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Techno Economic Assessment and ANFIS Driven Optimization for Solar PV-Biomass Hybrid Energy System

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Abstract
This research project aims to design and evaluate a solar PV-biomass hybrid energy system for rural electrification in the Ugandan district of Kebisoni Rukungiri. The study uses the Adaptive Neuro-Fuzzy Inference System (ANFIS) method to improve precision and modeling accuracy. Solar radiation levels and biomass sources are sourced from NASA's website and the Uganda Meteorological Center. MATLAB/Simulink tools are used to model and simulate various hybrid system setups. Results show trade-offs between cost of energy and net present value, with significant NPV reductions ranging from 68.75% to 77.95%. Comparisons with existing systems reveal substantial cost savings and potential financial gains. This cost-effective and sustainable approach to rural electrification offers a viable solution for meeting electricity demands in remote areas, fostering economic development and enhancing living standards.

List of Abbreviations

Renewable energy sources	RES
Photovoltaic	PV
Renewable energy sources	HRES
Equilibrium Optimizer	EO
Particle Swarm Optimization	PSO
Bonobo Optimizer	BO
Quasi-Oppositional Bonobo Optimizer	QOBO
Ant bee colony	ABC
Standalone micro-grid	SMG
Invasive Weed Optimization	IWO
Model predictive control	MPC
Loss of Power Supply Probability	LPSP
Response Surface Methodology	RSM
Energy Management Strategy	EMS
Storage System Energy	SSE
State of charge	SOC
Electric cars	EVs
Net present value	NPV
Capital recovery factor	CRF

1.0 Introduction

Uganda has significant potential for renewable energy sources, including hydropower, biomass, peat, geothermal, and solar energy. However, conventional biomass and hydropower dominate energy generation, hindering economic progress (Qudrat-Ullah et al., 2021). The energy shortfall, affecting over 5.3 million households, is primarily due to supply-side deficiencies. Over 70% of Ugandans use biomass or fossil fuel-fueled equipment, causing environmental and health issues. The economic potential of solar PV systems is immense, and affordability could increase interest in these alternative electricity-generating technologies (Aarakit et al., 2021).

Electricity is scarce in remote regions, and conventional solutions like grid expansion and diesel generators have drawbacks. Renewable energy sources (RES) are being explored as a reliable and affordable alternative (Li et al., 2020). Hybrid distributed off-grid systems are more effective for providing steady electricity supply in isolated rural locations. Biomass, more reliable than solar and wind energy, is more accessible and simpler to store and transport. Utilizing biomass is feasible and necessary in remote rural areas, and it may reduce greenhouse gas emissions. Previous studies on renewable hybrid power systems have only included one or two RES (Li et al., 2020).

Kebisoni, a populous area in Rukungiri (latitude 0.85, longitude 30.0), is far from the grid system and faces economic challenges in expanding standard power supply systems. However, the region has underdeveloped renewable energy resources that could help bridge the demand-supply gap (Government, 2017). The average solar radiation ranges from 2.35 to 6.85 kWh/m^2/day, with stronger values in the north and lower values in the south. Wind speeds vary, but the region has biomass energy potential with a capacity of 1560 MW(NASA, 2023).

The current grid system limitations in Kebisoni prompt exploration of alternative energy solutions. A proposed hybrid RES combining solar and biomass energy sources could enhance power production. Solar panels harness abundant solar radiation to generate electricity, while biomass energy from organic matter offers further potential. However, due to low wind speeds in the area, wind power may not be as viable (Gumisiriza, 2020). Uganda, facing energy challenges, possesses rich RES resources including solar, hydro, and biomass. The country primarily relies on hydroelectric production, supplemented by solar, heavy fuel, and co-generation. Rural electrification is crucial for Uganda's socio-economic advancement (Kavuma et al., 2021). Hybrid power systems integrating solar PV, energy storage, and diesel backup have demonstrated significant economic benefits, including reduced fuel usage and increased overall economic gains. This sustainable approach promotes rural development by providing uninterrupted electricity while reducing dependence on fossil fuels, ultimately improving living conditions (Puglia et al., 2017).

The strategy aims to establish a reliable and cost-effective power system, particularly beneficial for rural communities in developing countries lacking access to modern energy services. A study conducted in Uganda's Kalangala region focused on developing a wind-solar hybrid system for irrigating banana crops. Results indicated the system's operability at a wind speed of 20 m/s, with a net present value of 12,935,468 UGX and a net real rate of return of 3.5% annually over five years. This research highlights the feasibility and economic sustainability of utilizing wind-solar hybrid systems for irrigation, particularly in banana production (Ssenyimba et al., 2020). Additionally, an analysis of grid-connected PV systems in Uganda projected a solar penetration rate of 6.1% by 2021, yielding an annual energy production of 69.52 GWh. These findings emphasize the technical and economic potential of grid-connected solar PV systems to enhance Uganda's energy portfolio and align with its developmental objectives (Kavuma et al., 2022).

Kebisoni Rukungiri was chosen as a case study for a Techno Economic Assessment and ANFIS Driven Optimization for Solar PV-Biomass Hybrid Energy System due to its significant energy challenges, abundant biomass resources, and unique socio-economic characteristics. The study aims to provide insights into the practical implementation and economic viability of solar PV-biomass hybrid energy systems in similar rural contexts, contributing to sustainable energy development and rural electrification efforts.

Overall, the selection of ANFIS for our research is motivated by its proven effectiveness in addressing the complex optimization challenges inherent in renewable energy systems. By leveraging the adaptive and nonlinear modeling capabilities of ANFIS, we aim to provide valuable insights into the techno-economic feasibility and optimization potential of solar PV-biomass hybrid energy systems. The hybrid system will replace traditional biomass for lighting, baking, and cooking, and dry cells for radios and cassette players. The study will assess the feasibility of using solar PV-Biomass energy from a technological and budgetary perspective, providing guidance for policymakers and stakeholders in electrifying rural areas

2.0 Literature review

The study emphasizes the importance of exploring hybrid energy sources to address the growing demand for sustainable energy solutions. By harnessing renewable resources such as solar, wind, and energy storage technologies, it becomes possible to enhance energy resilience and mitigate environmental impacts (Alzahrani et al., 2021). Various methodologies, including simulation, advanced control strategies, optimization techniques, and mathematical modeling, are employed in the design, operation, and control of hybrid energy systems (Bakare et al., 2023). Research in this field encompasses conventional, software-based, and optimization techniques, each facing challenges in managing complex systems. Furthermore, the development of software tools facilitates the design process, offering assistance in navigating the complexities of hybrid system design and operation. The comparison of several programs is shown in (Nallolla & Perumal, 2022).

The effectiveness and dependability of off-grid hybrid renewable energy systems are assessed using various planning theories and techniques (Odou et al., 2020). HOMER, a widely used software, is used for designing, scaling, and planning off-grid or grid-connected power systems due to its wide range of renewable resource inputs and system architecture. It has been used in countries like China (Li et al., 2020), Ethiopia (Gebrehiwot et al., 2019), Nigeria (Salisu et al., 2019), Ghana (Awopone, 2021), Iraq (Hassan et al., 2022) to conduct techno-economic analysis using different RES configurations, achieving better results.

Techno-economic feasibility studies assess a project's viability based on technical, economic, and environmental issues. These studies include Resource Assessment, System Integration, Performance Analysis, and System Design and Configuration (Hassan et al., 2022). Due to challenging terrain and high investment costs, expanding the grid in remote areas presents challenges. However, localized renewable energy generation systems may be a feasible solution. A recent study in West China suggests the viability of hybrid off-grid renewable energy systems, which are cost-effective and reliable for various sectors. The research emphasizes the affordability and practicality of a hybrid power system integrating solar, wind, and biomass energy, demonstrating its cost and viability benefits over grid expansion (Li et al., 2020).

Several studies have contributed to the advancement of microgrid optimization strategies. Ndiaye et al., focused on energy management strategies within a DC microgrid, utilizing an ANFIS approach with to optimize energy distribution and battery management (Ndiaye et al., 2021), Alamoudi et al. optimized the operational parameters of a PV system at a hospital using RSM and ANFIS, showcasing the system's potential for efficient energy utilization (Alamoudi et al., 2021). Madhu et al., proposed ANFIS-based strategies for power control in PV-centered DC microgrids, improving system performance (Madhu & Bijjur, 2020). Rajkumar et al. employed ANFIS for sizing hybrid renewable energy systems, ensuring reliable power delivery (Rajkumar, Ramachandaramurthy, Yong, & Chia, 2011). Thakkar et al used the Satin Bowerbird algorithm to optimize standalone microgrid component sizes, demonstrating improved solution quality (Thakkar & Paliwal, 2021). Yadav et al. investigated ANFIS application in microgrid optimization, highlighting its effectiveness in enhancing reliability and availability (Yoshida & Farzaneh, 2020).

Kharrich et al. implemented Equilibrium Optimizer (EO) for a hybrid microgrid in Dakhla, Morocco, achieving 97% renewable energy production and demonstrating quick convergence characteristics (Kharrich et al., 2021). Another study by Kharrich et al. introduced the Quasi-Oppositional Bonobo Optimizer (QOBO) for hybrid microgrids in Aswan, Egypt, addressing economic design concerns effectively (Kharrich et al., 2020) . Singh et al. proposed a small-scale microgrid for rice straw management integrating solar, battery, and the main utility grid, targeting a satisfactory Levelized Cost of Electricity (LCOE) (A. Singh & Basak, 2021). Samy et al. explored a hybrid biomass-PV microgrid in Egypt, optimizing system sizing with the HIWO/PSO algorithm (Samy & Barakat, 2019). Kamal et al., proposed a rural microgrid model for Indian villages integrating various RES to ensure dependable electrification (Kamal et al., 2023). Yadav et al., investigated the application of ANFIS in microgrid optimization, demonstrating its effectiveness in maximizing reliability and availability (Yadav et al., 2022). Murty et al., discussed cost considerations and biomass integration limitations in microgrid optimization studies, suggesting further research in these areas for comprehensive insights (Murty & Kumar, 2020).

The literature review highlights the growing importance of integrating RES to address climate change and achieve sustainable energy transitions. Hybrid RES offer a promising solution by combining multiple technologies to enhance system efficiency, reliability, and flexibility. Various optimization techniques, such as EO, QOBO, Satin Bowerbird algorithm etc, have been employed to design and optimize microgrid systems. However, there is a notable gap in research concerning the integration of biomass in optimization methods, as well as limited consideration of cost elements beyond solar and biomass integration. Exploring these aspects could provide valuable insights into enhancing the viability and functionality of HRES, addressing the need for comprehensive techno-economic feasibility studies and optimization strategies in diverse renewable energy applications.

3.0 Methodology

This chapter examines a case study in Uganda's Kebisoni Rukungiri district, focusing on the development and assessment of a Photovoltaic (PV) - Biomass hybrid energy system. The system aims to address the specific energy needs of the area by combining solar PV technology with biomass resources. The research methodology is detailed, highlighting the steps taken to assess and optimize the system's economic feasibility. On-site evaluations and surveys are conducted to collect information on solar irradiance, biomass availability, and energy demand trends. The study also uses NASA website and Uganda meteorological center to model and simulate various hybrid system setups, considering local conditions and limitations.

3.1 Description of case study

A data-driven strategy is required to determine a typical load profile for the case study. Start with collecting historical data on energy use in Kebisoni Rukungiri. This information is to be acquired through site visits, interviews, questionnaires, and data recording. The time span of the data collection will be for a day which is should be long enough to predict the daily energy trends. Kebisoni, located in Rukungiri District, Uganda, at a latitude of -0.80808 and a longitude of 29.93273, spans 77.9Km^2. It houses a population of 28,650, with a fairly even split between genders: 47.5% males and 52.5% females, as per the 2021 census. Comprising 7 parishes and 92 villages, the area's livelihood primarily revolves around agriculture. Operating independently from the main power grid, it relies on solar, generators, and biomass for energy. With roughly 420 households, there's a pressing need for sustainable energy solutions to fuel homes and support the predominantly agriculture-based economy. The hourly energy consumption, detailed in Table 1.0.

3.2 Solar irradiation data

Hourly solar irradiation data for the year 2022 at latitude -0.80808 and longitude 29.93273 was sourced from NASA's website for this study (NASA, 2023). The average hourly data obtained is depicted in Figure 1.

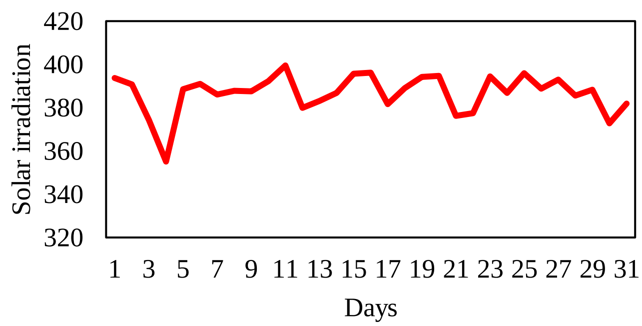

Figure 1: Hourly solar irradiation (NASA, 2023)

3.3 Biomass

Since 1989, the National Biomass Study in Uganda has tracked the country's wood resources by analyzing land cover, biomass density, forestry, agricultural crops, and animal waste. By 1995, Uganda held 477.2 million tons of woody biomass, yielding 20.4 million U-years of wood, 8.0 million years of crop residues, and 4.7 million tons per year of animal waste. For energy, there were 275.9 million tons of wood in stock, with annual yields of 14.46 million tons of wood, 1.73 million tons of residues, and 236,000 tons of animal waste. Consumption-wise, 20.2 million tons were used, primarily as 80.5% firewood, 14.5% charcoal, and 4% residue (Drichi, 2001).

The analysis conducted by (Drichi, 2001) revealed a significant shortfall in sustainable biomass flow projections, particularly emphasizing a deficit of 4.9 million tons/year in woody biomass by 1995. Due to the absence of direct biomass data for the case study, estimates were derived based on Drichi's study. Utilizing linear regression analysis, the study projected biomass consumption for the case, demonstrating a robust correlation between years and predicted biomass energy output ($y = 0.78x - 1539.3$, $R^2 = 0.9996$) as shown in Figure 2. The consistent increase in forecasted biomass energy indicates a positive trend, suggesting a continuous growth in biomass resources over time. These findings offer valuable insights for future energy planning and resource allocation strategies.

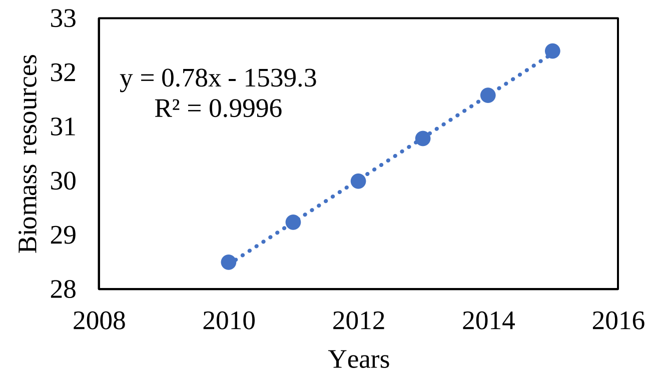

Figure 2: Correlation between the year and biomass energy resources

This study covers a population of 28,650 within a total population of 45.85 million in Uganda. This ratio helps estimate the probable biomass consumption in Kebiosoni. The forecasted values for biomass energy display a consistent upward trend from 2016 to 2022. The predicted biomass energy output steadily increases over these years, showing an incremental rise annually. This growth is illustrated by the ascending values from 33.17 kWh in 2016 to 37.88 kWh in 2022 as shown in Figure 3.

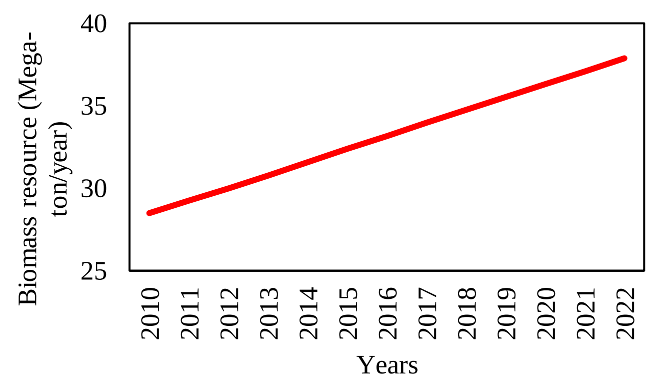

Figure 3: Forecasted biomass resources for Kebiosoni

Table 1.0: Estimated load demand for Kebidoni, Rukungiri District

Category	Load type	Power rating (W)	Quantity	Time (h)	Operating period (h)	Power usage (W)	Energy usage (kWh)
Residential	Lighting	6	150	14	18:00-06:00	900	12.6
	Radio	8	200	7	16:00-20:00	1600	11.2
	Telephone	5	20	4	14:00-05:00	100	0.4
	Fans	100	72	18	10:00-05:00	7200	129.6
	Refrigerator	800	8	24	00:00-24:00	6400	153.6
	Laptops	100	10	6	14:00-16:00	1000	6
	Water heaters	1500	3	3	06:00-12:00	4500	13.5
Commercial	Water pump	1000	2	2	16:00-18:00	2000	4
	Street light	100	10	12	18:00-04:00	1000	12
	Schools	3000	5	10	12:00-18:00	15000	150
	Health Centre	6000	3	18	19:00-08:00	18000	324
	Worship Centre	2000	6	6	18:00-20:00	12000	72
Industrial	Milling machine	1800	4	5	17:00-19:00	7200	36
	Lathe machine	2000	3	8	16:00-18:00	6000	48
	Drilling machine	1800	2	6	17:00-19:00	3600	21.6

3.4 The Proposed PV-Biomass Hybrid System

The proposed system combines solar panels, a biomass generator, a battery, and a converter. Figure 4.0 shows how these parts connect. The system gets power from solar panels and the biomass generator, without relying on the main power grid. Biomass, which includes things like agricultural leftovers and animal waste, is a plentiful energy source worldwide. It's popular for generating power, especially in rural Uganda, and it's cleaner than fossil fuels. Because it's so abundant, it's a good option for making electricity, especially in places like Uganda where animal waste can be used for power through absorption or burning. This system uses both solar and biomass power, specifically choosing biomass because it's easily available as manure year-round. This mix of solar and biomass, with a battery for storing electricity, is cost-effective and can generate power even when it's cloudy

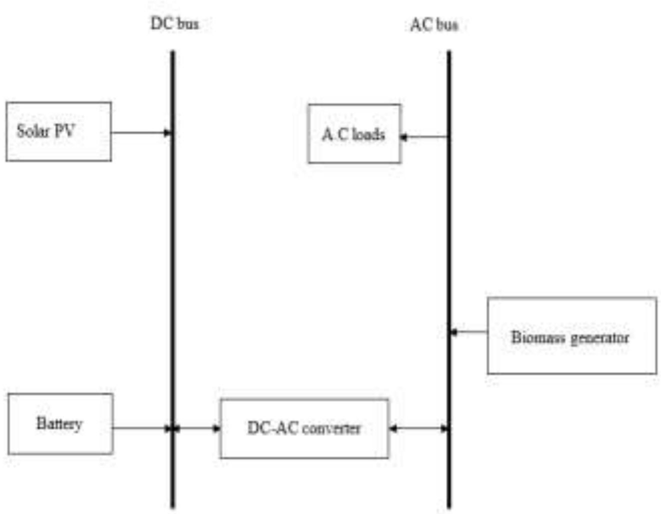

Figure 4: Proposed system configurations

3.5 ANFIS Controller Design

First introduced in 1965, the ANFIS employs approximate reasoning as opposed to exact reasoning, operating within a multi-valued logic framework. Its extensive utilization within electrical power systems revolves around the modeling of intricate energy storage management control strategies and non-linear processes. (Khaleel et al,, 2023). Blending the learning capability of artificial neural networks with rule-based fuzzy logic control, the ANFIS constructs a feed-forward neural network equipped with supervised learning prowess. This hybrid learning approach excels in modeling nonlinear systems, discerning real-time nonlinear parameters for control purposes, and making predictions. ANFIS finds effectiveness in intricate electrical systems, including Integrated Power Systems (IPS) and isolated power grids (Gaber et al,, 2021).

This ANFIS design comprises a single hidden layer, as indicated in Figure 5, and comprises five nodes: First Layer for input nodes, Second Layer for fuzzification nodes, Third Layer for product nodes (hidden), Fourth Layer for defuzzification nodes, and Fifth Layer for the output node. Moreover, certain nodes will be categorized as either adaptive or fixed nodes, determined by their updateability (Gaber et al., 2021).

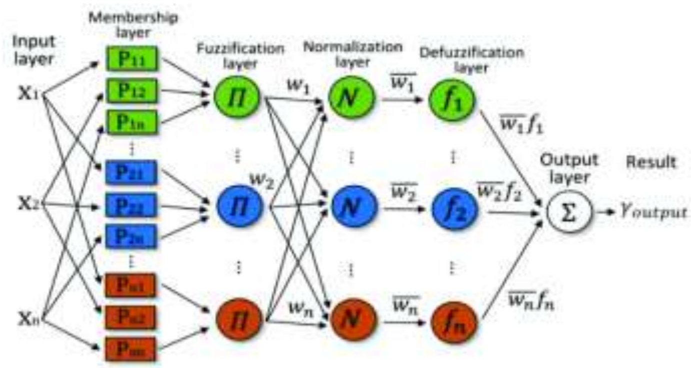

Figure 5 ANFIS architecture (Khaleel et al., 2023)

In the developed model, Table 2 encapsulates the parameters utilized, outlining the crucial elements that define the ANFIS system's structure and behavior. These parameters encompass various aspects such as membership functions, learning algorithms, and rule base, providing the foundational elements governing the model's operation.

Table 2: ANFIS parameters

S/n	Parameter	Value
1	Range of influence	0.5
2	Squash factor	1.25
3	Accept ratio	0.5
4	Reject ratio	0.15
5	Epochs	5000

The input data is segregated into three segments: 70% for training, 15% for testing, and the remaining portion reserved for checking the model's performance. The ANFIS structure employed in this study comprises two inputs and six membership functions, forming the backbone of the system's computational framework. These inputs are crucial variables that influence the system's decision-making process. Each input is associated with six membership functions, defining the range and scope of influence for these variables within the system. The membership functions aid in defining the degree to which input variables contribute to the system's output.

3.6 Operational strategy of the proposed PV-Biomass-Battery HRES

The operational strategy governing the HRES orchestrates the efficient allocation and regulation of renewable energy resources to ensure reliable power supply. Integrating solar PV, biomass, and battery technologies, the system is tactically designed to manage power distribution in accordance with a structured operating procedure, outlined in Figure 3.6.

1. Initially, surplus power generated by solar panels beyond the load demand is directed to charge the battery bank after meeting the load requirements.
2. Excess power from the solar PV system is stored in the battery bank solely when it surpasses the entire load demand.
3. If solar energy and stored battery power fall short of meeting the load, the biomass engine acts as a backup power source, supplying electricity to fulfill the load requirements.

These meticulously designed steps facilitate optimal power management within the system, considering varying conditions and trade-offs. The strategic operational guidelines aim to enhance overall system performance and achieve specific optimization objectives within the predefined operational constraints. Figure 6 illustrates the robust simulation and testing capabilities provided by MATLAB, which will be harnessed in this study.

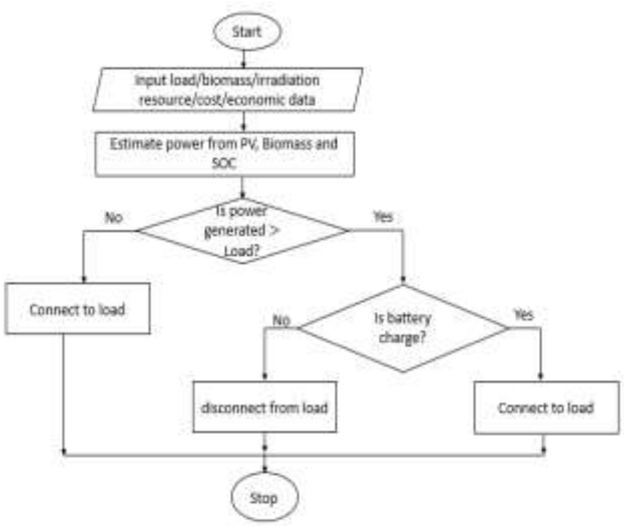

Figure 6: Proposed system methodology

3.7 System modeling

A feasibility study for a solar PV-biomass hybrid energy system is needed, involving technical, economic, and environmental aspects. The study will determine energy storage options, biomass resources, and solar panels, as well as installation and operating costs. The economic study will calculate NPC and LCOE metrics to determine the project's financial viability. The research aims to demonstrate the techno-economic feasibility of a solar-wind-biomass off-grid hybrid power system for distant rural electrification, using ANFIS for construction and analysis on a Kebisoni Rukungiri district town.

3.7.1 Mathematical model of the solar energy

A photovoltaic array's output is affected by elements such as rated capacity, module derating factor, incoming solar radiation, temperature coefficient of power, and cell temperature (1-4) (Bana & Saini, 2016). The equivalent circuit of the solar PV model is shown in Figure 7

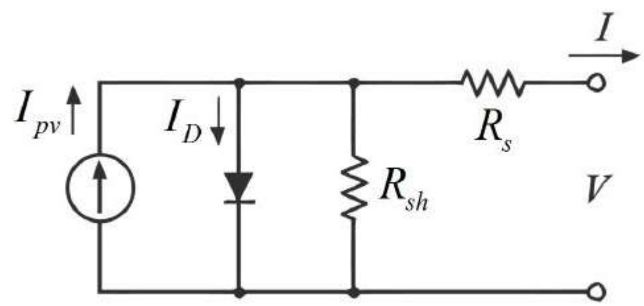

Figure 7: Solar PV equivalent circuit modelling (Bana & Saini, 2016)

Module photo current:

$$I_{ph} = \left[I_{SCr} + K_i(T - 298)\right] * \lambda / 1000 \quad (1)$$

Module reverse saturation current

$$I_{rs} = I_{SCr} / [\exp(qV_{OC} / N_s KAT) - 1] \quad (2)$$

The module saturation current varies with the cell temperature which is given by:

$$I_o = I_{rs}\left[\frac{T}{T_r}\right]^3 \exp\left[\frac{q * E_{go}}{BK}\left\{\frac{1}{T_r} - \frac{1}{T}\right\}\right] \quad (3)$$

The current output of PV module is:

$$I_{pv} = N_p * I_{ph} - I_o\left[\exp\left\{\frac{q * (V_{pv} + I_{Pv} R_s)}{N_s AKT}\right\} - 1\right] \quad (4)$$

The following equations are used to determine a PV module's output voltage (V_{pv}) and output current (I_{pv}): I_{ph} = light produced current; Io = saturation current; A = B; B = 1.6; ISCr = short-circuit current at 25°C; K_i = short-circuit current temperature co-efficient at I_{scr}; = illumination (W/m^2); Vpv = 298 K; Ipv = Io; A = B; B = 1.6; Boltzman constant = 1.3805 10-23 J/K; The band gap for silicon is E_{go}; The number of series-connected cells is N_s, whereas the number of parallel-connected cells is N_p

3.7.2 Biomass resources modeling

The solid biomass-to-electricity conversion process initially transforms the solid material into a gaseous fuel. This fuel then powers a biomass generator. The equation calculates the yearly amount of electricity generated by the biomass gasifier(Singh et al., 2016).

$$E_B = P_B \times 8760 \times C_f \tag{5}$$

When evaluating the accessible biomass, the calculation factors in the yearly biomass quantity (in tons) and the operational duration of the gasifier. The correlation between the biomass gasifier's rating and other significant factors is established as follows:

$$P_B = \frac{T_B \times 1000 \times C_B \times \eta_B}{365 \times 860 \times T} \tag{6}$$

Where: E_B represents the biomass gasifier rating, C_f stands for the gasifier capacity utilization factor set at 0.197%. C_B denotes the biomass's calorific value, fixed at 18MJ/Kg, while A represents the overall conversion efficiency of the gasifier, set at 25%. T stands for the operating hours per day.

3.7.3 Mathematical model of the battery

The cumulative aggregate of the daily charge or discharge transfers determines the battery's state of charge (SOC). It is expressed as the ratio of the usable current capacity to the nominal capacity of the battery. SOC reflects a battery's charge state and is critical for safely and effectively running electric cars (EVs). To improve battery longevity and performance, accurate SOC estimate is required (Gebrehiwot, Mondal, Ringler, & Gebremeskel, 2019):

$$SOC = 1 - \int i\eta dt / Cn \tag{7}$$

Batteries play a pivotal role in hybrid systems, particularly those that operate independently from the power grid. These systems ensure a consistent power supply, even during periods of minimal or no energy generation, and uphold a steady voltage level during periods of high demand.

The battery capacity ($\boldsymbol{C_b}$) is represented as:

$$C_b = \frac{E_t \times D_a}{l_b \times DoD \times V_b} \tag{8}$$

In this context, the variables are defined as follows: "i" represents the battery current, "Cn" stands for the nominal capacity, "t" signifies time, while "η" denotes the coulombic efficiency, calculated as the ratio of charging energy to discharging energy required to restore the initial capacity. "A" represents the autonomy days, "DoD" corresponds to the depth of discharge, "l_b" represents battery loss, "Et" signifies the total energy demand, "Vb " represents battery voltage, and "η^{inv}" and "η^{B}" denote the efficiency of the inverter and battery, respectively

3.7.4 Economic modeling

The net present value (NPV) is computed using the following formula (Oladigbolu et al., 2020):

$$C_{NPC} = \frac{TAC}{CRF(i,N)}, \tag{9}$$

TAC is for total annualized cost ($/year), N stands for project lifespan (year), and i stands for yearly real discount rate (%). The capital recovery factor (CRF) is defined as being connected to both N and i, as seen below:

$$CRF(i,N) = \frac{i(1+i)^N}{(1+i)^N - 1}, \tag{10}$$

The levelized cost of energy (COE) is defined as follows in (Oladigbolu et al., 2020):

$$COE = \frac{TAC}{E_{anloadserved}}, \tag{11}$$

where is $E_{anloadserved}$, the total yearly load (kWh) provided by the system.

4.0 Discussion of results

This section presents the results of Load Estimation, Solar PV, biomass, and battery simulation conducted in MATLAB/Simulink, alongside the Net Present Value (NPV) and Cost of Energy (COE) analysis for various energy mix scenarios, as well as the daily energy contribution from different sources, which are elaborated upon in subsequent discussions.

4.1 Load Estimation

The Kebisoni community's load profile shows varying peaks, off-peak, and base load periods throughout the day. Peak load hours occur around midday and early evening, indicating high demand during high activity periods. Off-peak hours occur at night, with readings at 33.6 kWh, indicating reduced consumption. The base load remains stable, with readings between kWh and 29.7 kWh, indicating the minimum power level consumed consistently. This load profile helps understand when the community requires higher or lower energy resources for effective energy management and distribution planning. The data is presented in Figure 8.

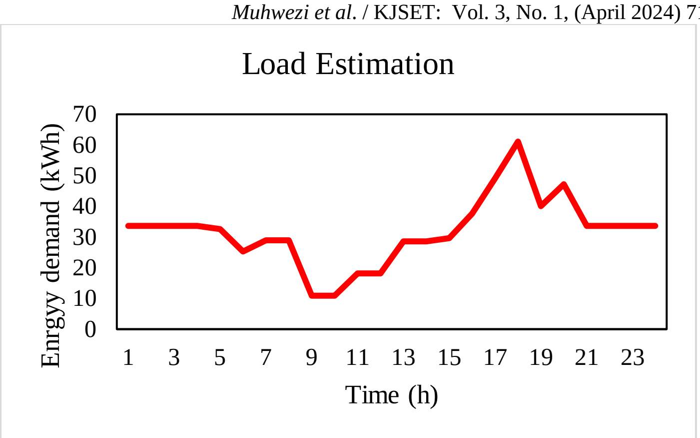

Figure 8: Kebisoni community load estimation

4.2 Solar PV simulation in MATLAB/Simulink

Solar PV modeling in MATLAB/Simulink involves creating a mathematical representation of a photovoltaic system to simulate its behavior. It accounts for solar radiation input based on geographical location, time of day, and weather conditions. This data feeds into a mathematical representation of the PV cell, considering its electrical characteristics, current-voltage, and power-voltage curves. Equations like the single-diode model encapsulate the complex relationship between the PV cell's electrical parameters, environmental conditions, and temperature. MATLAB/Simulink enables the simulation of the entire PV system's performance, allowing analysis under various conditions and facilitating the design and optimization of control algorithms for maximum power extraction and efficiency enhancement. Accurate model construction relies significantly on data from the manufacturer's datasheet, particularly parameters acquired under standard test conditions (STC). Table 3 illustrates the crucial parameters of the KC200GT solar array at nominal conditions, forming the cornerstone for precise model development and fidelity. The complete modeling of solar PV is shown in Figure 9.

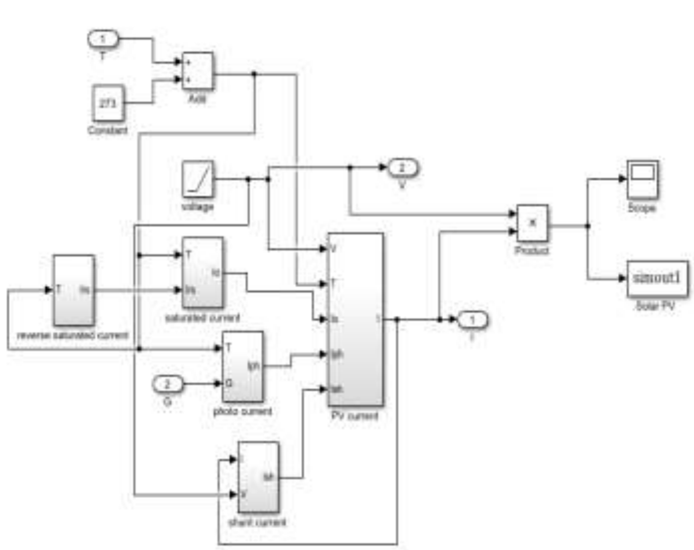

Figure 9: Complete solar PV modeling

The solar PV model's energy output varies with varying solar irradiation levels. At minimal irradiation, energy production remains zero, increasing as irradiation intensifies. The output rises proportionally, reaching a peak of 44.72kWh at maximum irradiation as shown in Figure 10. Post-peak, energy generation declines back to zero, demonstrating the system's sensitivity to irradiation changes. The model's lowest and highest energy outputs are 0 units during minimal irradiation and 44.72kWh at the peak at 13 hours.

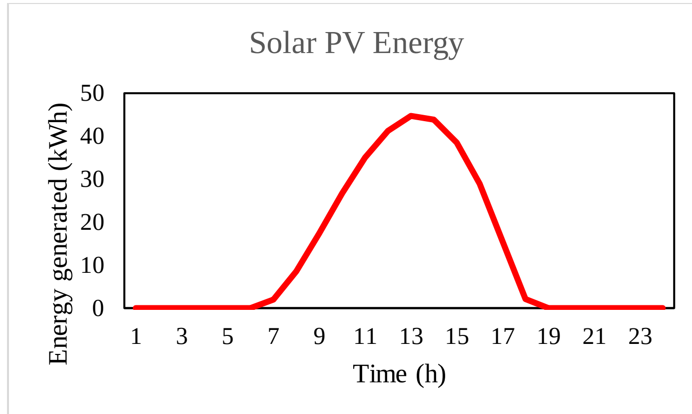

Figure 10: Hourly solar PV energy generated

4.3 Biomass simulation in MATLAB/Simulink

MATLAB/Simulink is a software used for modeling biomass systems, allowing for the creation of mathematical representations of the system. This includes data on biomass characteristics like energy content, moisture content, and composition, which affect combustion properties. The model then incorporates these data as shown in Table 4 into equations representing the conversion process, accounting for parameters like combustion efficiency, heat transfer rates, and thermal losses. It integrates modules like combustion, gasification, and pyrolysis, each with unique mathematical models. This helps in analyzing

Table 3: Solar PV module data specification (datasheet, 2019)

Parameter	Value
Maximum Power (Wp)	300
Open-Circuit Voltage (V)	44.9
Short-Circuit Current (A)	9.61
Voltage at Point of Maximum Power (V)	32.54
Current at Point of Maximum Power (A)	9.22
Module Efficiency (%)	18.44
Length (mm)	1640
Width (mm)	992
Depth (mm)	35
Weight (Kg)	18
Operating Temperature (°C)	-40 to 85

the complex thermochemical conversion processes within the biomass system, optimizing energy production and enhancing efficiency strategies.

Table 4: Biomass gasifier parameters used in simulation of the HRES configuration

S/n	Parameter	Value
1	Capacity utilization factor (%)	0.197
2	Calorific value of biomass (MJ/kg)	18
3	Conversion efficiency of gasifier (%)	25
4	Lifetime (years)	15
5	Operating time (h)	10
6	Biomass gasifier power rating (kW)	3.87

The recorded energy output from biomass is consistently 66.827kWh during the hours when solar irradiation is absent. For 10 hours a day, when solar irradiation is not present, the biomass generates this constant energy output. During these specific hours, when solar irradiation is minimal (and consequently solar PV energy production is at zero), biomass serves as a reliable and consistent source of energy, consistently providing the recorded energy output of 66.827kWh per hour as shown in Figure 11. This indicates biomass's capacity to maintain consistent energy production during periods when solar energy isn't available, showcasing its reliability as an alternative energy source in scenarios where solar power is limited.

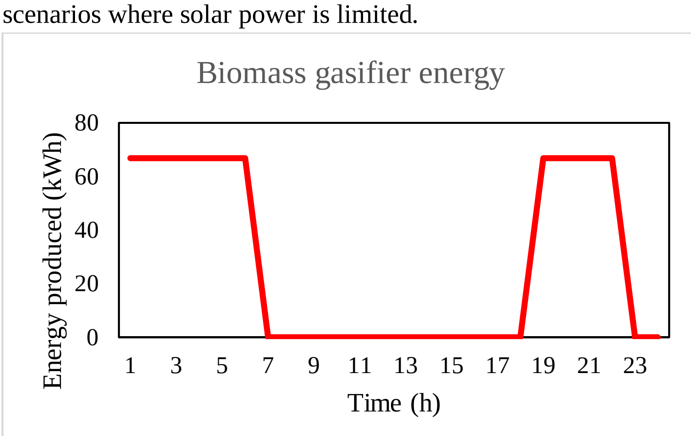

Figure 11: Hourly energy produced from biomass

4.4 Battery simulation in MATLAB/Simulink

The modeling of batteries in MATLAB/Simulink involves representing the behavior and characteristics of battery systems in a mathematical format for simulation purposes. Initially, this model considers the electrochemical behavior of the battery, accounting for its charge and discharge cycles. Mathematical equations depict the relationship between the battery's voltage, current, and SOC. These equations encapsulate various parameters, including internal resistance, capacity, and voltage response, which define the battery's behavior under different conditions. MATLAB/Simulink's simulation parameters have shown in Table 5 is used for the analysis of the battery's behavior under varying loads, temperatures, and charging/discharging cycles.

Table 5: Battery storage parameters used in the optimization of the HRES

Parameter	Value
Capacity (Ah)	200
Battery Lifetie (years)	5
Battery efficiency (%)	95
Minimum state of discharge (%)	30
Maximum state of charge (%)	100
Maximum charging current (A)	150
Norminal voltage (v)	12.8
Max continuous discharge current(A)	100
Charge voltage(v)	14.6
Pulse discharge current(A)	200

The MATLAB interface for simulation of battery is shown in Figure 12, the depth of discharge of the battery is set as 30% for this research, which implies that the battery will halt at that predefined value. The battery lifetime depends on the SOC of the battery. The result of this battery simulation is shown in Figure 13

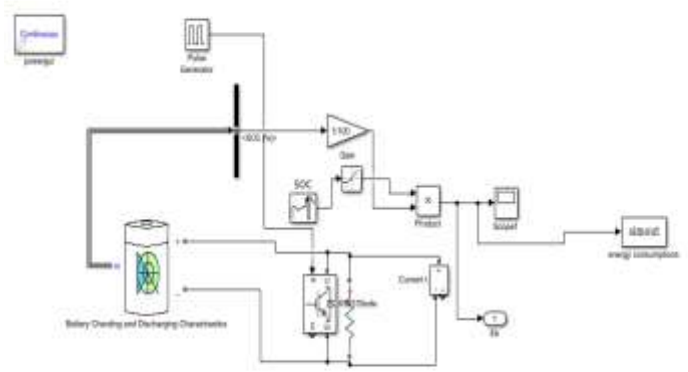

Figure 12: The battery simulation on the MATLAB interface

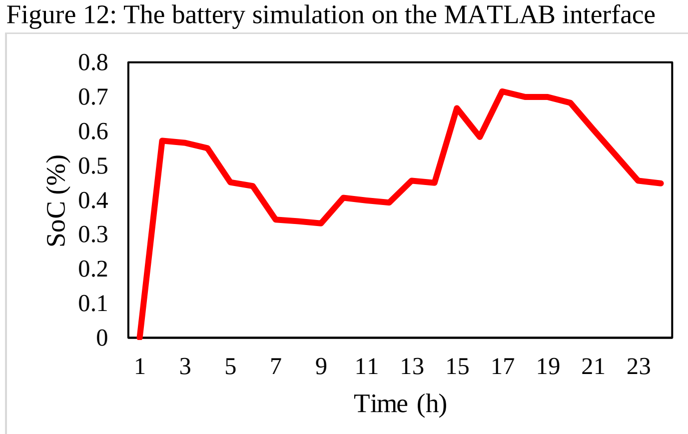

Figure 13: Charging and discharging of battery

4.6 Complete system simulation

The results from the integrated solar PV, biomass, and battery energy system, controlled by an ANFIS controller as shown in Figure 14, exhibit a varied hourly energy output. The ANFIS controller optimizes energy management within the system, and the produced energy output fluctuates throughout the day. At the system's peak operational periods, the output energy stabilizes at 32.05 kWh, reflecting the optimized performance during high-energy production phases, likely corresponding to abundant solar irradiation. However, during periods of reduced solar irradiation or biomass availability, the energy output diminishes significantly, dropping to 10.8996 kWh to 18.1006 kWh. This decline in output demonstrates the system's reliance on solar PV and biomass sources and their dependency on environmental conditions. Notably, the ANFIS controller aids in stabilizing the system's output by adjusting the energy flow based on available resources, ensuring a consistent energy supply despite fluctuations in individual energy sources. Overall, the integration of these renewable energy sources with the ANFIS controller showcases the potential for optimized energy management and stability in renewable energy systems, albeit with some dependency on varying energy sources and environmental conditions.

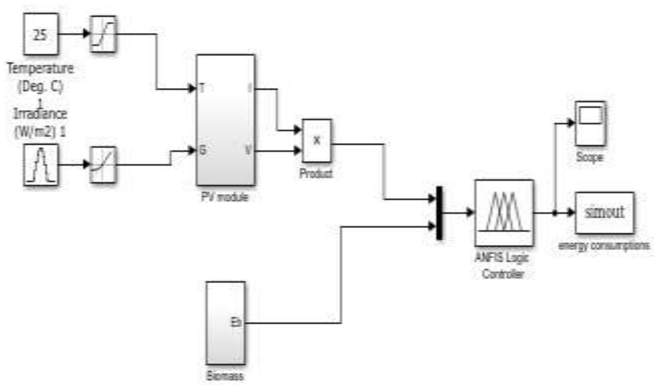

Figure 14: Complete system modeling

4.6.1 Solar PV-Biomass and Battery (Case 1)

The study evaluated the solar PV energy potential in a hybrid system with biomass as a backup using ANFIS optimization techniques. The total cost of energy (COE) for each component was found to be 809.99 Ugx/kWh, with a total net present value (NPV) of 1010189842 Ugx and a total annual cost (TAC) of 50509492.1 Ugx/year. The optimal sizing for solar PV, biomass, battery, and inverter components was determined to be 127, 4, 139, and 35, respectively. Replacement and salvage costs were considered, except for the battery, which had a replacement cost of 1268000 Ugx and a salvage cost estimated at 10% of the capital cost as shown in Table 6.

4.6.2 Solar PV-Battery (Case 2)

Case 2 combines a Solar PV system and a battery without a Biomass gasifier, with the PV system as the primary energy source. The battery storage system is strategically used, aligning with the operational strategy. The optimal configuration is shown in Table 4.6, with a total cost of energy (COE) of 284.01 Ugx/kWh and a total net present value (NPV) of 1302733567 Ugx and a total annual cost (TAC) of 65136678.34 Ugx/year. The optimal sizes for solar PV, battery, and inverter components are 319, 161, and 35, respectively. Replacement and salvage costs are factored in, except for the battery, which incurs a replacement cost of 1268000 Ugx and a salvage cost of 10% of the capital cost as shown in Table 7.

4.6.3 Biomass-Battery (Case 3)

Case 3 combines a biomass system and a battery without a solar PV system, using the biomass system as the primary energy source. The battery storage system is strategically used, aligning with the operational strategy. The optimal configuration is shown in Table 4.7, with a total cost of energy (COE) of 751.35 Ugx/kWh and a total net present value (NPV) of 922201521.6 Ugx and a total annual cost (TAC) of 46110076.08 Ugx/year. The optimal sizes for biomass, battery, and inverter components are 4, 143, and 35, respectively. Replacement and salvage costs are factored in, except for the battery, which incurs a replacement cost of 1268000 Ugx and a salvage cost of 10% of the capital cost as shown in Table 8

Table 6: Breakdown of sizing, COE, NPV and TAC for case

S/n	Component	Solar PV	Biomass	Battery	Inverter	Total
1	No of component	127	4	139	35	--------
2	capital cost (Ugx)	844375	0	1268000	442900	2555275
3	Replacement cost (Ugx)	0	0	1268000	0	1268000
4	Salvage cost (Ugx)	0	0	126800	0	126800
5	fuel cost (Ugx)	0	0	0	0	0
6	COE (Ugx/kWh)	58.64	525.98	221.98	3.38	809.99
7	NPV (Ugx)	107194391.4	2348969.05	885144981.5	15501500	1010189842
8	TAC (Ugx/year)	5359719.568	117448.4525	44257249.08	775075	50509492.1

Table 7: Breakdown of sizing, COE, NPV and TAC for case 2

S/n	Component	Solar PV	Biomass	Battery	Inverter	Total
1	No of component	319	0	161	35	----------
2	capital cost (Ugx)	844375	0	1268000	442900	2555275
3	Replacement cost (Ugx)	0	0	1268000	0	1268000
4	Salvage cost (Ugx)	0	0	0	0	0
5	fuel cost (Ugx)	0	0	0	0	0
6	COE (Ugx/kWh)	58.64	0	221.98	3.38	284.01
7	NPV (Ugx)	268968795.7	0	1018263271	15501500	1302733567
8	TAC (Ugx/year)	13448439.79	0	50913163.55	775075	65136678.34

Table 8: Breakdown of sizing, COE, NPV and TAC for case 3

S/n	Component	Solar PV	Biomass	Battery	Inverter	Total
1	No of component	0	4	143	35	----------
2	capital cost (Ugx)	0	0	1268000	442900	1710900
3	Replacement cost (Ugx)	0	0	1268000	0	1268000
4	Salvage cost (Ugx)	0	0	0	0	0
5	fuel cost (Ugx)	0	0	0	0	0
6	COE (Ugx/kWh)	0	525.9850061	221.9887955	3.379441901	751.35
7	NPV (Ugx)	0	2348969.05	904351052.5	15501500	922201521.6
8	TAC (Ugx/year)	0	117448.4525	45217552.63	775075	46110076.08

The study evaluated three hybrid system cases sequentially. Case 1 integrated solar PV with biomass, resulting in a total cost of energy (COE) of 809.99 Ugx/kWh, an NPV of 1,010,189,842 Ugx, and a TAC of 50,509,492.1 Ugx/year. Case 2, which solely incorporated solar PV and a battery, had a lower COE at 284.01 Ugx/kWh, a higher NPV at 1,302,733,567 Ugx, and a TAC of 65,136,678.34 Ugx/year. Case 3, which incorporated biomass and a battery, had a COE of 751.35 Ugx/kWh, an NPV of 922,201,521.6 Ugx, and a TAC of 46,110,076.08 Ugx/year.

Kebisoni, an off-grid region in Nigeria, lacks a connection to the national grid. To assess the economic viability of potential energy solutions, the net present value (NPV) was calculated considering factors like solar system installation, fuel procurement, and generator maintenance. The existing hybrid system had a NPV of 4,172,144,458.4 Ugx. Comparing alternative hybrid system configurations (Case 1, Case 2, and Case 3) revealed significant reductions in NPV values as shown in Figure 15, highlighting the relative economic feasibility and cost-effectiveness of implementing alternative energy solutions in off-grid regions like Kebisoni.

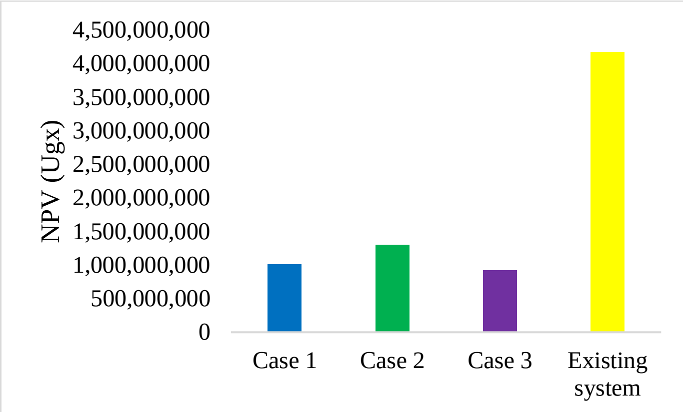

Figure 15: NPV comparison between different system

4.7 Daily Energy contribution

Figure 16 illustrates the energy contribution from various components to the total electrical load within the hybrid system across three distinct cases. In Case 1, solar PV contributed 304.6828kWh, 764.5005kWh in Case 2, and no input in Case 3. Biomass contributed 359.874kWh in Case 1, no input in Case 2, and 678.9765kWh in Case 3, while the battery provided 99.9432kWh in Case 1, -0.0005kWh in Case 2, and 85.5235kWh in Case 3. The battery serves as a backup when the primary energy sources are unavailable, ensuring continuous energy supply to the system. Battery contribution indicates the surplus or deficit after fulfilling the daily load requirements.

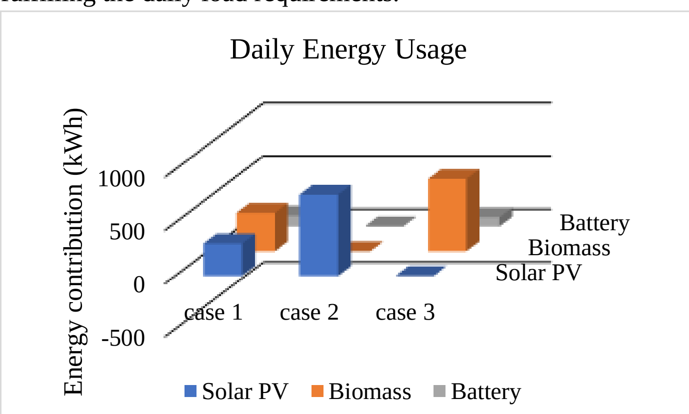

Figure 16: Daily Energy contribution for all cases

5.0 Conclusion

The study's analysis of Kebisoni's load profile highlighted distinctive energy consumption patterns across various periods, emphasizing peak, off-peak, and base load phases. From the load survey, the peak load was estimated at 49.1kWh-61.1kWh, the off-peak load at 47.2 kWh-33.6kWh, and the baseline load at 29.7kWh Solar PV simulations in MATLAB/Simulink accurately modeled energy generation relative to varying solar irradiation levels, offering insights into system responsiveness. Biomass simulations showcased its reliability during minimal solar irradiation, providing a consistent energy output. Battery modeling elucidated its behavior and efficiency under diverse conditions. The ANFIS control displayed the system's fluctuating energy output, optimized during peak operation but reliant on resource availability.

Three hybrid system configurations were assessed, revealing varied trade-offs between COE and NPVs. Case 1 with solar PV and biomass exhibited moderate costs and lower NPV, while Case 2 solely integrating solar PV and a battery demonstrated reduced costs but a higher NPV. Case 3 integrating biomass and a battery showcased higher costs and moderate NPV. Comparatively, these configurations presented distinct cost-performance balances, signifying potential economic advantages with varied hybrid system setups.

Furthermore, when compared with the existing system, the proposed hybrid configurations displayed significant NPV reductions ranging from 68.75% to 77.95%, indicating substantial cost savings and potential financial gains. The study underscores the potential for renewable energy systems to have access to power for lighting, cooking, and other productive uses, having a significant influence on the economic and social development of rural areas. It is thought that assessing these investments in light of the sustainability of rural livelihoods will help decision-makers create policies and investment decisions that are well-informed and that would benefit both people and the environment. Both the public and private sectors have committed to investing more money to encourage solar energy technologies including solar photovoltaic-biomass hybrid energy systems.

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Declaration of conflict of interest

The authors have collectively contributed to the conceptualization, design, and execution of this journal. They have worked on drafting and critically revising the article to include significant intellectual content. This manuscript has not been previously submitted or reviewed by any other journal or publishing platform. Additionally, the authors do not have any affiliation with any organization that has a direct or indirect financial stake in the subject matter discussed in this manuscript.

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