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

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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.

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

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 WaterEnergy 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].](image-url)
In the year 2015, total domestic transport sector emissions in Kenya amounted to 11.25 MtCO$_2$ e (see Figure 2). Kenya has set a target to reduce its transport sector emissions to 3.46 MtCO$_2$ e by 2030. Therefore, to achieve the set target, the annual emissions must not increase by more than 0.4 MtCO$_2$ e per year. However, the average annual emissions increased by 0.6 MtCO$_2$ e between 2010 and 2015, thereby putting the sector off track towards meeting its 2030 target [14].

![Figure 2. Trend of transport sector emissions (MtCO$_2$ e), excluding waterborne navigation (data according to [14]).](image)

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, CO$_2$ 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.
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 | • 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 | • 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 | • 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 | • 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     | • 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 | • 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 | • 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 | • 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 | • 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   | • 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   | • 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 | • Using HOMER, the paper investigates how local taxi services in Daejeon may leverage prospective renewable power producing systems.  
• In Daejeon, 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  | • 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.

![Image of the Water-Energy Hub at Mbita, Kenya](image-url)

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

| 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.

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 Meteonorm [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](image-url)

**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.
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).
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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 9. 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 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.

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. 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.](image)

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].
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:

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

where:
- \(P\) = output power of the PV module in W.
- \(S_R\) = solar radiation.
- \(I_R\) = incident radiation at STC: 1000 W/m\(^2\).
- IAM = incidence angle modifier: 1 for vertical direct solar radiation. It follows the reflection law of Fresnel.
- \(P_{\text{max}}\) = peak power (W\(_p\)) at STC in W.
- \(T_a\) = ambient temperature.
- \(T_d\) = temperature difference to ambient at full solar radiation (1000 W/m\(^2\)): 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.
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.
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 16. Battery electricity demand depending on the road surface (OpiBus).

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-tarmacad 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.

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 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 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).
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.

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.](image)

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:

```
Minimize \( f^T x \) subject to
```

\[
\begin{align*}
c(x) & \leq 0 \\
ceq(x) & = 0 \\
A.x & \leq b \\
Aeq.x & = beq \\
lb & \leq x \leq ub
\end{align*}
\]

\( b \) 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

\[
\text{fun} = \sum_{k=1}^{n} \left( LP_k(t) \times Aeq_k(t) \times x_k(t) \right)
\]

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.

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

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

\[
\sum_{k=1}^{n} \left( Aeq_k(t) \times x_k(t) \right) = beq
\]

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 \((i.e., lb_k, ub_{k+1})\) 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:

\[
lb_k(t) \leq x_k(t) \leq ub_k(t)
\]

\[
lb_{k+1}(t) \leq x_{k+1}(t) \leq ub_{k+1}(t)
\]

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

| Type of Loads       | Daily Battery Target | Peak Sun Hours (h) | Charging 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                            |
| Opibus bike         | 9                    | 6.5                | 2.7                           | 4                             | 800                           | 2160                           |
| BodaWerk bike       | 9                    | 6.5                | 2.4                           | 4                             | 900                           | 2200                           |

Hourly target = daily battery target \(\div\) (peak sun hours \(\div\) 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 todays 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.
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.

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