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Optimal Sizing and Analysis of Sustainable Solar PV-Biomass Hybrid Energy System for Learning Institutions

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ABSTRACT

Energy access is a significant challenge globally due to limited access to electricity together with the unreliability of grid extension. The main backup system is often diesel generators which suffer from high maintenance, running costs and harmful emissions. The abundance of solar irradiation in the equatorial region and biomass due to the high population and agricultural activities provides a green energy solution to improve access to electricity through distributed generation. This study presents a design and analysis of a sustainable, and optimal configuration of a hybrid power system based Solar PV-Biomass energy system. The proposed system was designed and optimized using Hybrid Optimization of Multiple Energy Resources with the most optimal system being solar PV, Biomass Generator, and Diesel generator with storage. A sensitivity analysis using inflation rate and solar irradiation established that with increasing solar irradiation and reducing inflation rate, the Least Cost of Energy decreases. A sustainability analysis based on Multi-Criteria Decision-Making techniques showed that the most sustainable energy alternatives was solar PV, Biomass Generator with storage of specifications 360 kW of solar PV array, 540 kW of Biomass Generator, 142 kW converter and 576 strings of 1 kW lead-acid batteries storage bank with least cost of energy of 0.1026 USD/kWh. If this proposed hybrid energy system is implemented, it will improve energy access, reliability and reduce costs of energy compared to conventional grid extension

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1. Introduction

The growing world population and industrialization have resulted in an increasing demand for clean and quality energy (Nowotny et al., 2018). Currently, over 75% of the total world's energy emanates from unsustainable fossil fuels (Al-Shahri et al., 2021; Elkadeem et al., 2019). The Kenyan economy had a growth rate of 5.4% in 2019 and thus the country experienced an annual increment in power demand of 3.7% (Energy and Petroleum Regulatory Authority, 2022). Despite Kenya's main electricity generation systems being renewable, there is still an energy crisis due to poor investment in modern power production techniques, over-reliance on hydro-power and monopolization of power distribution systems (Takase et al., 2021). Currently, power outages result in a financial loss average of USD 52,940 per month to the Kenyan economy (Takase et al., 2021). To help achieve energy sustainability, there is a need to develop a decentralized energy system based on renewable technologies.

Researchers are working on improving the efficiency of renewable energy technologies as a means of powering institutions and rural areas due to the availability of renewable energy technologies (Panwar et al., 2011). The Government of Kenya has prioritized renewable energy development for rural electrification to achieve Kenya's Vision 2030 and the United Nation's 7th goal of sustainable development (Ndiritu & Engola, 2020). Several research on the potential of different Hybrid Power systems (HPS) have been carried out based on their techno-economic feasibilities such as stand-alone solar Photo-voltaic (PV), Standalone Wind turbine, Solar PV-biomass (PV-B), Wind-Biomass (W-B), Diesel-Biomass-Battery (D-B-B), and Solar PV-Wind-Biomass (PV-W-B) (Bet & Zare, 2018; Dhunny et al., 2019; Shahzad et al., 2017; Vendoti & Kiranmayi, 2020). Most

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of these studies have recommended the Solar PV-Wind as the most suitable off-grid HPS (Al Busaidi et al., 2016; Garg, 2022; Sawle et al., 2017; Zhang et al., 2022). However, the availability of biomass in learning institutions due to high population creates opportunities for its exploration as a solution to the growing energy demand in a hybrid energy system that is decentralized with high applicability to learning institutions.

The application of HPS helps to improve power reliability by switching between different renewable resources, reducing the cost of energy and enabling remote areas to access power due to the decentralized nature of renewable energy systems (Kashif et al., 2020). Inspite of this, HPS still faces challenges in implementation due to designs that require specialized skills, high initial cost and storage complexities. (Uwineza et al., 2021; Yaqoot et al., 2016). Studies have been done on the development, improvement, and application of Solar PV-B HPS as a means of energy sustainability. More emphasis was put on the optimization of the produced power, the sensitivity and sustainability of the PV-B system (Ahmed et al., 2015; Child et al., 2018; Chowdhury et al., 2019; Ghenai & Janajreh, 2016; Habib & Mahmood, 2017; Sawle et al., 2017, Ji et al., 2021; Shahzad et al., 2017).

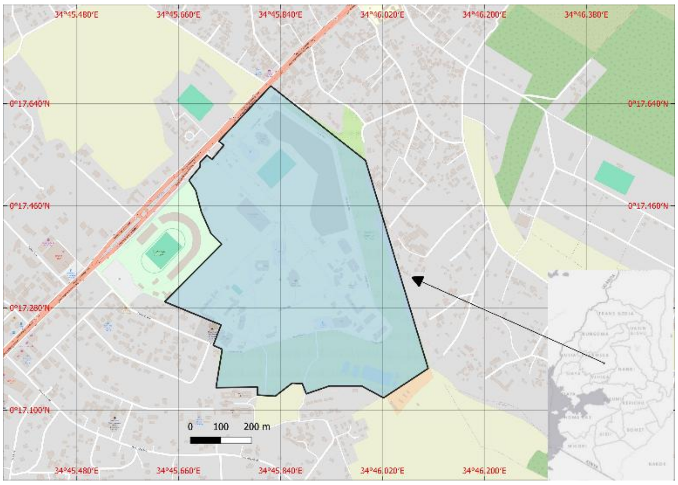

Fig. 1: The Study area (MMUST)

According to Shahzad et al. (2017), a PV-B system with a mix of 18 KW was capable of serving a peak load of 17.08kW at a Cost of Energy (COE) of $ 0.066 for rural Pakistan. Similarly, Suresh et al. (2020), observed that an off-grid model of a PV-W, fuel cell and Battery with a combined peak load of 149.21kW at a COE of $ 0.163 could comfortably run three villages in Kollegal block in India. Although several studies have implemented several optimization algorithms such as Particle swarm optimization (PSO), Genetic Algorithm (GA), differential evolution, Fuzzy Decision Making (FDM), Artificial Neural Network (ANN), Constant Voltage (CV) simulated annealing, and evolutionary metaheuristics to improve renewable power production and HPS system sizing, their power conversion efficiencies are still low (Alshammari & Asumadu, 2020; Dhunny et al., 2019; Elsheikh et al., 2019; Jyoti et al., 2018).

The main objective of this study is to design a feasible, sustainable, and efficient HPS based on solar PV and Biomass renewable energy resources. The specific objectives for this research were: Determination of the most optimal energy mix from the available alternative energy resources; examination of the sensitivity of the optimal energy mix alternative based on variation on solar irradiation levels and inflation rates; and investigation of the sustainability of the alternative energy mix based on technical, economic, and environmental parameters for learning institutions. The design and analysis of the proposed PV-B system present an opportunity for a low-cost energy and improved power reliability to institutions.

2. Materials and Methods

2.1. The study area

In this research, the study site was Masinde Muliro University of Science and Technology (MMUST), a high learning institution located in Kakamega, Kenya with latitude and Longitude coordinates of 0.288234° and 34.765522° respectively as shown in Fig. 1.

The university at its full peak is estimated to have a total population of over 21,000 students. Due to its location, the university receives plenty of solar irradiation levels averaged at 5.9 $kWhm^{-2}day^{-1}$ throughout the year and the high population also leads to huge biomass resources.

2.2. Data Collection

2.2.1. Load Demand

Data was collected for a period of 12 months (September 2021 to August 2022) using three power loggers ENO038-EGauge (eGauge Systems LLC, version 4.5). The power loggers were connected to three different terminal intake points (Main campus gate, hall Four and Star Annex). Each power logger was connected to the three-phase supply terminal using three current transformers. Additionally, the power logger was connected to the internet for data transmission and retrieval using ENO038-EGauge software installed in a remote computer Microsoft Windows 10 PC (intel core i7-4500U CPU, 4GHz, 8GB (intel, Santa Clara, CA, USA)).

2.2.2. Energy Resource Data

Biomass can only be made useful when it is converted into heat through combustion or a clean useable form of energy such as biofuel, bio-syngas or biogas through biological, chemical, and thermochemical biomass conversion processes (pyrolysis, gasification, and liquefaction) which eventually can be converted to electrical energy (Ahmed et al., 2015). The conversion to electrical energy is done by using steam turbine generators, high-temperature biomass fuel cells, and microbial fuel cells (Ahmed et al., 2015; Liu et al., 2020). Biomass is a non-intermittent energy resource and its incorporation into this research provides a cover-up for the intermittent nature of solar energy.

MMUST has a high potential for biomass due to the huge population (high population density) and agricultural biomass. Therefore, the biomass data applied in this study were from agricultural biomass, human wastes, and solid wastes. The mass of sludge was computed by sampling the sewage at the inlet valve. The sewer flow rate was determined by a venturi meter connected to the inlet. The sample collected was poured into a V-shaped volumetric flask. The mixture was allowed to settle and the volume of sludge was gotten which further led to the determination of the mass of sludge in the same sample. Eq. 1 shows the expression for the daily mass of sludge.

$$M = \frac{V \times m}{v} \tag{1}$$

Where, M is the Daily mass of sludge in tons, V is the daily sludge volume, m is the mass of solid sludge in the collected sample, v is the volume of collected sewer sample. The agricultural biomass from animals estimation from the farm was calculated by Eq. 2 (Shahzad et al., 2017).

$$B_M = \sum_{n=1}^{i} N_i m_i + \sum_{k} PY \tag{2}$$

Where, B_M is the Total Biomass produced in tons, n is the number of specified animals' groups, N_i is the total number of animals, m_i is the manure produced per head of the animal, PY is the monthly agricultural production in tons per acre, k is the number of acres for agricultural produce.

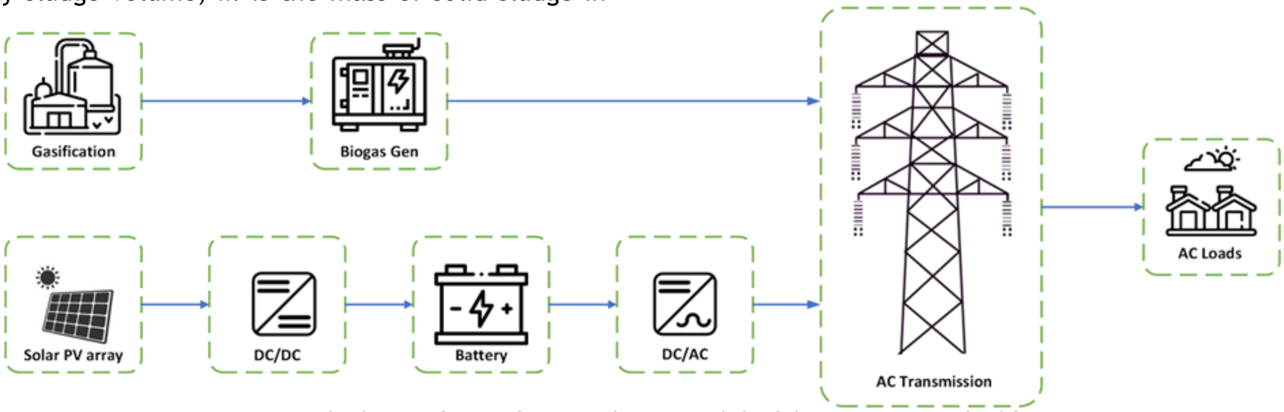

Fig. 2: Hybrid Power System Conceptual Framework for Solar PV-Biomass Hybrid System

The solar irradiance data used in this study was based on the Global Horizontal Irradiance (GHI) which represents solar irradiance level on a horizontal surface (Yan et al., 2019). The average monthly GHI is based on data collected over 22 years and recorded by the National Aeronautics and Space Administration (NASA) in their online public repository in Hybrid Optimization of Multiple Energy Resources software (3.16.1, NREL, Colorado) (HOMER). The GHI is used together with the clearness Index. The clearness index is a dimensionless value between 0 and 1 that defines the clearness of the atmosphere. The monthly temperatures were collected for over 30 years, from January 1984 to December 2013 and from the NASA database in HOMER Pro.

2.2.3. System Design

This research aimed at designing an optimal solar PV-B with storage as a green energy solution alternative. Based on energy demand and load optimization, sensitivity and sustainability analysis were key approaches for the analysis of the HPS. HOMER pro software was applied in the simulation of the design, optimization, and sensitivity of the proposed energy mix. Fig. 2 presents the generalized layout of the proposed system.

HOMER Pro is a hybrid energy optimization software used in the design and modelling of hybrid microgrid energy systems whose capabilities are simulation, optimization, and sensitivity analysis. It uses economic, technical, and environmental parameters as input variables to achieve the most optimal energy mix during the design stage (Dawoud, 2021; Uwineza et al., 2021). In this study, a simulation of several energy alternatives was performed to achieve the most optimal alternative energy mix.

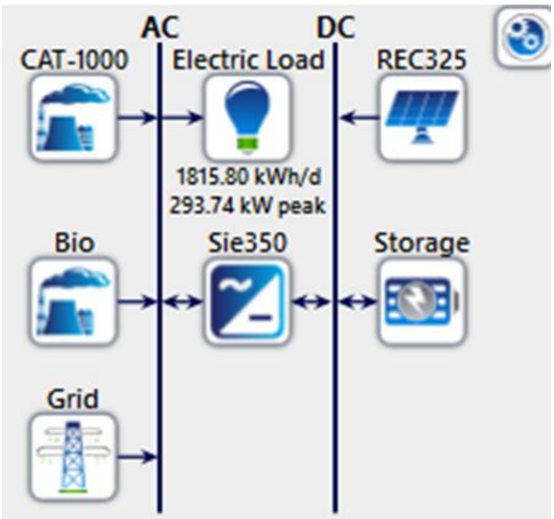

Fig. 3: Schematic Design of the proposed Hybrid energy system in HOMER Pro

Based on cost minimization (least NPV and LCOE), HOMER Pro uses user input parameters of energy demand profiles, renewable energy resources available and conventional energy resources to select system components to be included in the microgrid being modelled (Shahzad et al., 2017). The guiding optimization equations for these operations are the economic, technical, and environmental objective constraints. HOMER Pro uses two main algorithms which are Grid search Algorithm and Derivative free Algorithm in performing optimization. These optimization algorithms help in determining the optimal control strategies which help to achieve minimum operating costs and maximize renewable energy penetration. This study applied the Derivative-Free Algorithm (DFO) which is preferred in HOMER optimization due to its faster convergence and its inexpensive nature compared to the grid search algorithm (Rios & Sahinidis, 2013). Moreover, HOMER Pro assesses different other system configurations and ranks different hybrid energy alternatives from the renewable energy, conventional and storage inputs-based Techno-economic parameters. Fig. 3 shows the design of the proposed system as implemented in a HOMER Pro environment.

Table 1: Properties of the simulated Solar PV Module

Solar PV Properties	Specifications
Selected PV Module	REC Solar325REC325PEM 72 PV
Life Cycle	25-year
Derating Factor Is	85%
Temperature Coefficient	0.4520% per degree Celsius
Standard Conditions	13%
Tracking System	No tracking system
Module Costs	USD 650 per kW
O&M Fee	USD 10 per year
Replacement Cost	USD 550

The amount of energy generated from the solar PV depends on several factors i.e., Solar insolation incident on the panel, the Sky Clearness Index, relative humidity, ambient temperature levels, panel type, and efficiency of conversion, shading, and orientation (Venkateswari & Sreejith, (2019)). The power generated by a PV module is given by Eq. 3 (Singh & Baredar, 2016). Table 1 presents the properties of the simulated solar module applied in this study.

$$P_{PV\ output} = P_{NPV}\left(\frac{G}{G_{Ref}}\right)\left[1 + K_T\left(T_C - T_{ref}\right)\right] \quad (3)$$

Where, G is the solar irradiation (Wm^{-1}), P_{NPV} is the rated power at reference conditions, G_{ref} is the solar irradiation at reference conditions ($G_{ref} = 1000\ Wm^{-1}$), T_{ref} is the reference temperature ($T_{ref} = 25^oC$), K_T is the maximum power temperature coefficient for monocrystalline silicon, T_C is the temperature for individual modules.

Battery storage was incorporated into this hybrid energy system due to the intermittency nature of the renewable energy resources (Sánchez et al., 2022). Additionally, they boost system stability and reliability (Tephiruk et al., 2018). According to (Singh & Baredar, 2016), The battery storage capacity is calculated by Eq. 4. Table 2 presents the properties of the simulated battery storage module applied in this study.

$$C_{wh} = [E_L * AD] * n_{inv} * n_b * DOD \quad (4)$$

Where, E_L is the total energy demand, AD is the Daily autonomy, DOD is the depth of discharge, n_{inv} is the efficiency of the inverter, n_b is the battery efficiency.

Table 2: Properties of the simulated Battery Storage

Battery properties	Specifications
Selected Storage Module	lead acid, Gel Solar Cell from chloride Exide battery technologies
Max. Charge capacity	3.04kAh
Max Charge Current	1.06kA
Terminal voltage	2V
life cycle	10-year
Depth of Discharge	40%
Round trip efficiency	95%
Battery rating	6.07 kW
module costs	USD 610 per kW
O&M fee	USD 10 per year
replacement cost	USD 600

Converters are electronic devices which raise the level of the DC power produced by solar Panels from a lower level to a higher level maintain it at a specific level and convert it to AC power to be used by AC loads (Lupangu & Bansal, 2017). Table 3 presents the properties of the converter module applied in this study.

Table 3: Properties of the Converter Module

Converter properties	Specifications
Selected Converter Module	Siemens Industry SININVERT PVS351
Max. capacity	350 kW
Inverter design	Inbuilt
Efficiency	96%
Connection Mode	parallel with the biomass AC generator
Life cycle	15-year
module costs	USD 280
O&M fee	USD 30 per year
replacement cost	USD 280

Biomass conversion to electricity has attracted more interest due to the numerous applications of electrical power (Liu et al., 2020). More technologies have been introduced to convert biomass energy to electrical energy i.e., steam turbine generators, high-temperature biomass fuel cells, and microbial fuel cells (Liu et al., 2020).

Table 4: Specifications of the Biomass Generator

Biomass Gen set properties	Specifications
Selected Genset Module	Free size
Max. rated capacity	540 kW
Rated voltage	400 (50Hz)
Phases	3 phase, 4 wires
Gasification ratio	0.7
Rated rotation speed	600rpm
Life cycle	25-year
module costs	USD 90,180
O&M fee	USD 88,337.58.
replacement cost	USD 90,180

Turbine-based steam generators have predominantly been used for biomass to electricity conversion due to their initial use in the conversion of coal to electricity (Liu et al., 2020). Gasification, pyrolysis, and liquefaction processes are the intermediate processes used to provide the primary substrate used by turbine-based steam generators. The biomass-operated steam turbines are big (in size) as a huge amount of biomass is needed to sustain their operation (Liu et al., 2020). Table 4 shows the specifications of the biomass generator chosen for this study. Table 5 shows the specifications of the diesel generator selected for this study.

Table 5: Specifications of the diesel generator

Diesel Gen-set properties	Specifications
Selected Genset Module	800 kW Cummins Generator Set
Prime power	800 kW/1000 kVA
Standby power	880 kW/1100 kVA
Phases	3 phase, 4 wires
Diesel Engine	Cummins KTA38-G5
Rated rotation speed	1500rpm/50Hz
Power factor	0.8Lag
Weight	12300kg
Space size	6000x2600x2800mm
Life cycle	25-year
Module costs	USD 200,000
Replacement cost	USD 200,000

This research aimed at reducing overreliance on the grid and therefore by design the grid was designed to be off most of the time with a sell-back of USD 0.05/kWh. There were no extra connection costs for the grid as the university had already been connected to the grid. With the rapidly growing net metering system, it was to cater for the sales of the excess power produced by the solar PV-Biomass hybrid energy system.

2.2.4. Economic Parameters

HOMER Pro carries out optimization feasibility through cost-benefit analysis considering cash flow for the 25-year expected life span. Net Present Value (NPV), Least Cost of Energy (LCOE), Capital Expenditure (CAPEX) and Operating Expenditure (OPEX) are some key economic parameters utilized in the HOMER tool for optimal economic analysis and optimal configurations. However, NPV and LCOE are the most cost-effective metrics in the HOMER tool for optimization (Uwineza et al., 2021).

NPV represents the life cycle cost and examines the current or potential investment (Roche & Blanchard, 2018). It is a way of determining the Return on Investment (ROI), which measures its profitability as shown by Eq. 5.

$$ROI = \frac{I - P}{P} \tag{5}$$

Where, I is the investment gain, P is the investment cost. NPV is used to calculate the time value of money and it takes into the project expenses, which include initial capital, component replacement, maintenance, and fuel costs. The calculations are done based on the present values of the anticipated cash flows as shown by Eq. 6

$$NPV = -C_0 + \sum_{t=1}^{n} \frac{C}{(1+i)^t} \tag{6}$$

Where, C_0 is the initial capital, C is the cash flow, t is time in years, i is the interest rate. LCOE is the cost per unit of electricity which considers all the project's lifetime costs against the total produced electricity and was calculated by Eq. 7 (Roche & Blanchard, 2018)

$$LCOE = \frac{C_0 + \sum_{t=1}^{n} \frac{L_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} E_t} \tag{7}$$

Where, L_t is the investment expenses in year t, M_t is the O&M costs expenses in year t, E_t is the produced electricity in year t, F_t is the fuel expenses in year t, r is the discount rate, n is the system life.

CAPEX is the expenditure incurred while purchasing the HPS fixed assets such as solar PV, Biomass generator, storage and converters while OPEX is the daily to daily expenses incurred while operating the HPS such as cost of fuel, labour payments and routine maintenance aimed at keeping the HPS in good working conditions (Uwineza et al., 2021).

2.2.5. Sensitivity Analysis

Sensitivity analysis is a technique for analyzing how the optimal components of a system fluctuate when some input variables are changed and measuring the impact of each change on the project's result (Ji et al., 2021; Roche & Blanchard, 2018). It evaluates the impacts of changes in various parameters on the energy systems' technical, economic, and environmental performance indicators, e.g., storage capacity, LCOE and system costs. Through sensitivity analysis, the ranges of the sensitivity parameters beyond which the system becomes infeasible were known for the microgrid designed.

Table 6: Sensitivity variables

Solar Irradiation (kWhm^{-2}day^{-1})	Expected Inflation (%)
4.00	9.20
5.90	10.00
6.50	8.00

In this study, solar irradiation and inflation rates were the chosen sensitivity parameters (Ji et al., 2021). The costs of solar panels and storage accounted for high costs during the optimization analysis, a sensitivity analysis was then conducted on solar irradiation levels to evaluate its effect on the system cost and overall sizing of the hybrid energy system. The effect of expected inflation on sensitivity analysis will help evaluate how resistant the design is to economic changes due to global economic practices. The choice of expected inflation as a sensitivity parameter was informed based on its importance in risk management, its impact on capital cost and future project viability. Table 6 lists the sensitivity variables that were used in the simulations.

2.2.6. Sustainability Analysis

Sustainability analysis aims to evaluate the environmental, economic, technical, and social impact of the project's energy-generating capability to provide long-term energy planning and selection of sustainable energy resources based on the optimized solutions from optimization analysis (Ojong, 2021). The main indicators for sustainability analysis are economic parameters (Capital Cost (CC), NPV, Operating Cost (OC), Internal Rate of Return (IRR), Return on Investment (ROI), Simple Payback period (SPP), and LCOE), environmental impact parameters such as pollution, land use and GHG emissions (Carbon dioxide, carbon monoxide, Sulfur Dioxide, and Nitrogen Oxides levels emitted during energy generation), social parameters such as regional development and job creation, maximum capacity parameters (Technical parameters) such as reliability, service life and even the installed capacity (Campos-Guzmán et al., 2019). Sustainability analysis enabled the making of informed decisions by efficiently exploring energy alternatives and it was performed on the optimal hybrid energy alternatives from HOMER optimization.

Algorithm 1: SAW Methodology

1 $Column\ normalization\ for\ each\ i^{th}\ row\ and\ results\ store$
2 $For\ i = matrix\ row,$
$j = matrix\ column,$
$n = number\ of\ criteria,$
$S_i = overal\ score$
3 $For\ W_{ij} = N_{ij} * W_j$
4
$$S_i = \sum_{j=1}^{n} (W_{ij})$$

The multi-criteria decision-making model (MCDM) approach was used for the performance of sustainability analysis. This approach enabled all the critical evaluation criteria to be merged and analyzed in a decision-making process. MCDM thus helped in evaluating the most feasible energy alternative from the available options. Four MCDM approaches were used for this project which were; Simple Additive Weighting (SAW), Multi-Attributive Border Approximation Area Comparison (MABAC), COmplex PRoportional Assessment (COPRAS) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The methodology for the approaches is as described below.

Algorithm 2: TOPSIS Methodology

1 $Determination\ of\ the\ decision\ matrix\ A, X = [X_{ij}]_{m*n}$
2 For $P_{ij} = normalized\ decision\ matrix,$
$V_{ij} = weighted\ normalized\ decsion\ matrix,$
$w_j = weight\ of\ the\ j^{th}\ criterion,$
$A^* = Positive\ ideal\ solution,$
$A^- = negative\ ideal\ solution,$
$S^*{}_i = Separation\ measures,$
$RC^*{}_i = Relative\ closeness\ to\ the\ ideal\ solution$
3
$$P_{ij} = \frac{A_{ij}}{\sqrt{\sum_{i-1}^{m} (A_{ij}{}^2)}}$$
4 $Weights\ coeficients\ assigning\ For\ V_{ij} = P_{ij} * w_j$
5 $A^* = \{max\ v_{ij}\ , min\ v_{ij}\}\ and\ A^* = \{min\ v_{ij}\ , max\ v_{ij}\}$
6
$$S^*{}_i = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j{}^*)^2}\ while\ S_{-i} = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j{}^-)^2}$$
7
$$RC^*{}_i = \frac{S_{-i}}{S^*{}_i + S_{-i}}$$
8 $Ranking\ of\ alternatives\ based\ on\ RC^*{}_i$

SAW: This MCDM method consists of three major steps which are decision matrix X normalization, weight vector assigning and finally overall score calculation for each alternative (Goodridge, 2016). Algorithm 1 illustrates the SAW methodology.

Algorithm 1: MABAC Methodology

1 $Formulation\ of\ the\ decision\ matrix\ X$
2 $For\ X_{ij} = performance\ of\ the\ i^{th}\ alternative\ wrt\ j^{th},$
$x_i{}^+ = max\ value\ of\ the\ observed\ alternatives,$
$x_i{}^+ = min\ value\ of\ the\ observed\ alternatives,$
$n_{ij} = benefit\ type\ criteria$
$V_{ij} = Weighted\ matrix,$
$g_i = The\ boarder\ approx\ Decison\ matrix\ normalization$
3 $Weights\ coeficients\ assigning\ For\ V_{ij} = w_i * (n_{ij} + 1)$
4
$$g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{\frac{1}{m}}$$
5 $Distance\ from\ the\ boarder\ area\ (Q) = V - G$
6 $Ranking\ of\ alternatives$

TOPSIS: The TOPSIS method used in this research involved assigning two sets of reference points when finding the ideal solution (positive and negative). The positive ideal solution maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Goodridge, 2016). TOPSIS determines the best alternative by minimizing the distance to the ideal solution and maximizing the distance to the negative ideal solution. This method assumes that each attribute is monotonically increasing or decreasing. TOPSIS utilized Euclidean distances to measure the alternatives with their positive ideal solution and negative ideal solution. The preference order of alternatives is yielded by comparing the Euclidean distances. The preference order of alternatives is yielded through a comparison of Euclidean distances (Goodridge, 2016; Yadav et al., 2018). Algorithm 2 shows the TOPSIS methodology.

Algorithm 2: COPRAS Methodology

1 $Determination\ of\ the\ decision\ matrix\ X, X = [X_{ij}]_{m*n}$
2 $ForX_{ij} = performance\ of\ the\ i^{th}\ alternative\ wrt\ j^{th},$
$m = alternatives, n = number\ of\ criteria,$
$Q_i = Relative\ significance,$
$S_{+i}\ and\ S_{-i}\ are\ sums for\ max\ and\ min\ criteria$
$U_i = Coefficient\ od\ efficiency\ alternative$
3 $Decison\ matrix\ normalization,$
4 $Weights\ coeficients\ assigning\ For\ W_{ij} = N_{ij} * W_j$
5
$$S_{+i} = \sum_{j=1}^{n} (W_{ij})\ and\ S_{-i} = \sum_{j=1}^{n} (W_{ij})$$
6 $Decison\ matrix\ normalization$
7
$$Q_i = S_{+i} + \frac{S_{-min} \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{S_{-min}}{S_{-i}}}$$
8
$$U_i = \frac{Q_i}{Q_{i\,max}} * 100\%$$
9 $Ranking\ of\ alternatives\ based\ on\ percentages$

MABAC: The MABAC algorithm involved the formation of a primary decision matrix as the first step (Bose et al., 2019). This was followed by the normalization of the ultimate decision matrix. Thirdly, the weighted normalized decision is calculated and finally, the overall alternative was computed (Bose et al., 2019). Algorithm 3 shows the MABAC methodology.

COPRAS: This method involved ranking the alternatives in order of their relative importance. The first step involved the formulation of the decision matrix; the decision matrix is then normalized (Stanojkovic & Radovanovic, 2017). Finally, the coefficient of efficiency is then determined and then the alternatives are ranked from higher percentage to lower percentage (Stanojkovic & Radovanovic, 2017). Algorithm 4 shows the COPRAS methodology.

3. RESULTS

3.1. Load Assessment

The total annual load as shown in Table 7 was established to be 662,682.99 kWh for a period between September 2021 and August 2022. Consumption was high at the main campus with a total of 569,625.38 kWh and low at Star-Annex with 8,185.32 kWh.The highest monthly consumption was in March with 69,573.88 kWh and the lowest consumption by month being in August 2022 at 41,021 kWh.

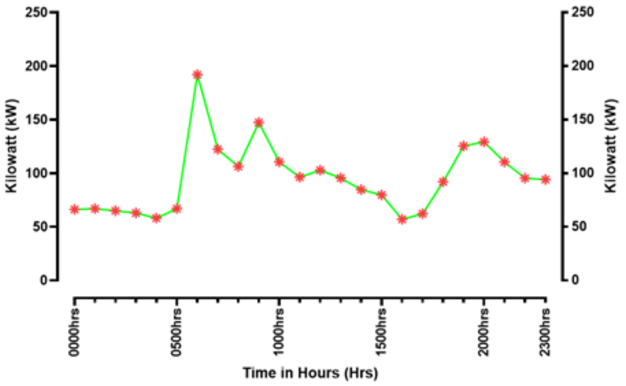

Fig. 4: Daily load demand for a day in January

A typical load profile for a selected day in March (Monday, 6th March 2022) is given in Fig. 3 while Fig. 4 shows the seasonal load profile for an academic year. The Average hourly Energy Demand was 75.66 kW with the peak demand being 293.74 kW (with the considered day-to-day swing of 5%). The monthly average load demand was 54,474 kWh. The mean seasonal consumption was found to be 54,474.5825 kWh with a standard deviation of 11,274.07 as depicted in Table 8.

Fig. 5: Seasonal load profile

3.2. Resource Assessment

3.2.1. Biomass Energy Resource

It was established that the average monthly biomass was 2.1 tons of biomass with a standard deviation of 1.081597094. The minimum biomass collection was 0.45 tons and a maximum of 2.925 tons as shown in Table 8. The sewer flowrate was established as 0.0029 m^3s^{-1}. The biomass resource was highest in November at 2.925 tons and was lowest in June, July, and August at 0.45 tons as depicted in Fig. 6.

3.2.2. Solar Energy Resource

Solar irradiation data showed that the annual scaled average solar irradiation was 5.90 $kWhm^{-2}day^{-1}$ with the scaled annual average clearness index being 0.5897. September had the highest solar irradiation of 6.279 5.90 $kWhm^{-2}day^{-1}$ while May had the lowest solar irradiation levels at 5.3635.90 $kWhm^{-2}day^{-1}$. Table 9 shows the GHI resource (clearness Index, Daily radiation, and Daily temperature).

Table 7: MMUST Monthly Power Consumption

Month/Year	Main Campus (kWh)	Hall Four (kWh)	Star Annex (kWh)	Total Energy demand (kWh)
Sep-21	40,612.56	5,038.7	138.01	45,789.27
Oct-21	52,833.08	1,0375.38	918.77	64,127.23
Nov-21	55,773.35	12,542.57	1,009.46	69,325.38
Dec-21	44,563.55	8,343.65	918.77	53,825.97
Jan-22	48,422.66	9,020.9	500.1	57,943.66
Feb-22	52,189.89	10,700.46	869.42	63,759.77
Mar-22	56,600.31	12,271.67	701.9	69,573.88
Apr-22	54,854.52	10,890.09	920.68	66,665.29
May-22	42,450.23	1,462.85	619.09	44,532.17
Jun-22	41,255.74	1,083.6	662.46	43,001.8
Jul-22	41,531.39	1,002.32	583.6	43,117.31
Aug-22	38538.1	2140.1	343.06	41021.26
	569,625.38	**84,872.29**	**8,185.32**	**662,682.99**

3.3. Optimization Analysis

The best architecture presented in Table 10 after optimization analysis based on NPV and LCOE was a combination of 360 kW of REC Solar325REC325PEM 72 (Solar PV), 576 Strings of lead acid- Gel Solar Cell (storage battery), a 142 kW Siemens Industry SININVERT PVS351 (converter with inbuilt inverter), 800 kW diesel generator (standby supply for the hybrid system), and a 540kW biomass generator with HOMER Load Flow (LF) dispatch strategy at a NPV of USD 1.93M, Capital cost of USD 915,505.30, LCOE of USD 0.10032, operating costs of USD 34,868.61 per year, electricity production of 74,790.1 kW and excess energy of 49,062.51kW with a potential of being sold back to the grid.

However, the base case scenario (Diesel generator) was established to be a diesel generator of 800kW having capital expenditure (CAPEX) of USD 200000, NPV of USD 23.2M, operating cost (OPEX) of USD 795,631 per year with an annual electricity production of 1,753,472 kWh and 1,465,253 kilograms of CO2 per year. With its standard capacity, it consumes 554,381.5 liters of fuel per year which amounts to USD 776,134.1. It had the LCOE of USD 1.2 for every unit of electricity it produced.

Table 8: Descriptive Statistics for the Seasonal Load and Biomass Resource

Descriptive Statistics	Load Assessment Values (kWh)	Biomass Values (tons)
Mean	54,474.5825	2.104545455
Standard Error	3254.542628	0.326113794
Median	55884.815	2.775
Standard Deviation	11,274.06638	1.081597094
Sample Variance	127,104,572.6	1.169852273
Kurtosis	-1.924501209	-0.899731796
Skewness	0.005797329	-1.065738749
Range	28552.62	2.475
Minimum	41,021.26	0.45
Maximum	69,573.88	2.925
Sum	662,682.99	23.15

The optimal alternative compared with the base case scenario, the NPV would rose to USD 23.2M which is USD 21.27M greater than the optimal scenario. Consequently, the LCOE also increased to USD 1.2109 under the base case scenario which is USD 1.1106 higher than the optimal scenario. The diesel generator used in the base case scenario would operate the whole year with an annual OPEX of USD 795,631, and annual electricity production of 1,753,472 kWh (which is higher than the electricity produced by optimal solution by 1,005,564.9 kWhyr-1) while consuming 554,381.5 liters of fuel per year which amounts to USD 776,134.1 while emitting 1,465,253 kilograms of CO2. It had an investment cost of USD 200,000.

The capital investment for this most optimal project would be USD 915,505.27 where storage contributes to 38.38% followed by solar PV at 25.58%. Diesel generator, Biomass generator and converter would make up 21.85%, 9.85% and 4.34% respectively. The operational and Maintenance costs were USD 587,072.30 with solar PV taking the bulk of this O&M at 35.54%, storage at 28.41% followed by converter at 21.00% and Biomass generator at 15.05%. Table 12 below shows the NPV summary of the individual components of the optimal alternative. Fig. 7 shows the shared energy generation between solar PV and Biomass generator. The results show that solar PV generated the bulk of the power throughout the year with an annual generation of 612,535.915 kW (81.9%) as compared to annual generation by biomass generator of 135,371.185 kW (18.1%).

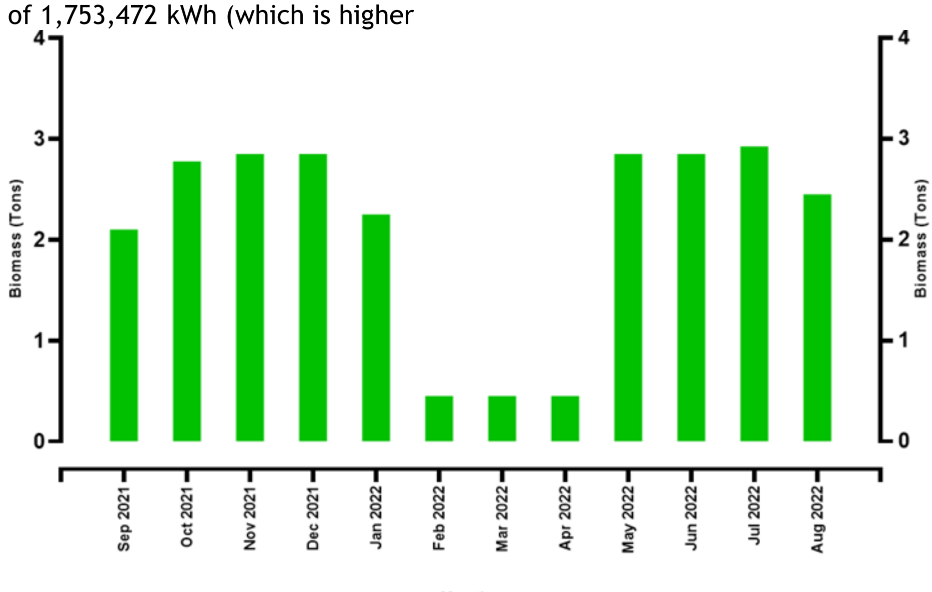

Fig. 6: MMUST Biomass Resource

3.4. Sensitivity Analysis

Based on inflation and irradiation factors, the sensitivity analysis established that the system was stable from a solar irradiation level of 5.904 to 6.5. An increase in solar irradiation levels from 4 to 6.5 kWhm^{-2}day^{-1} saw a reduction in the LCOE from USD 0.1029471, USD 0.09395795, and USD 0.09271287. This is 9.94% reduction in the LCOE when the solar irradiation was at 6.5 kWhm^{-2}day^{-1} and the inflation rate at 10%. Additionally, this saw an increment in the generated energy by 9.75% and the level of emissions was also reduced by 71.34% as bulk energy will be supplied by solar making biomass generator to only supply a small quantity of power. The capital investment and NPV also reduced by 6.67% and 9.94% respectively.

At an inflation rate of 8%, and with solar irradiation levels varying from 4 to 6.5 kWhm^{-2}day^{-1}, saw an increment in the LCOE from a minimum of USD 0.0927 which was realized at an inflation rate of 10% to a minimum of USD 0.10797 at this discounted rate of 8%. However, at 8% of the expected inflation rate, there is an increment in the operation cost of the renewable energy system by 23.57%. With this inflation rate, the system becomes more sustainable as the diesel generator is eliminated from the system and the maximum emission produced at this level drops from 272.9243 kgyr-1 to 115.4709 kgyr-1 which is a 57.69% reduction in GHG emitted to the atmosphere. This inflation rate produced the least NPV of 1,789,013 indicating how viable the project would be with a drop in the inflation rate. The capital needed for investment during this period was also low at USD 714,462.1 when compared to USD 914,392.3 (21.86% reduction in investment cost) when the inflation rates were 10%. The system size was smaller in this scenario at 900 kW as compared to inflation rates of 10% and 9.2% when the system size was 1700 kW minimum.

Table 9: Solar Energy Resource Data

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec	Average
Clearness Index	0.619	0.621	0.594	0.531	0.554	0.601	0.585	0.592	0.607	0.578	0.566	0.628	0.5897
Daily radiation ($kWhm^{-2}$ day^{-1})	6.205	6.438	6.242	5.425	5.363	5.607	5.532	5.877	6.279	5.984	5.700	6.199	5.9043
Daily Temperature (°C)	21.180	22.20	22.69	21.60	20.60	19.80	19.380	19.81	20.63	20.84	20.56	20.65	20.8283

However, as the inflation moves to 9.2%, the system size increases with the addition of the diesel generator. Consequently, the emissions to the atmosphere also increased beyond the levels experienced when the inflation rates were 8%. The optimal hybrid configuration was sensitive to both inflation rates and solar irradiation levels where low inflation rates and high solar insolation led to smaller energy system size with low NPV cost and smaller capital invested for the same project. Table 11 shows how the top two optimization results responded to the variations in solar irradiation levels and expected inflation rates.

3.5. Sustainability Analysis

The sustainability result was based on four MCDM techniques to select the best of the nine alternatives. The parameters used for sustainability analysis are presented in Table 13. SAW, TOPSIS. MABAC and COPRAS were used for the sustainability analysis and Table 14 shows the results obtained from each of the MCDM Criteria based on Sum and Vector, Maximum and Minimum, DEA. It was established that using the SAW MCDM technique, the best alternative was A3 using the sum-vector normalization, A2 using Max-Min normalization and A2 using DEA normalization. According to the TOPSIS technique, it was established that the best alternative was A3 using the sum-vector normalization, A2 using Max-Min normalization and A2 using DEA normalization. It was established that using the MABAC MCDM technique, the best alternative was A3 using the sum-vector normalization, A2 using Max-Min normalization and A2 using DEA normalization. According to the COPRAS technique, it was established that the best alternative was A2 using the sum-vector normalization, A2 using Max-Min normalization and A2 using DEA normalization.

The average rankings based on all the applied MCDM criteria is presented in Fig. 8. It was established that A2 was the most sustainable alternative. The sustainability analysis revealed the most sustainable alternative had the following configurations: The best architecture (Table 10) after optimization analysis based on NPV and LCOE was a combination of 360 kW of REC Solar325REC325PEM 72 (Solar PV), 576 Strings of lead acid- Gel Solar Cell (storage battery), a 142 kW Siemens Industry SININVERT PVS351 (converter with inbuilt inverter), and a 540 kW biomass generator with HOMER Load Flow (LF) dispatch strategy at 100% renewable energy at a NPV of USD 1.97M, Capital cost of USD 715,505.30, LCOE of USD 0.1026, operating costs of USD 43,302.48 per year, electricity production of 74,790.1 kW and excess energy of 49,062.51 kW with a potential of being sold back to the grid.

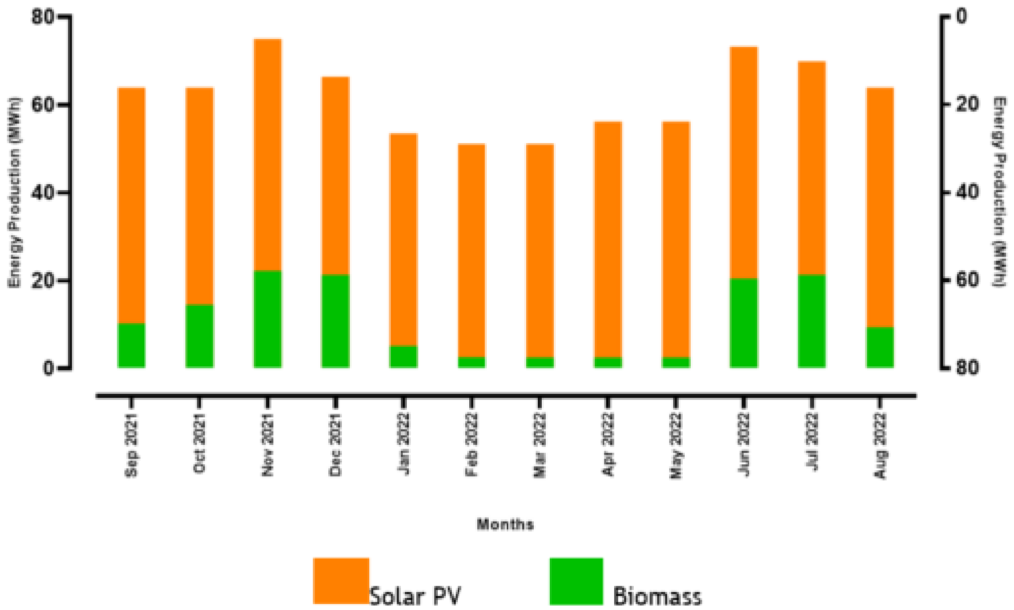

Fig. 7: Shared energy generation between solar PV and Biomass generator

A comparison between the optimal HPS (A1) and Sustainable HPS (A2) shows a reduction of 43.24% in GHG emissions, reduced system capacity to 900 kW and a 21.85% reduction in the capital expenditure for the energy system. Moreover, the renewable penetration also grew to 100% from 98% as depicted in Table 10. Table 15 presents the NPV Summary for the sustainable alternative.

Table 10: Optimization Results

	PV	D. Gen (kW)	Bio Gen (kW)	Storage	Converter (kW)	Dispatch	NPC (USD)	LCOE (USD/kWh)	Operating cost ($yr-1)	CAPEX ($)	OPEX ($yr-1)	Ren Frac (%)	Elec Prod (kWhyr-1)	Excess Energy (kWhyr-1)	Unmet load (kWhyr-1)	Emissions (kgyr-1)
A1	360	800	540	576	142	LF	1.93M	0.1003	34,868.61	915,505.30	20,276.27	98	747,907.10	49,062.51	0	150.30737
A2	360		540	576	142	LF	1.97M	0.1026	43,302.48	715,505.30	20,276.27	100	747,907.10	49,062.51	0	85.30737
A3	609	800		576	256	LF	2.41M	0.1255	47,966.72	1,019,070	25,710.12	97.21624	1,054,718	345,774.40	0	15,408.86
A4	902			816	274	LF	3.06M	0.1597	65,711.35	1,161,008	34,433.24	100	1,534,146	825,192.20	0	0
A5	920	800	540	576	1118	LF	6.72M	0.1016	178,489.70	1,552,698	-177,060.80	70.42544	2,456,648	28,304.23	0	564,993.90
A6	920	800	540		657	LF	8.00M	0.0976	239,189.40	1,072,252	-275,787.90	60.06177	2,906,469	12,966.90	0	945,011.30
A7		800	540	576	154	LF	8.28M	0.4314	262,297.30	684,765	18,960.65	25.68828	700,103.40	359.8881	0	411,732.90
A8	920	800		576	1125	LF	8.89M	0.1379	256,212.80	1,464,565	-172,215.60	62.26529	2,403,993	26,458.38	0	701,711.60
A9		800		576	157	LF	10.8M	0.5611	351,315.90	595,250	14,025.50	0	712,846.30	407.5748	0	595,709.70
A10	920	800			657	LF	10.8M	0.1298	340,077	982,072	-287,703.50	51.69023	2,956,314	12,966.90	0	1,163,033
A11		800	540	576	119	LF	12.7M	0.3826	415,377.30	674,790	-52658.23	13.62987	1,202,654	77.9827	0	827,727
A12	920	800	540		138	LF	13.8M	0.7203	445,389.60	926,750	33,619.70	0	2,675,986	2,007,791	0	759,103.40
A13		800		576	147	LF	14.6M	0.4736	484,892.90	592,590	-44,794.23	0	1,137,881	75.92556	0	950,968.30
A14		800	540			LF	15.5M	0.3179	524,281.90	290,180	-139,608.10	12.57025	1,680,721	0	0	1,228,009
A15		800	540			LF	17.5M	0.9101	593,153.10	290,180	12,792.80	0	1,487,966	825,199.30	0	1,072,192
A16		800				LF	18.5M	0.3643	632,001.60	200,000	-154,869.70	1.11E-14	1,753,632	0	0	1,465,253
A17	920	800			137.75	LF	19.8M	1.0210	653,726.40	836,570	29,487.50	0	2,956,714	2,289,194	0	1,163,368
A18		800				LF	23.2M	1.2109	795,631.30	200,000	8,760	0	1,753,632	1,090,865	0	1,465,253

Table 11: Sensitivity Analysis Results

Sensitivity Parameter		**Sizes of the Individual System Architecture**					**Economic Parameters**					**Technical Parameters**		**Environmental Parameters**
Expected Inflation (%)	**Solar Irradiation ($kWhm^{-2}$ day^{-1})**	**Solar PV (kW)**	**D.Gen (kW)**	**B. Gen (kW)**	**Storage (No.)**	**Converter (kW)**	**LCOE ($/kWh)**	**OC ($yr-1)**	**CAPEX ($yr-1)**	**OPEX ($yr-1)**	**NPV ($)**	**Elec Prod ($kWhyr^{-1}$)**	**Excess Energy ($kWhyr^{-1}$)**	**CO_2 Emissions ($Kgyr^{-1}$)**
10	4	468.1599908	800	540	576	126.3133425	0.1029471	37579.86	981211.8	22885.3	2184269	722125.8	24954.59	272.9243
10	5.904	360	800	540	576	138.7580829	0.09395795	33709.39	914392.3	20235.84	1993543	749213.4	50336.55	86.59445
10	6.5	360.803463	800	540	576	141.693234	0.09271287	32842.21	915736.4	19948.47	1967126	792583.5	92933.16	78.21137
8	4	444.7178444		540	576	124.4000421	0.1192305	48404.47	765438.6	22795.46	1975550	708536.7	12559.96	115.4709
8	5.904	360		540	576	139.0075017	0.1093284	43880.79	714462.1	20240.63	1811482	749119	50241.77	86.53197
8	6.5	360		540	576	140.1577981	0.1079724	42969.16	714784.2	19907.93	1789013	791749.4	92132.23	78.65888
9.2	4	454.861939	800	540	576	124.3216789	0.1096056	39071.75	972010.3	22802.59	2103280	714844.5	18395.84	278.5603
9.2	5.904	360.3368172	800	540	576	141.9512247	0.1003193	34868.61	915505.3	20276.27	1925079	747907.1	49062.51	85.30737
9.2	6.5	360.8091684	800	540	576	141.6996138	0.09906077	34026.36	915741.9	19948.77	1900929	792594	92943.67	78.21135

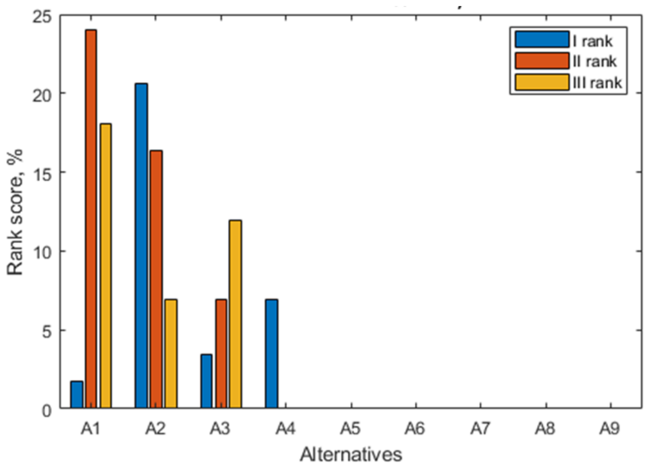

Fig. 8: Ranking of the alternatives in sustainability analysis

4. DISCUSSION

4.1. Load Assessment

The daily load curve in Fig. 4 shows the electrical power consumption based on the activities taking place within the study area. The consumption remains relatively low 0000hrs to 0500hrs due to minimized students and learning activities (street and security lights mostly on). This reduced activities also relates to the power consumption between 1600hrs and 1700hrs.

Power consumption is high between 0600hrs and 1100hrs due to increased student activities and learning activities which start from 0700hrs. Moreover, between 1800hrs and 2200hrs, power consumption is also high due to increased student activities back in the hostels. The daily load demand as curve concurs with a study of Popoola et al. (2018) for covenant university based in Nigeria in their smart campus energy data research.

The high-power consumption between January to April and October to December as depicted in Fig. 5 was attributed to increased academic activities (First and second academic semesters) i.e., increased learning activities and student activities within the university. The period between May and September is associated with reduced power consumption due to reduced academic activities associated with semester breaks and minimal administrative work. The University also carries out scheduled maintenance during this period switching off many energy-consuming equipment hence reducing power consumption during this time. Only school-based students which are few are the ones present during that time and their power consumption is low. The seasonal load data trends evidenced in this research concur with the MMUST academic calendar (MMUST Almanac, 2021).

Table 12: Cost summary of the most Optimal architecture (A1)

Component	Capital ($)	Replacement Cost ($)	O&M ($)	Fuel ($)	Salvage ($)	Total ($)
Diesel Gen	200,000.00	0.00	0.00	0.00	(244,191.36)	(44,191.36)
Storage	351,360.00	830,696.10	166,773.02	0.00	(231,576.45)	1,117,225.67
Bio. Gen	90,180.00	105,062.98	88,337.58	0.00	(66,910.41)	216,670.16
PV	234,218.93	0.00	208,661.42	0.00	(0.00)	192,494.35
Converter	39,746.34	46,911.62	123,300.27	0.00	(17,464.17)	192,494.06
System	915,505.27	982,643.70	587,072.30	0.00	(560,142.39)	1,925,078.88

4.2. Optimization Analysis

The PV and Biomass generator were considered a primary source of supplying the loads within the university due to the abundance of solar irradiation and biomass within the university. Solar PV and biomass HPS show a complementary characteristic which helps in minimizing the intermittency associated with individual renewable sources majorly the solar energy resource. Due to the variability of renewable energy resources throughout the year which was a design consideration for this project, there arose excess power generation which would be sent back to the grid using a net metering system. The introduction of a diesel generator in the optimization analysis provided a means of backup during extreme weather conditions as it contributed to almost 0% of the total energy generated due to the efficiency of the utilized LF dispatch strategy which declined the operating hours of the diesel generator, leading to negligible fuel consumption and limiting the GHG generation. This diesel generator behavior concurs with a study by Elkadeem et al. (2019) where solar PV was used to generate 63.1% of total power supplied in Dongola, Sudan for rural agricultural electrification while wind generator generated only 33% and less than 1% of power demand was supplied by the diesel generator. The availability of solar irradiation throughout the year as opposed to biomass whose bulk tends to be during academic peak moments, led to solar PV contributing to the bulk of power generation (81.9%) as opposed to biomass generator (18.1%) as depicted in Fig. 7. Moreover, this availability of solar irradiation makes it cheaper to maximumly use solar panels to generate the bulk of power which concurs with a study by Ghenai & Janajreh (2016) where solar PV was used to generate 74% of total power supplied for electrification of Sharjah city, United Arab Emirates while Biomass generator generated only 26%.

From Table 11 on the Cost summary of the NPV of the optimal HPS, it is observed that storage constitutes the bulk of the capital invested for the project at 38.38% leading to the overall NPV of the system at USD 1.93M. With the rapidly advancing technology, production of cheaper storage is expected and this will lead to reduced storage costs furthermore leading to reduced NPV and low COE. The comparison between the optimal scenario and base case scenario (oversized diesel generator of 800 kW) reveals a high difference in NPV and LCOE due to the high maintenance costs of the diesel generator, high fuel consumption throughout the year and high GHG emission making it the least likely system to be used as the main power source for learning institutions. With the proposed project having the LCOE of USD 0.1026 as compared to USD 1.2109 of the base case scenario, this project will substantially lower the cost of power and

Table 13: Hybrid energy alternatives system parameters considered for sustainability analysis

Hybrid Energy Systems Alternatives	Technical Parameters					Economic Parameters				Environmental Parameters			
	STC (kW)	EP (kW)	EE (kW)	UL (kW)	RF (%)	NPC ($)	CAPEX ($)	OC ($/yr)	LCOE ($/kWh)	CO_2 (kg)	CO (kg)	SO_2 (kg)	NO_x (kg)
PV-D. Gen-Storage-Bio Gen	1700	747,907.1	49,062.51	0	98	1.93M	915,505.3	34,868.61	0.1003	95.3	1.947	0	0.992
PV- Bio Gen -Storage	900	747,907.1	49,062.51	0	100	1.97M	715,505.3	43,302.48	0.103	85.3	0.947	0	0.592
PV-D. Gen-Storage	1409	105,4718	345,774.4	0	97.3	2.41M	1,019,070	47,966.72	0.1255	15,409	10.4	38.2	98.3
PV-Storage	902	1,534,146	825,192.2	0	100	3.06M	1,161,008	65,711.35	0.1597	0	0	0	0
PV-D. Gen-Storage-Bio Gen-Grid	2260	2,456,648	28,304.23	0	70.4	6.72M	1,552,698	178,489.7	0.1016	564994	384	1402	3604
D. Gen-Storage-Bio Gen-Grid	2260	2,906,469	12,966.9	0	60.06	8.0M	1,072,252	239,189.4	0.0976	945011	641	2345	6029
D. Gen -Bio Gen-Storage	1340	700,103.4	359.8881	0	25.69	8.3M	684,765	262,297.3	0.4314	411733	280	1022	2627
PV-D. Gen-Storage-Grid	1720	2,403,993	26,458.38	0	62.27	8.9M	1,464,565	256,212.8	0.1379	701712	475	1742	4477
D. Gen-Storage	800	712,846.3	407.5748	0	0	10.8M	595,250	351,315.9	0.5611	595710	403	1479	3800

Table 10: Ranking of the alternatives in sustainability analysis

MCDM methods	Alternatives based on the Normalization of DM																										
	Sum and Vector									Max-Min									DEA								
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A1	A2	A3	A4	A5	A6	A7	A8	A9	A1	A2	A3	A4	A5	A6	A7	A8	A9
SAW	3	2	1	4	7	5	8	9	6	2	1	3	4	7	5	8	9	6	2	1	3	7	5	8	9	6	4
TOPSIS	3	2	1	4	7	5	8	9	6	2	1	3	4	7	5	8	9	6	2	1	3	4	7	5	8	9	6
MABAC	3	2	1	4	7	5	8	9	6	2	1	3	4	7	5	8	9	6	2	1	3	7	5	8	9	6	4
COPRAS	2	1	3	4	5	8	7	6	9	2	1	3	4	5	8	6	7	9	2	1	3	4	7	5	8	6	9

Table 15: NPV Summary for the most sustainable alternative (Solar PV-Biomass Energy system)

Component	Capital ($)	Replacement Cost ($)	O&M ($)	Fuel ($)	Salvage ($)	Total ($)
Storage	351,360.00	830,696.10	166,773.02	0.00	(231,576.45)	1117225.65
Bio. Gen	90,180.00	105,062.98	88,337.58	0.00	(66,910.41)	216,670.16
PV	234,218.93	0.00	208,661.42	0.00	(0.00)	442,880.35
Converter	39,746.34	46,911.62	123,300.27	0.00	(17,464.17)	192,494.06
System	715,505.27	982,643.70	587,072.30	0.00	(315,951.03)	1,969,270.23

with its breakeven period of 5.2 years, the project will be self-sustainable and generate profits to help the university be energy sufficient. This breakeven period is in line with studies of Chowdhury et al., (2020), where PV-B HPS yielded 7.2 years as its breakeven period.

According to Pradhan (2017), the use of such hybrid energy system also leads to the advancement of technology within the country and in learning institutions while at the same time improving the overall power efficiency at reduced levels of GHG emission as evidenced in this research where the optimal scenario had emissions of 150.30737 kgyr^{-1} compared to the base case which had 1,465,253 kgyr^{-1}. This finding concurs with Ayadi et al. (2020) in their research on renewable integration in smart grid, the environmental effects of fossil fuels as a result of renewable energy integration into the system were reduced and overreliance on fossil dropped as well as the creation of more jobs in the field of renewable energy development.

4.3. Sensitivity Analysis

From Fig. 7, Solar PV constituted the bulk of the power generated, a sensitivity analysis was conducted to evaluate the impact of solar irradiation levels and variation in inflation rates on the economic, technical and sustainability parameters. With the increasing solar irradiation levels, there was a reduction in the solar PV capacity as well as the capital invested in the project i.e., more power would be drawn from the system and more batteries would be charged. Moreover, as the inflation rate increases, there is a corresponding increase in the system cost and the COE also increases. This concurs with Shahzad et al. (2017), who carried out a sensitivity analysis on PV-B for rural Pakistan where the higher the solar irradiation was, the smaller the system cost and the lower the COE. As depicted in Table 11, the optimal configuration converged at an 8% inflation rate with solar irradiation of 6.5 kWhm-2 day-1 as it had the lowest NPV making the system cost more attractive to investors due to the low capital investment required. At this inflation rate, PV-B HPS had superior economic and technical parameters compared to PV-B-DG. The exclusion of generator at this inflation rate led to a low GHG emission. The variations in inflation rates and climatic conditions have a greater impact on the system, these parameters thus need to be of key concern to renewable energy developers at the design stage.

4.4. Sustainability Analysis

Hybrid energy projects use modern technologies which promise affordable electricity costs and sustained environmental and improved social welfare of the people whose lives depend on such technological advancements. The elimination of the diesel generator from the system ensured reduced dependency on fossil fuels which contributes to GHG emissions. Moreover, it also resulted in reduced investment costs. The renewable energy penetration also increased to 100% as the system fully became dependent on PV-B HPS. This study concurs with a study by Elkadeem et al. (2019), where a sustainability analysis for techno-economic analysis for off-grid HPS (based on PV, W and DG) in Dongola, Sudan reduced the GHG emission from 351,3972 kgyr-1 to 168,786 kgyr-1 due to reduced dependency on diesel generator.

5. CONCLUSIONS

This research paper presented a simulation of a hybrid energy system based on solar PV and Biomass with storage for learning institution based on optimization analysis, sensitivity analysis and sustainability. Technical, economic and sustainability factors were considered for the system modelling with a hybrid combination of Solar PV, Biomass generator with storage being the most sustainable power alternative to run the institution. With 100 % renewable penetration, the GHG emissions reduced by 43.24% when compared to the optimal alternative which had diesel generator included. Additionally, the sensitivity analysis trend led to elimination of diesel generator when solar irradiation and inflation rates were varied with NPV and COE being dependent on these variations. Moving forward, it is vital for the government and policy makers to collaborate in advancing these technologies, fostering innovation, and implementing policies that promote the widespread adoption of solar PV and biomass HPS. For future research, the study should be extended to other fields of energy planning. The Solar PV-Biomass HPS adoption will be limited to appropriate technology, location, and effective storage to cater for the intermittency of these HPS. The techno-economic study given in this research shows that other places with similar climatic and economic conditions are prospective candidates for deployment of the proposed hybrid system for electricity generation.

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