*WeTu Hub*) around *Lake Victoria* in Western Kenya. The paper presents the analysis of the measured electricity consumption data of the *WeTu Hub*, a simulation model of the *WeTu Hub* using the CARNOT simulation toolbox in MATLAB/Simulink environment, identification of potential energy surplus for e-bikes integration. The paper also presents a measurement investigation on distance-related energy consumption of e-bikes in kWh/100 km. The e-bikes considered in this study were provided by *WeTu Ltd.* through Siemens foundation and these comprise e-OpiBus, e-BodaWerk, and Anywhere Berlin e-cargo bikes.

Figure 3. Study Location: Mbita, Kenya along the shore of *Lake Victoria* [17].

3. Reviews on Optimal Modeling and Sizing of EV Charging Infrastructure

The transition and penetration of EVs into the society have been made possible due to the investments in battery charging infrastructure. However, this increases the pressure on the conventional electricity distribution networks (CEDN). Therefore, the capacity of electricity distribution systems needs to be upgraded through the integration of RESs into the charging stations to reduce potential overload challenges. Moreover, it is the most demanding task to fulfill the expanding demands of EVs by optimizing their charging infrastructure size and operation. Several studies to overcome the above difficulties have been documented and are presented in Table 1.

From Table 1, it can be seen that research on off-grid and on-grid PV systems used for electric vehicle charging had been conducted. This paper intends to adapt the work of [18] by integrating e-bikes (e-motorcycles and e-cargo) into a rural off-grid PV system. This paper will also present the optimal integration of the e-bikes using a load optimization algorithm that utilizes 7 days PV forecast which is missing in the work of [18]. The developed load optimization algorithm presented in this work also has the capability of shifting the loads to days with better PV production depending on the 7 days PV forecast.

Table 1. Summary of literature reviews on EV charging infrastructure.

Study	Configuration	Type of Vehicle	System Size	Location/Year	Research Findings
[19]	Off-grid PV	E-car	281 kWp PV with 420 kWh battery storage	Spain/2018	<ul style="list-style-type: none"> The system was optimized using Hybrid Optimization Model for Electric Renewable (HOMER) software and then enhanced the outcome using the load shifting principle. Using 50 kW DC fast charge with 281 kWp of solar units over 13.5 h per day, 12 EVs had complete recharges of 35 kWh. Based on the findings, the suggested pricing for the off-grid PV-BESS (0.4 EUR/kWh during (15–19 h) and (8–11 h), and 0.25 EUR/kWh during (11–15 h)) is relatively competitive when compared to grid-connected charging stations. The results show that off-grid PV-BESS are both technically and economically practical and dependable. Furthermore, they are lucrative while reducing air pollution significantly.
[20]	PV, grid, diesel genset	E-cars	300 kWp PV	Canada/2017	<ul style="list-style-type: none"> The possibility of isolated EV charging stations (EVCS) along highways was investigated in order to allow EV customers to travel long distances with ease. When compared to a diesel-based EVCS, the diesel-solar PV-BESS mix had the lowest net present cost (NPC) and a relatively modest carbon footprint. The NPC was greater, despite the fact that a 100% renewable-based EVCS with no carbon footprint was desired.
[21]	PV, wind	E-car	200 kW wind turbine; 250 kWp PV	Turkey/2021	<ul style="list-style-type: none"> The hybrid system's ideal solution includes 44.4% wind energy and 55.6% solar energy, for a total yearly power generation of 843 MWh at a cost of EUR 0.055 per kWh. The hybrid charging station is operational for 14 h a day, charging five electric vehicles each hour.
[22]	PV, grid	E-car	294 kWp PV	Sweden/2016	<ul style="list-style-type: none"> The results obtained show that 823.2 kWh daily energy was generated throughout the year with an approximate 136 kWh daily energy output in winter. The system can charge up to 27 electrical vehicles at once with 6.2 h of charging time and 15.1 h of charging time using the AC power grid.
[23]	Off grid PV	E-car	1.02 kWp	USA/2014	<ul style="list-style-type: none"> A smart electric car was efficiently charged using off-grid solar energy. Three months of testing showed that the car was able to strictly charge from the off-grid PV system without power supplied from the grid. The results showed that the system was able to provide 1–4 kWh a day which translated to 5–20 km of driving.

Table 1. Cont.

Study	Configuration	Type of Vehicle	System Size	Location/Year	Research Findings
[24]	PV, grid	E-bikes	2.61 kWp PV	Netherlands/2018	<ul style="list-style-type: none"> • A DC charger was used to provide DC power when charging from the PV panels and an AC charger when charging from the grid. • A 10.5 kWh battery storage was used to support off-grid and grid operations. The results obtained show that the system was able to provide DC, AC, and contactless charging from 2.6 kW PV power while considering the grid connection for backup supply.
[25]	PV, grid	E-car	50 kWp PV	South Korea/2013	<ul style="list-style-type: none"> • The research analyzed the charging schedule of an electric vehicle based on electricity consumption and PV output predictions for smart homes. • The electricity consumption and PV output predictions were made by a time series model with weather forecast and variability. • The study considered 50 kWp PV panels and three electric vehicles for numerical analysis. The proposed method showed that the vehicles can be charged during a low peak period, thereby, efficiently minimizing charging costs. Effective electric vehicle charging exclusively based on numerical assumptions and simulation, however, can never be accurate. Similarly, the paper did not show the impacts of the electricity consumption and PV output forecast error.
[26]	PV, grid	E-cars	10 kWp PV	Netherlands/2016	<ul style="list-style-type: none"> • A 10 kW solar-powered EV charger with V2G for workplaces in the Netherlands is investigated using grid, PV, and V2G. • Grid energy exchange was reduced by 25% using a 10 kWh local energy storage system. • It was demonstrated that local battery storage does not eliminate the EV-PV charger's grid reliance in the Netherlands, notably due to seasonal changes in insolation.
[27]	Microgrid-PV, Genset	E-car	13 kWp PV; 51 kVA Genset	Maldives/2016	<ul style="list-style-type: none"> • The energy management scheme for electric vehicle (EV) charging using photovoltaic (PV) and energy storage, connected to the microgrid, was presented based on heuristic rule-based strategies to optimize energy flow inside a microgrid. • EV demand is met by the GenSet when PV power is unavailable. • When PV is used as the primary source for charging EVs, the microgrid's load is reduced dramatically, making it more cost-effective than charging from a standalone generator.

Table 1. Cont.

Study	Configuration	Type of Vehicle	System Size	Location/Year	Research Findings
[28]	Microgrid-PV, Genset	E-car	7497 kWp PV	Rwanda/2021	<ul style="list-style-type: none"> Using HOMER, integration of solar PV micro-grids in Rwanda to meet the needs of electric vehicles (EVs) was presented. The suggested research might result in a more efficient usage of Rwanda's national energy resources.
[18]	Standalone PV-mini-grid	E-car	4.5 kWp PV	Gambia/2021	<ul style="list-style-type: none"> The study was carried out in Gambia and it looks at the business potential of employing electric vehicles (EVs) recharged by solar mini-grids to provide transportation services in off-grid settlements, using 4.5 kWp of photovoltaic modules installed on the roof of a car parking shelter. The findings show that there are numerous modes of operation in which solar-powered electric taxis might be financially feasible in Gambia. The employment of lightweight vehicles such as tuk-tuks (autorickshaws) and cargo bikes results in the most optimistic possibilities.
[29]	PV, grid, wind, hydro	E-car	3175 kWp PV, 60 wind turbines, 50.7 kW hydro	South Korea/2016	<ul style="list-style-type: none"> Using HOMER, the paper investigates how local taxi services in Daejeon may leverage prospective renewable power producing systems. In Dae-jeon, South Korea, solar, wind, battery, converter, and electrical grid-based systems are suggested for the third stage of the deployment of electric-powered taxis (EP taxis). The economic feasibility and dependability of the proposed grid-connected system are supported by the unpredictability of producing power from renewable energy resources. According to simulation results, creating renewable power generating systems with grid connections is a better choice than constructing standalone renewable electricity production systems. It may be more cost-effective to sell any excess power and purchase any insufficient electricity from the local grid as needed.
[30]	PV, grid	E-scooters	3 kWp PV	Germany/2013	<ul style="list-style-type: none"> The researchers conducted a study on six electric scooters used by university students, which were charged by using a grid-connected PV system. The charging from the PV system was obtained when the PV system generated enough energy to charge the electric scooters, otherwise charging from the grid was obtained. The field results showed that 94.3% direct charging from the 3 kWp PV system and 5.7% charging from the grid were obtained during the summer period and a higher percentage of grid charging during winter. The grid charging during winter periods makes the research not fully eco-friendly because a large extent of grid power was generated from fossil fuels.

4. About the Water-Energy Hub

WeTu Ltd. owns the Water-Energy Hubs (*WeTu Hub*), an off-grid PV-powered energy hub that allows Kenyans in remote areas surrounding *Lake Victoria* to have access to sustainably generated electricity [10,31]. The *WeTu Hub* (see Figure 4 top) are self-contained PV systems (about 30 kWp) in which the power generated is temporarily stored in appropriate battery storage systems (capacity roughly 104 kWh) and made available to the on-site residents. In addition to traditional usage (such as charging fishing lights), electricity is utilized to purify drinking water (see Figure 4, bottom) and therefore contributes positively to the environment. Tables 2 and 3 show the detailed information of the electricity generation and major electricity consumers at *Mbita WeTu Hub*, respectively.

Figure 4. Location of the case study area—Mbita, Kenya (*Lake Victoria*) [31].

Table 2. Detailed information on electricity generation at *Mbita WeTu Hub* [32–38].

System Components	System Specifications
PV Modules	Bosch Solar c-Si-M60-M240-3BB (240 W)
PV Module Quantity	126
PV Module Power Rating	30.24 kWp
PV Inverters	STP15000TL-30 (SMA Sunny Tripower 15 kVA)
PV Inverter Rating	30 kVA
Batteries	104 kWh

Table 3. Detailed information on major electricity consumers at *Mbita WeTu Hub* [39].

Major Electricity Consumers	Power Rating (W)	Number	Running/Charging Time (Hrs)	Energy Demand (kWh/d)
Fishing Lanterns	15–37	200	7	21–51
Water Purifier	120	1	24	2.8
Floodlight	40	1	12	4.8
CFL Light Bulbs	8	7	12	0.67
Fluorescent	18	2	12	0.43
Computer	150	2	4	1.2

5. Methodology

The methodology of this paper is divided into four sections: (1) analysis of the *WeTu Hub*, (2) measurement investigation on e-bikes, (3) integration of e-bikes into *WeTu Hub*, (4) development of a load management algorithm. Figure 5 shows the proposed methodology of this paper.

Figure 5. Proposed methodology.

5.1. Analysis of WeTu Hub

To analyze the *WeTu Hub*, measurement data between August 2020 and December 2020 of electricity consumption at the *Hub* was evaluated. Workdays, weekends during moon phases (i.e., full moon days and non-full moon days) based on the lunar calendar [40] for the year 2020 were identified from the measurement data. A synthetic load profile was generated using the identified workdays and weekends load profiles. This resulted in the generation of an annual load profile using MATLAB and was fed into a simulation model of the *WeTu Hub*. A historic annual weather data of *Mbita* (with one-hour resolution) obtained from Meeonorm [41] was also fed into the simulation model. Energy surplus was identified for e-bikes integration.

5.2. Field Measurement Investigation on e-Bikes

To determine the potential number of battery swaps a rider might require per day/100 km, a field measurement investigation was carried out on the e-bikes by MOI university and *WeTu Ltd.* engineers [10] considering factors such as trip distance, speed, payload weight. The outcome of the measurement was used to determine the distance-related energy consumption of the e-bikes in kWh/100 km.

5.3. Integration of e-Bikes into WeTu Hub

To integrate the e-bikes into the *WeTu Hub*, a daily and annual load profile for the e-bikes was generated and integrated into the existing *WeTu Hub's* load profile using

the outcome of the measurement investigation. Charging time, charging rate, battery capacity, etc., from the measurement investigation aided in the load profile generation for the individual type of bikes.

5.4. Development of a Load Management Algorithm

To optimize the load profile for optimum integration of the e-bikes into the *WeTu Hub*, a load management algorithm was developed using Non-linear programming (NLP). The generated hourly resolution simulation results such as annual PV electricity production, battery supply, battery state of charge (SoC), and electricity deficit were analyzed.

6. Analysis of Electricity Data from *WeTu Hub*

Electricity consumption during night and day was measured using the SMA data manager that was installed at *Mbita WeTu Hub*. A carpet plot (see Figure 6) of the electricity consumption was generated to help understand the energy usage at the *Mbita WeTu Hub* and generate the future load profiles of the e-bikes. The existing loads that constitute the carpet plot for the *WeTu Hub* electricity consumption can be seen in Table 3. It can be seen in Figure 6 that the normal operating period at the *WeTu Hub* was between August and October, while field measurement on e-bikes was between October and December. The least electricity demand was recorded in December due to partial lockdown to reduce Christmas activities.

Figure 6. Carpet plot of measured electricity consumption data from *Mbita WeTu Hub*.

6.1. Analysis of Electricity Demand during the Normal Operation Period

From Figure 6, it was identified that there was a normal operation period at the *WeTu Hub* from 27 August to 7 October 2020. The carpet plot in Figure 7 shows the extracted normal operation period.

Figure 7. Carpet plot of measured electricity consumption data from *Mbita WeTu Hub* during the normal operation period.

The 2020 Gregorian calendar was used to identify weekends and weekdays, while the 2020 lunar calendar [40] was used to identify moon phases. From Figure 7, it can be seen that there is less electricity demand from 27 August to 7 September, and from 27 September to 6 October. This was a result of full moon phases. Moon phases are days within the moon cycle in a month. These days consist of full moon days and non-full moon days. There are approximately 10 full moon days in every month of the year. During full moon phases, there is naturally a low fishing catch on *Lake Victoria* because there is too much light for the fish to come to the top, and otherwise happens during non-full moon phases. In the case of the latter (i.e., non-full moon phase), the fishermen utilize floatable electric lamps on the lake to attract small insects, yielding the fish to come to the water surface where they are caught by the fishermen. In the case of full moon conditions, however, the bright moonlight distracts the insects from the floatable lamps, and, as a consequence, there is less fishing catch.

Therefore, a smaller number of fishing lanterns are charged at the *Mbita WeTu Hub* during full moon phases. Figure 8 shows the daily electricity demand in correlation to moon phases for the normal operation period.

6.2. Extraction of Electricity Demand Profile for Weekdays, Weekends during Moon Phases

Weekdays, weekends during moon phases from 27 August 2020 to 6 October 2020 were extracted from the data of Figure 8. A MATLAB script was written to extract the average hourly electricity demand profile from the measurement data shown in Figure 8 for weekdays, weekends during a full moon phase, and non-full moon phases (see Figures 9–11).

Figure 8. Daily electricity demand in correlation to moon phases for the normal operation period.

Figure 9. Average hourly electricity demand profile from the measurement during moon phases.

Figure 10. Average hourly electricity demand profile from the measurement during moon phases.

Figure 11. Average hourly electricity demand profile from the measurement during moon phases.

6.3. Annual Load Profile Generation

An hourly resolution annual load profile for the *Mbita WeTu Hub* was generated using the extracted profiles in Figures 9–11. A MATLAB script was also used to generate the year 2021 annual electricity load profile of 6278 kWh/year (see Figure 12). Weekdays and weekends used the Gregorian calendar of 2021 and for moon phase days, the lunar calendar of 2021 was used.

Figure 12. Annual hourly electricity demand profile from the measurement during moon phases.

6.4. Simulation Model of the Mbita WeTu Hub

The annual load profile generated in the previous section was used as input to a simulation model. Similarly, corresponding historical annual weather data [41] of *Mbita* town was converted into a mathematical model and fed as input to the simulation model. The weather data was obtained from the Meteonorm weather database [41]. The weather data contained information such as temperature, solar irradiation, humidity, precipitation, wind speed, etc. The weather data contained information such as temperature, solar irradiation, humidity, precipitation, wind speed, etc. Figure 13 shows the global solar irradiation and temperature of the selected location. The selected location has an average annual temperature and annual global irradiation of 22.9 °C and 1838 kW/m², respectively. It can be seen from Figure 13 that January and May have the highest solar irradiation while February, April, and June have the lowest solar irradiation.

Figure 13. Solar irradiation and ambient temperature of the selected location.

The mathematical model is then able to calculate annual PV electricity production or annual electricity demand with sufficient accuracy in hourly resolution for one year. Consequently, for example, hours with a high electricity deficit can be identified.

6.4.1. Method

A suitable simulation model was developed using the CARNOT toolbox in MATLAB/SIMULINK simulation environment [42,43]. The relevant components such as PV modules, inverters, battery storage, battery inverters (see Figure 14) were parameterized according to the available datasheets. A PV field with a total of 30 kWp is converted into alternating current using a 30-kVA inverter (see Figure 14, left) to either cover the electrical load profile demands of the *Mbita WeTu Hub* (see Figure 10, above) or charge a central backup battery storage system of 104 kWh (see Figure 14, right).

Modeling the *Mbita WeTu Hub* PV system size to fulfill the electric demand requirements was done with the Conventional and Renewable Energy Optimization Toolbox (CARNOT). A time-series of input meteorological data, such as solar irradiation, ambient temperature, load profile, and other technical characteristics of the planned PV systems, is also required for yield simulation modeling [44].

Figure 14. The layout of the developed PV system simulation model.

The CARNOT tool enables a time-series analysis of the system's power generation, consumption, battery SoC, inverter efficiency, and electricity shortfall using MATLAB/Simulink.

The CARNOT PV model employs a CARNOT block set, which includes meteorological data, PV module orientation, and PV modules, in a MATLAB/Simulink environment. The CARNOT tool utilizes the 'PV module' block set to simulate and compute the PV module's output power (P) in watts (W) based on the module characteristic parameter using the equation below:

$$P = \frac{S_R}{I_R} \times IAM \times P_{\max} \times (1 - (T_a + T_d \times \frac{S_p}{I_R}) - M_T) \quad (1)$$

where:

P = output power of the PV module in W.

S_R = solar radiation.

I_R = incident radiation at STC: 1000 W/m².

IAM = incidence angle modifier: 1 for vertical direct solar radiation. It follows the reflection law of Fresnel.

$P_{\max}$ = peak power (W_p) at STC in W.

T_a = ambient temperature.

T_d = temperature difference to ambient at full solar radiation (1000 W/m²): 40 K.

S_p = solar power.

M_T = module temperature at STC: 25 °C.

6.4.2. Simulation Results

Figure 15 shows the total annual hourly PV electricity production of 37,785 kWh, the electricity demand of 6278 kWh, and the electricity surplus of 30,493 kWh. There was a 0 kWh electricity deficit obtained because the PV system can cover the whole annual electricity demand. It can also be seen in Figure 15 that the battery SoC was not below 80% because of low electricity demand. Therefore, the number of e-bike batteries to be charged daily at the *WeTu Hub* was assumed in line with the obtained electricity surplus.

Figure 15. Annual hourly PV electricity production, demand, surplus in kW.

7. Field Measurement Investigation on e-Bikes

Various driving tests were carried out on the e-bikes by MOI university and WeTu engineers at Mbita to measure the distance-related energy consumption (kWh/100 km) of the bikes. During the field measurement, trip distance, terrain, speed, and payload weight of the bikes were taken into consideration.

The test's outcome, which aims to quantify battery energy usage in kWh per 100 km, will aid in determining how many battery swaps a rider may require per daily trip distance. As a result, the data can be used to optimize the integration of e-bikes into the WeTu Hub.

7.1. Measurement Investigation on OpiBus Bike

The OpiBus bike batteries' energy recording and assessment results were determined. The distance traveled, the payload of the bike (driver + passenger), and the energy requirement (kWh/100 km) were among the other data determined (see Figure 16). Depending on the road surface, seven separate tests were conducted on tarmac-surfaced routes and six different tests on non-tarmac-surfaced routes (i.e., gravel or soil roads were evaluated). Figure 16 depicts a graphical representation of the OpiBus bike's battery energy requirement as a function of the road surface. It can be seen that driving on non-tarmac terrain consumes more energy than driving on tarmac. From the evaluation process, it can be seen that battery test number 4 has a lower energy consumption of 6 kWh/100 km at an average payload weight of 160 kg and an average speed of 45 km/h than in contrast to battery test number 3 with higher energy consumption of 6.3 kWh/100 km at a payload 80 kg at speed of 45 km/hr. This may be attributed to the landscape (i.e., gradient angle) of the road surface which was not recorded during the measurement investigation. The average battery electricity demand on tarmac terrain was 5.7 kWh/100 km at an average payload of 145 kg at 50.7 km/h. The average battery electricity demand on non-tarmac terrain was 7.3 kWh/100 km at an average payload of 136 kg at 45.8 km/h. The total test distance-related average electricity consumption on both terrains was 6.4 kWh/100 km at an average payload of 141 kg at 48.5 km/h. Therefore, it can be concluded that an OpiBus bike with 2.16 kWh battery capacity running at an average payload of 141 kg and, at an average speed of 48 km/h would require at least two battery swaps to cover a trip of 100 km/day. This is comparatively in line with the report of [34] that an electric motorcycle has a real-world energy consumption varying from 0.71 to 9.3 kWh/100 km.

Figure 16. Battery electricity demand depending on the road surface (OpiBus).

7.2. Measurement Investigation on BodaWerk Bike

An investigation on the BodaWerk bike was done in the same manner as the investigations on the OpiBus batteries. Among other metrics, the distance traveled, the payload of the bike, and the energy usage (kWh/100 km) were determined. Five distinct tests were carried out on tarmac-surfaced routes. Figure 17 depicts a graphical representation of the battery energy requirement for the BodaWerk bike on a tarmac road surface. According to Figure 17, the average battery energy consumption on the tarmac terrain was 3.9 kWh/100 km at an average payload weight of 74 kg and an average speed of 39 km/h during the assessment phase. As a result, it is possible to deduce that a BodaWerk bike with 2.2 kWh battery capacity running at an average payload of 74 kg and, at an average speed of 39 km/h would require at least one battery swap to cover a trip of 100 km. This is comparatively in line with the report of [45] that an electric motorcycle has a real-world energy consumption varying from 0.71 to 9.3 kWh/100 km. This has further confirmed the report of [46] that a BodaWerk bike with 2.2 kWh battery capacity operating at an average payload of over 70 kg would require at least one battery swap for 100 km range.

Figure 17. Distance-related battery electricity demand depending on the road surface (Bodawerk).

7.3. Measurement Investigation on Cargo Bike

Furthermore, testing was performed on the business Anywhere Berlin's electrically powered cargo bicycles. Figure 18 depicts the evaluation of the particular, distance-related energy consumption in kWh/100 km. Four distinct tests were conducted on non-tarmac roads, and one test was conducted on mixed terrain (tarmac and non-tarmac). According to Figure 18, the average battery energy requirement over non-tarmac terrain was 3.3 kWh/100 km at an average payload of 86 kg and an average speed of 22.7 km/h during the assessment procedure. The average battery energy requirement over mixed terrain was 10.2 kWh/100 km with a payload weight of 210 kg and a speed of 24 km/h. On both terrains, the total test distance-related average power consumption was 4.2 kWh/100 km with a payload weight of 102 kg at 22.9 km/h. As a result, a cargo bike with a 1.1 kWh battery capacity and an average payload weight of 102 kg, and an average speed of 22.9 km/h would require at least three battery swaps to cover a 100 km journey. This is in line with the report of [46] that a 4 kWh battery capacity would be required for an 80 km range on Anywhere Berlin cargo bike.

Figure 18. Distance-related battery electricity demand depending on the road surface (Anywhere Berlin cargo bikes).

The summary of the future consumer (i.e., e-bikes) measurement results is shown in Table 4. It can be seen that the OpiBus bike has an average energy usage per recharge of 2.16 kWh with an average energy requirement of 6.3 kWh/100 km at 129 kg average payload (rider + passenger). The BodaWerk bike has an average energy usage per recharge of 2.2 kWh with an average energy requirement of 3.9 kWh/100 km at a 74.12 kg average payload. The cargo bike has an average energy usage per recharge of 1.05 kWh with an average energy requirement of 4.23 kWh/100 km at a 102.31 kg average payload. It is clear from Table 4 that the energy demand in kWh for the different bikes differs from each other. The BodaWerk bike has the lowest energy demand of 3.93 kWh/100 km while the OpiBus has the highest energy demand of 6.3 kWh/100 km. This can partly be attributed to the different payload weights on the bikes. However, further effects that were not considered during the measurement phase have to be further investigated such as the gradient of the road surface. The energy demands recorded during the measurement are still in line with what other studies have indicated that the certified and real-world energy consumption for e-bikes vary between 0.17 and 9.3 kWh/100 km [45].

Table 4. Summary of electric bike measurement results.

Type of Load	Battery Size in kWh	Distance Covered in km	Weight in kg	Speed in km/h	Charge Time in h	Charge Rate in W	Energy Demand in kWh/100 km
OpiBus	2.16	36.89	129.84	47.80	2.7	800.00	6.40
BodaWerk	2.20	48.12	74.12	39.40	2.4	900.00	3.60
E-Cargo	1.05	29.03	102.31	22.88	5.0	200.00	4.23

The measurement analysis determined the quantity of daily power and energy required to charge the e-bike batteries. The results of the measurement analysis aided in the development of hourly, daily, and annual load profiles (see **next chapter**) for each bike, considering energy consumption, battery capacity, charging power, and charging time.

8. Integration of e-Bikes and Additional Fishing Lanterns into WeTu Hub

A scenario was used to describe the prospective integration of the e-bikes into the *WeTu Hub* considering the surplus obtained in Figure 11. The scenario considered/assumed different numbers of e-bike batteries and additional lanterns depending on the type of day (see Table 5).

Table 5. System design scenario for load profile generation.

Type of Day	BodaWerk Battery Target	Cargo Battery Target	OpiBus Battery Target	Fishing Lantern Target	Total Electricity Demand in kWh/day
Full moon	9	6	9	100	51.9
Non-full moon	9	6	9	200	60.6

Realistic daily runtimes for the various major electric loads shown in Table 5 were estimated, generated based on the surplus in Figure 15, and integrated into the existing load profile in Figure 12. The annual electricity profiles from the daily profiles were generated using MATLAB. The annual electricity demand of 27,267 kWh was generated with the specific peak electricity demand of 14.8 kWh (see Figure 19).

Figure 19. WeTu Hub annual hourly electricity demand profile including e-bikes.

Result and Discussion

Figure 20 shows the annual monthly-hourly PV electricity production, electricity demand, and electricity deficit. It can be seen that June to August has the lowest electricity deficit. November has the highest electricity deficit followed by May, then April due to weather conditions. An annual PV electricity production of 37,785 kWh, the electricity demand of 27,267 kWh, and electricity deficit of 376 kWh were respectively obtained. Figure 21 shows the week in April with the lowest PV production, thereby yielding the highest energy deficit of 70.6 kWh across the month.

Figure 20. Annual hourly PV electricity production, demand, and deficit in kW.

Figure 21. Hourly PV electricity production, demand, and deficit in kW for a week in April (23.04–29.04).

It can be also seen from Figure 21 that an electricity deficit was obtained between hours 2768 and 2800 due to low PV electricity production and the central battery was drained to its set minimum SoC of 40%. In order to reduce the energy deficit, an optimization algorithm was developed and presented in the next section.

9. Development of a Load Optimization Algorithm for Mbita WeTu Hub

A load optimization algorithm was developed, which resulted in a nonlinear programming (NLP) problem, for energy deficit reduction and optimal integration of electric mobility into the Mbita WeTu Hub PV system. The optimization problem assisted in minimizing the energy deficit without having to increase the size of the PV system, usage of the grid, or diesel generator. The optimization model was created to handle the NLP problem by optimizing electric loads such as e-bikes and fishing lights to better use the PV power, lowering energy deficit and cost. For the successful simulation of the load optimization algorithm, a metrological hourly dataset for the entire year was employed. A sensitivity analysis of the NLP optimization model was carried out to evaluate the impact of the electric loads on the objective function.

9.1. Load Optimization Using Non-Linear Programming (NLP)

The main purpose of the load optimization concept is to design a system that captures the maximum amount of variable PV generation, then sizes and schedules a finite number of electric loads to track available PV power. The approach is to use the MATLAB fmincon solver for NLP.

NLP is the optimization problem of minimizing an objective function expressed by variables, subject to nonlinear equality and inequality constraints. Constraints are necessary to ensure that the load sizing is adequate, avoiding system overloads at the same time. Figure 22 shows the architecture of the NLP-based load optimization algorithm.

Figure 22. The architecture of the NLP-based load optimization algorithm.

The branch and bound, branch and cut, and branch and price algorithms are frequently used to tackle the NLP optimization problem. An objective function, general constraints, and variable boundaries must all be solved, much like in linear programming. A nonlinear program, on the other hand, must include at least one nonlinear function, which might be the objective function or some or all of the constraints.

MATLAB nonlinear programming solver finds the minimum of a problem specified by:

$$\text{Minimize } f^T x \text{ subject to } \begin{cases} c(x) \leq 0 \\ ceq(x) = 0 \\ A.x \leq b \\ Aeq.x = beq \\ lb \leq x \leq ub \end{cases}$$

b and beq , are vectors, A and Aeq are matrices, $c(x)$ and $ceq(x)$ are functions that return vectors, and $f(x)$ is a function that returns a scalar. $f(x)$, $c(x)$, and $ceq(x)$ can be nonlinear functions. x , lb , and ub can be passed as vectors or matrices. $Aeq.x = beq$ is an equality, $A.x \leq b$ and $lb \leq x \leq ub$ are inequality constraints that are considered in the optimization problem for attaining the accurate, efficient optimal solution of the objective function.

9.1.1. Formulation of the Load Optimization Problem

The load optimization problem is formulated by the objective function which considers the charging capacity and operational priority of each load as well as the maximum number of loads charged per hour. The *fmincon* solver then minimizes the objective function at a given PV generation by optimally scheduling the different loads. The objective function is defined as

$$\text{fun} = \sum_{k=1}^n (LP_k(t) \times Aeq_k(t) \cdot x_k(t)) \quad (2)$$

where LP_k is the load priority for each load at any given time (t), x_k is the hourly target of various loads that can be optimized at any given time (t), Aeq_k is the charging rate of each load per hour in kW, n is the total number of the different loads as shown in Table 6. The final objective function for the given problem is shown in equation 5 where the first priority goes to lanterns, second, third, and fourth priorities go to e-bikes, respectively.

$$\text{fun} = (1 \times 37 \cdot x_1) + (2 \times 200 \cdot x_2) + (3 \times 800 \cdot x_3) + (4 \times 900 \cdot x_4) \quad (3)$$

To maintain the balance in the system and to meet the load demand, the total demand of the loads must not exceed the PV-generated power (beq) at any given time (t). This is given by

$$\sum_{k=1}^n (Aeq_k(t) \cdot x_k(t)) = beq \quad (4)$$

The hourly target of each load (i.e., x_k , x_{k+1}) that can be charged at any given time (t) should not be less than the minimum required number of each load (i.e., lb_k , lb_{k+1}) which is 0 and should not exceed the maximum hourly target of each load (i.e., ub_k , ub_{k+1}) at any given time. This is given by:

$$lb_k(t) \leq x_k(t) \leq ub_k(t) \quad (5)$$

$$lb_{k+1}(t) \leq x_{k+1}(t) \leq ub_{k+1}(t) \quad (6)$$

Table 6. Detailed information of the major loads at *Mbita WeTu Hub*.

Type of Loads	Daily Battery Target	Peak Sun Hours (h)	Charing Time (h) per Device	Hourly Battery Target (x_k)	Charging Rate (W) per Device	Energy Required (Wh) per Device
Cargo bike	6	6.5	7	5	200	1050
Lanterns	200	6.5	2.8	193	37	105
<i>OpiBus</i> bike	9	6.5	2.7	4	800	2160
<i>BodaWerk</i> bike	9	6.5	2.4	4	900	2200

Hourly target = daily battery target ÷ (peak sun hours ÷ charging time).

9.1.2. Simulation Results with NLP Load Optimization Algorithm

Load demands for fishing lanterns and e-bike batteries were generated based on the MATLAB developed *NLP* load optimization algorithm. The developed load optimization algorithm captures the maximum amount of variable solar generation, which then sizes and schedules a finite number of loads (i.e., e-bikes, fishing lanterns) to track available intra-day solar PV power. The annual load profiles were also generated for workdays and weekends based on the moon phase.

The *NLP* load optimization algorithm also can check for today's and tomorrow's PV power production and if there is a potential lack of energy in tomorrow's PV power production, part of tomorrow's loads will be shifted to today in order to avoid the risk of not meeting the daily target of tomorrow. This concept checks the surplus of today and shifts tomorrow's loads to today.

After *NLP* optimization, an annual load profile of 30,767 kWh was generated which is an 11% increase over the non-optimized load profile of 27,267 kWh. This increase is enough to charge four additional *OpiBus* bike batteries daily. Figure 23 shows the hourly results of the electricity PV production, demand, and deficit after load shifting and optimization.

An annual PV electricity production and a reduced deficit of 37,785 kWh and 1 kWh were, respectively, obtained from the simulated PV system.

Figure 23. Hourly results after load shifting and optimization.

Figure 24 shows the result of Figure 21 after load shifting. After optimization, the electricity deficit was reduced by shifting and optimizing the major daily loads which are shown in Figure 24. However, some loads of hours 2744–2756 in Figure 24 were shifted to hours between 2718 and 2730 because of the potential lack of energy in hours 2744–2756. The load shifting is limited to the number of available devices to be charged for hours 2744–2756 and the energy surplus of hours 2718–2730. Figure 25 shows the flowchart of the NLP load optimization algorithm with the load shifting concept.

Figure 24. A week in April after load shifting and optimization.

Figure 25. Flowchart of the *NLP* load optimization algorithm with load shifting concept.

The development of a load optimization scheme using MATLAB *NLP* algorithm for optimum integration of the e-bikes solutions into the *Mbita WeTu Hub* off-grid PV system helped in reducing energy deficit without necessarily increasing the PV system size, the use of grid connection or diesel generator.

The results obtained show that the system with the *NLP* algorithm was able to prioritize, schedule, and optimize the major loads' demand in line with intra-day PV production. The *NLP* algorithm was also able to shift loads of days with a potential lack of energy to the days with surplus energy based on the moon phase.

Furthermore, the *NLP* algorithm was able to generate more annual electricity demand of 30,767 kWh which is 11% more than the annual electricity demand of 27,276 kWh for the system without *NLP* optimization.

The further obtained results show that the system with *NLP* algorithm was able to reduce the annual energy deficit for the system without *NLP* optimization from 376 to 1 kWh. Hence, it is concluded that the load optimization algorithm using MATLAB *NLP* has helped in the optimal integration of the e-bikes solutions into the *Mbita WeTu Hub's* 30 kWp off-grid PV system at a low cost.

10. Conclusions

This paper investigated the integration of e-bikes into an off-grid 30 kWp *WeTu Hub* PV system, which is located in rural Kenya using MATLAB/Simulink/CARNOT 7.0 Toolbox. Analysis of the electricity PV production, demand, and deficit was carried out. The obtained annual PV electricity production stood at 37,785 kWh, with an annual electricity demand of 27,267 kWh (non-optimized load profile). As PV system size and performance are highly dependent on meteorological variables such as solar irradiation, wind speed, and ambient temperature, the findings obtained reveal a 376 kWh yearly electricity deficit for the system with the non-optimized load profile. As a result of the PV system's variabilities, the system was unable to provide the whole power demand at the *WeTu Hub*.

Therefore, to avoid increasing the technical size of the PV system or the use of diesel generators or grid connections for electricity deficit reduction, a load management algorithm (*NLP* algorithm) was developed to optimally integrate the e-bikes solutions into the *WeTu Hub*. The load management algorithm captured the maximum amount of variable solar generation, which then sizes and schedules a finite number of devices to track available solar PV power. After the load optimization, an annual electricity demand of 30,767 kWh was obtained which is 11% more than the non-optimized load profile of 27,267 kWh. This 11% increase (3500 kWh) is enough to charge 80 additional lanterns or four additional OpiBus batteries per day.

The further obtained results show that the system with *NLP* algorithm was able to reduce the annual energy deficit for the system without *NLP* optimization from 376 to 1 kWh by maintaining the same PV and battery capacities of 30 kWp and 104 kWh, respectively, for both systems. Similarly, PV modules, inverters, and battery costs were significantly avoided by using *NLP* load optimizer-based system. Hence, the *NLP*-based system also helped in the optimal integration of electric mobility solutions into the *Mbita WeTu Hub* off-grid PV system at a low cost. This has greatly contributed to improving the work of [18].

Finally, with the developed *NLP* algorithm an APP was developed using MATLAB App designer to give any off-grid PV operator the ability to schedule, optimize and shift e-mobility and non-e-mobility loads in line with 7 days PV forecast.

Author Contributions: Conceptualization, A.B., M.E., W.Z.; methodology, A.B., M.E.; resources, A.B.; writing—original draft preparation, A.B.; writing—review and editing, A.B., C.T., M.E.; visualization, A.B., M.E.; supervision, M.E., W.Z. All authors have read and agreed to the published version of the manuscript.

Funding: The project on which this paper is based was implemented by Siemens Stiftung and funded by the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) under contract number 81247156.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Joseph, R. CLEAN TRANSPORT: Electric Boda-Bodas Launch—A Promising Day For Electric Transportation in East Africa. Available online: <https://cleantechnica.com/2021/03/02/electric-boda-bodas-launch-a-promising-day-for-electric-transportation-in-east-africa/> (accessed on 10 March 2021).
2. Casals, L.C.; Martinez-Laserna, E.; García, B.A.; Nieto, N. Sustainability analysis of the electric vehicle use in Europe for CO₂ emissions reduction. *J. Clean. Prod.* **2016**, *127*, 425–437. [CrossRef]
3. Åhman, M. Primary energy efficiency of alternative powertrains in vehicles. *Energy* **2001**, *26*, 973–989. [CrossRef]
4. Kempton, W. Electric vehicles: Driving range. *Nat. Energy* **2016**, *1*, 16131. [CrossRef]
5. Hardman, S.; Shiu, E.; Steinberger-Wilckens, R. Comparing high-end and low-end early adopters of battery electric vehicles. *Transp. Res. Part A Policy Pract.* **2016**, *88*, 40–57. [CrossRef]
6. Alkaws, G.; Baashar, Y.; Abbas, D.U.; Alkahtani, A.A.; Tiong, S.K. Review of Renewable Energy-Based Charging Infrastructure for Electric Vehicles. *Appl. Sci.* **2021**, *11*, 3847. [CrossRef]

7. Von Jouanne, A.; Husain, I.; Wallace, A.; Yokochi, A. Gone with the wind: Innovative hydrogen/fuel cell electric vehicle infrastructure based on wind energy sources. *IEEE Ind. Appl. Mag.* **2005**, *11*, 12–19. [\[CrossRef\]](#)
8. Shukla, A.; Verma, K.; Kumar, R. Impact of EV fast charging station on distribution system embedded with wind generation. *J. Eng.* **2019**, *2019*, 4692–4697. [\[CrossRef\]](#)
9. Patrick, C. Design of rural photovoltaic water pumping systems and the potential of manual array tracking for a West-African village. *Sol. Energy* **2014**, *103*, 288–302. [\[CrossRef\]](#)
10. WeTu Ltd., WeTu. Available online: <https://wetu.co.ke/> (accessed on 21 April 2020).
11. Akindare, O. The World is Leaving Africa Behind in Electric Vehicle Adoption. Available online: <https://techcabal.com/2018/08/20/the-world-is-leaving-africa-behind-in-electric-vehicle-adoption/> (accessed on 25 April 2019).
12. Gilbert, N. Africa Urged to Use Electric Cars to Cut Air Pollution. Available online: <https://techcabal.com/2018/08/20/the-world-is-leaving-africa-behind-in-electric-vehicle-adoption/> (accessed on 26 April 2019).
13. SLoCaT, Transport and Climate Change Global Status Report. Partnership on Sustainable, Low Carbon Transport (SLoCaT). Available online: http://slocat.net/sites/default/files/slocat_transport-and-climate-change-2018-web.pdf (accessed on 3 August 2019).
14. Martin, E. Transport Sector Climate Change Team Coordinator; Esther, G; Climate Change focal Person. Transport Sector Climate Change Annual Report: Performance and Implementation of Climate Change Actions. Available online: https://www.international-climate-initiative.com/fileadmin/Dokumente/2020/2019_Transport_Sector_Climate_Change_Annual_Report_Kenya.pdf (accessed on 4 April 2021).
15. Ochieng, R. URBAN SUSTAINABILITY REVIEW (USR) MBITA: HOMA BAY COUNTY. Available online: <http://symbiocitykenya.org/wp-content/uploads/2017/12/USR-HomabayMbita-highres-SymbioCity.pdf> (accessed on 22 November 2019).
16. Kumar, A. Understanding the Emerging Role of Motorcycles in African Cities: A Political Economy Perspective. Sub-Saharan Africa Transport Policy Program (SSATP) Discussion Paper. Available online: <https://openknowledge.worldbank.org/handle/10986/17804> (accessed on 27 November 2019).
17. Tomonori, H.; Yoshito, F.; Samson Muuo, N.; Chihiro, T.; Ibrahim, K. Spatial Distributions of HIV Infection in an Endemic Area of Western Kenya: Guiding Information for Localized HIV Control and Prevention. *PLoS ONE* **2016**, *11*, e0148636. [\[CrossRef\]](#)
18. Gammon, R.; Sallah, M. Preliminary Findings From a Pilot Study of Electric Vehicle Recharging From a Stand-Alone Solar Minigrid. *Front. Energy Res.* **2021**, *8*, 374. [\[CrossRef\]](#)
19. Grande, L.S.A.; Yahyaoui, I.; Gómez, S.A. Energetic, economic and environmental viability of off-grid PV-BESS for charging electric vehicles: Case study of Spain. *Sustain. Cities Soc.* **2018**, *37*, 519–529. [\[CrossRef\]](#)
20. Hafez, O.; Bhattacharya, K. Optimal design of electric vehicle charging stations considering various energy resources. *Renew. Energy* **2017**, *107*, 576–589. [\[CrossRef\]](#)
21. Ekren, O.; Hakan Canbaz, C.; Güvel, Ç.B. Sizing of a solar-wind hybrid electric vehicle charging station by using HOMER software. *J. Clean. Prod.* **2021**, *279*, 123615. [\[CrossRef\]](#)
22. Liang, X.; Tanyi, E.; Zou, X. Charging Electric Cars from Solar Energy. 2016. Available online: <http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A935136&dswid=-2621> (accessed on 10 March 2021).
23. Mueller, O.M.; Mueller, E.K. Off-grid, low-cost, electrical sun-car system for developing countries. *IEEE Glob. Humanit. Technol. Conf. (GHTC 2014)* **2014**, *34*, 14–17.
24. Gautham, R.; Chandra, M.; Peter, V.; Tim, V. Solar Powered E-Bike Charging Station with AC, DC and Contactless Charging. In Proceedings of the 20th European Conference on Power Electronics and Applications EPE'18 ECCE Europe, Riga, Latvia, 17–21 September 2018; pp. 1–10.
25. Wi, Y.-M.; Lee, J.-U.; Joo, S.-K. Electric vehicle charging method for smart homes/buildings with a photovoltaic system. *IEEE Trans. Consum. Electron.* **2013**, *59*, 323–328. [\[CrossRef\]](#)
26. Chandra Mouli, G.R.; Bauer, P.; Zeman, M. System design for a solar powered electric vehicle charging station for workplaces. *Appl. Energy* **2016**, *168*, 434–443. [\[CrossRef\]](#)
27. Bhatti, A.R.; Salam, Z.; Ashique, R.H. Electric Vehicle Charging Using Photovoltaic based Microgrid for Remote Islands. *Energy Procedia* **2016**, *103*, 213–218. [\[CrossRef\]](#)
28. Bimenyimana, S.; Wang, C.; Nduwamungu, A.; Asemota, G.N.O.; Utetiabo, W.; Ho, C.L.; Niyonteze, J.D.D.; Hagumimana, N.; Habineza, T.; Bashir, W.; et al. Integration of Microgrids and Electric Vehicle Technologies in the National Grid as the Key Enabler to the Sustainable Development for Rwanda. *Int. J. Photoenergy* **2021**, *2021*, 9928551. [\[CrossRef\]](#)
29. Park, E.; Kwon, S.J. Renewable electricity generation systems for electric-powered taxis: The case of Daejeon metropolitan city. *Renew. Sustain. Energy Rev.* **2016**, *58*, 1466–1474. [\[CrossRef\]](#)
30. Dziadek, P.-E.; Feucht, W.; Mitnacht, A.; Kula, H.-G.; Frank, H. Eco-friendly application of EVs for home-to-work and home-to-education transports. In Proceedings of the 2013 IEEE International Conference on Industrial Technology (ICIT), Cape Town, South Africa, 25–28 February 2013; pp. 705–709.
31. Siemens Stiftung, WeTu Social Business Model with New Technologies. Available online: <https://www.siemens-stiftung.org/en/projects/wetu/> (accessed on 2 August 2020).
32. Sitati, S. *Report on the Measurement Campaign E-Mobility for Rural Africa*; MOI University: Eldoret, Kenya.
33. Mbita Solar Hub Engineering Documentation. Knights Energy.

34. HOPPECKE. Accumulatorenwerke HOPPECKE Carl Zoellner & Sohn GmbH OPzS Solar. Power. Vented Lead-Acid Battery for Cyclic Applications. Available online: https://www.europe-solarstore.com/download/hoppecke/opzs/OPzS_solar.power_en.pdf (accessed on 21 September 2019).
35. SMA Solar Technology AG. Off-Grid Inverter SUNNY ISLAND 5048. Technical Description. Available online: <https://rexel-cdn.com/Products/SMA/SI5048U.pdf?i=216B015B-AA7E-4040-8D56-CE07DEC2145F> (accessed on 5 February 2020).
36. SMA Solar Technology AG, Operating Manual SUNNY TRIPOWER 15000TL/20000TL/25000TL. Available online: <https://www.sma.de/en/products/solarinverters/sunny-tripower-15000tl-20000tl-25000tl.html> (accessed on 4 April 2020).
37. SolarWorld, Sunmodule SW 220 Poly. Available online: http://www.iwr.de/solarworld/SWM_220_poly_05-8.pdf (accessed on 10 September 2019).
38. Bosch Solar. Powerful Performance—High Stability. Bosch Solar Module c-Si M 60 EU30117. Available online: <https://www.solarchoice.net.au/wp-content/uploads/Bosch-Solar-Module-c-Si-M-60-Australia.pdf> (accessed on 5 April 2020).
39. WeHub Technical Performance Assessment Report. SERC—Strathmore University Energy Research Centre: Kenya.
40. Time and Date, Moon Phases 2020—Lunar Calendar for Mbita, Homa Bay, Kenya. Available online: <https://www.timeanddate.com/moon/phases/@187028?year=2020> (accessed on 1 January 2021).
41. Meteotest, A.G. Meteonorm Software Worldwide Irradiation Data. Available online: <https://meteonorm.com/en/> (accessed on 4 April 2020).
42. Arnold Wohlfeil, CARNOT Toolbox. Available online: <https://nl.mathworks.com/matlabcentral/fileexchange/68890-carnot-toolbox> (accessed on 8 February 2020).
43. Bugaje, A.; Ehrenwirth, M.; Trinkl, C.; Zörner, W. Investigating the Performance of Rural Off-Grid Photovoltaic System with Electric-Mobility Solutions: A Case Study Based on Kenya. *J. Sustain. Dev. Energy Water Environ. Syst.* **2021**. [CrossRef]
44. Shukla, A.K.; Sudhakar, K.; Baredar, P. Design, simulation and economic analysis of standalone roof top solar PV system in India. *Sol. Energy* **2016**, *136*, 437–449. [CrossRef]
45. Weiss, M.; Cloos, K.C.; Helmers, E. Energy efficiency trade-offs in small to large electric vehicles. *Environ. Sci. Eur.* **2020**, *32*, 46. [CrossRef]
46. Siemens Stiftung, E-Mobility Solutions for Rural Sub-Saharan Africa: Leveraging Economic, Social and Environmental Change. Available online: <https://www.siemens-stiftung.org/wp-content/uploads/medien/publikationen/publication-emobility-emobilitysolutionsforruralsubaharanafrica-siemensstiftung.pdf> (accessed on 4 April 2021).