Optimisation of Renewable Energy Microgrid Systems for Developing Countries

by

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Student Declaration

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Abstract

This research proposes a strategy for reducing the running costs of hybrid microgrids which include both renewable and conventional power generation. The developed system uses metaheuristic methods for microgrid optimisation enabling the planning, maintenance, and effective cost management of the system. The target application for the research is a typical Nigerian remote rural community, not connected to any form of centralised power supply with the dwellers of the community practising peasant farming.

The location for application of the proposed microgrid is first examined to determine renewable resources available, current power supply source, their behaviour and electricity consumption patterns, future plans for consumption, and willingness to purchase electricity if provided. In the absence of smart metering, energy use data are gathered through questionnaires and the bottom-up approach adopted for hourly time-step load demand profiles development. Using both end-use and econometric indices, a ten year load forecast is done with the fifth year forecast employed in design analysis. These forecast based on real world questionnaire will provide good resource in real world application.

The Hybrid Microgrid (HMG) system is designed using HOMER to cope with variability from both weather and unexpected changes in the load, and has photovoltaic panels, wind turbines, battery storage systems, and a diesel generator in its configuration.

The research compares the effectiveness of three optimization strategies, the Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), and Simulated Annealing (SA) by tuning algorithm parameters to improve the speed and quality of solutions. This is the first time its being used for developing country microgrids.

The HMG optimisation objective is to minimise its operating costs by reducing the generator running hours. The optimisation is constrained by the requirement to meet the variable load demand at all times. The results showed PSO had the lowest diesel generator run hours, a 65.2% reduction in the diesel running hours is achieved compared to HOMER simulations of the HMG. The adaptability of the system means that the operator can choose the optimisation strategy based on the required output.

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Special thanks to my parents - Dr and Mrs J.O Abah, my siblings - Juliet, Gift and family, and Samuel, and my kids - Christabel and Jesse. Your ceaseless prayers, support and encouragement has brought me thus far.

Dedication

To my adorable kids - Christabel and Jesse. Its been so many years of sacrifice. I love you both.

Contents

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List of Abbreviations

AC: Alternating Current

BSS: Battery Storage System

CERTS: Consortium for Electric Reliability Technology Solutions

DSM: Demand Side Management

DG: Diesel Generator

DC: Direct Current

DER: Distributed Energy Resource

DISCOs: Distribution Companies

ECN: Energy Commission Nigeria

ESS: Energy Storage System

EU: European Union

FGN: Federal Government of Nigeria

FMPW&H: Federal Ministry of Power, Works and Housing

GENCOs: Generation Companies

GA: Genetic Algorithm

GoN: Government of Nigeria

HMG: Hybrid Microgrid

IPP: Independent Power Producers

LGA: Local Government Area

NEPP: National Electric Power Policy

NPC: Net Present Cost

NDPHC: Niger Delta Power Holding Company

PSO: Particle Swarm Optimisation

PV: Photovoltaic

PHCN: Power Holding Company of Nigeria

REMP: Renewable Energy Master Plan

RER: Renewable Energy Resource

REA: Rural Electrification Agency

SA: Simulated Annealing

SoC: State of Charge

SSM: Supply Side Management

TCN: Transmission Company Nigeria

V2G: Vehicle-to-Grid

WT: Wind Turbine

Wi-Fi: Wireless-Fidelity

WV: With Variability

WoV: Without Variability

List of Symbols

α : Ground friction coefficient

α_{DG},β_{DG},γ_{DG} : Diesel generator coefficients

i' : Nominal interest rate

ρ : Air density

a : Start-up cost

A : Swept area of rotor disc

AD : Days of autonomy

b : Fixed cost

B_{eff} : Battery efficiency

c : Variable cost

c_1, c_2 : Cognitive and social parameters

COE : Cost of electricity

C_{NPC} : Net Present Cost

C_p : Power coefficient

CRF : Capital recovery factor

DOD : Depth of discharge

ΔE : Change in energy

E : Energy

E_{AC} : AC primary load

E_{DC} : DC primary load

f : Annual inflation rate

F_{min} : Objective function

GEN : Diesel generator fuel consumption cost

G_C : Irradiance at operating point

G_{STC} : Solar irradiance at STC

h_{hub} : Hub height

h_{ref} : Reference height

i : Population size

i_R : Real interest rate

I_0 : Saturation current

I_c : Cell current

I_D : Voltage-dependent current lost to recombination

I_M : Module current

INV_{eff} : Inverter efficiency

I_{PH} : Light-generated current in the cell

I_{sh} : Current loss due to shunt resistances

j : Number of decision variables

Lav : Daily average load

LF : Load factor

k : Boltzmann's constant ($1.381 \times 10^{-23} J/K$)

K_t : Temperature coefficient

n : Diode ideality factor ($unitless$)

N : Project lifetime

N_p : Number of cell in parallel

N_s : Number of cell in series

ON : Plant online

P : Power

$P_{Battery}$: Battery rated power

P_{BSS} : Battery power output

P_{DG} : Diesel generator output power

P_{DG-nom} : Diesel generator nominal power

P_{DG-out} : Diesel generator power output

P_{MaxC}, P_{MaxD} : Maximum charging and discharging power

P_{ij}, P_{gj} : Best individual and global particle position

P_L : Load demand

P_{max}, P_{min} : Maximum and minimum power

P_{PV-out} : Photovoltaic hourly power output

P_{STC} : Rated photovoltaic power output under STC

$P_{WT}(v)$: Power from the wind

$P_{WT-rated}$: Wind turbine rated power output

q : Elementary charge $(1.602 \times 10^{-19} C)$

r_1, r_2 : real random numbers

R_s : Series resistor

R_{sh} : Shunt resistor

S_{cap} : Storage capacity

$SoC, SoC_{min/max}$: State of charge, minimum and maximum SoC

STC : Standard test conditions

t : time

T : Temperature

T_{amb} : Ambient temperature

T_c : Cell temperature

T_{STC} : Photovoltaic temperature at STC

U_{New} : Number of new consumers per year

v : Wind speed

v_{ci} : Cut-in wind speed

v_{co} : Cut-out wind speed

v_r : Rated wind speed

v_{ref} : Wind speed at reference height

V : Wind velocity

V_c : Cell voltage output

V_{ij} : Particle velocity

V_M : Module voltage

V_T : Thermal voltage

w : Inertia coefficient

X_{ij} : Particle position

X_{minj}, X_{maxj} : Minimum and maximum value of the individual in the population

Chapter 1

Introduction

1.1 Background

Typical Nigerian rural communities are inaccessible due to their geographical terrain, causing difficulty to access both grid electricity and fossil fuels as a result of poor roads and economic feasibility [1]. These communities are characterised by load demand, population density, income, and education at low levels. Dwellers in these communities rely on generators to meet electricity needs, wood fuel, charcoal and waste for cooking and heating purposes.

However, due to the income levels and inaccessible roads to purchase and transport fuels, running generators for 24 hours a day is a challenge, also taking into account the maintenance and fuel costs, amongst other constraints. As a result, candles, kerosene lanterns, and time spent to fetch woods for cooking and heating activities are used as substitutes. These rural communities are endowed with Renewable Energy Resources, RERs, such as solar, wind, small hydro sources of power [2]. Deploying varying RERs mix (onshore wind turbines and solar photovoltaic systems) can achieve a 100% renewable energy supply by 2050, also reducing harmful gas emissions [3].

In recent times, countries around the globe continually invest in the growth, development and deployment of more sustainable RERs to cater for the electricity and heat demands of their citizens [4]. Ongoing research by government organisations, parastatals, businesses and academics have looked at the efficient use of RERs, demand-side energy management, optimised designs and operations as the solution to shifting complete reliance on the depleting coal/oil reserves and also preserve the ecosystem.

A single or combination of RERs forms an island microgrid when operating independently or grid-tied microgrids when connected to the national grid. Microgrids have proven to be the solution to the relentless shift to clean and sustainable sources of power generation.

1.2 Motivation

Lack of access to electricity supply limits access to essential life-sustaining facilities such as clean water, food storage, a comfortable schooling environment, basic health facilities with power supply and limitations to how much and what kind of businesses to run.

Nigeria forms 10% of unelectrified Sub- Saharan Africa [5] and the Nigerian grid system suffers from reliability, blackouts, vandalization, and inefficiencies to meet its vastly growing population. Renewable energy resource-based microgrids for rural electrification controlled by its community dwellers could help alleviate the problems of both the national grid and populace by reducing dependence on the grid, creating awareness, and also job opportunities to the community members on how to manage their power plants.

The unpredictable nature of the RERs, which is a drawback to implementing isolated power systems, gave rise to the mix and combination of the renewable resources to form the microgrid system design, allowing for reliability, flexibility, efficiency and cost-effectiveness. It is a challenge designing renewable energy microgrid systems to account for cost, socio-economic and environmental impacts; as such, accurate knowledge of the factors that influence the system performance and accurate modelling is essential to develop the right system. In Nigeria, stand-alone systems comprising solar or wind or solar and wind technologies are standard in use. In this research, a system consisting of solar, wind, battery and diesel generator will be investigated.

For this study, a load demand profile is developed and forecasted, an isolated microgrid design using Homer Pro design software is carried out. In order to develop a cost-effective and reliable system that considers load variability, the need for optimisation of the designed system using metaheuristic optimisation strategies are employed to manage the system operation.

1.3 Nigerian Energy Scenario

Nigeria's energy sector in recent years has experienced grid failure and collapse. Since the privatisation of the electricity sector in 2013 up to 2020, the grid has experienced grid failure and collapse 84 and 43 times respectively [6]. According to the World Bank, Nigeria has a yearly population growth rate of 2.5% [7], it generates less than 5 Gigawatts (GW) annually [8]. As a result, insufficient and unreliable electricity severely constrains its economic growth and development.

In 2019, the Federal Government of Nigeria (FGN) through financing from the World Bank and the African Development Bank signed an agreement to upgrade Nigeria's electricity transmission infrastructure, and supply to 25GW in what is called the Presidential Power Initiative [6]. The FGN seems to be incapacitated in handling the issues associated with the grid. Continuous blackout appears to be the order of the day for the average Nigerian, with individuals sourcing alternatives to power their homes and businesses.

The privatised generation companies are contractually obligated to increase generation for each plant over certain years, achieving 6GW of installed capacity. Finally, an additional 2GW increase will stem from investments by new Independent Power Producers (IPP). In achieving these goals, the FGN focuses on sustained and established investment climate for the participation of the private sector, expansion of the transmission and distribution networks to meet customers power needs, establishing cost-reflective tariffs, sustaining a creditworthy off-taker of electricity, and reducing inefficiency in support of affordable end-user tariffs.

As at early 2015, the FGN in accordance with established contracts, instructed the electricity market to operate, including the Power Purchase Agreements for generators and Vesting Contracts for the delivery of power to distribution companies. All market members had to pay or receive for what they receive from or supply to the system, which is a crucial stride to gaining investor confidence in the sector.

Also, The Renewable Energy Master Plan (REMP), seeks to improve on the supply from RERs from 13% of total power generation in 2015 to 23% in 2025 and 36% by 2030. With RER accounting for 10% of the country's total power consumption by 2025.

The Plan also considers installed capacity targets for some RERs as follows [9]:

- Solar PV: 0.5GW by 2025.
- Windpower: 40MW for wind energy by 2025.
- Smallhydro: 0.6GW in 2015 and 2GW by 2025.
- Biomass power plants: 50MW in 2015 and 0.4GW by 2025.

1.4 Nigerias' Policies on Microgrid

Microgrid is a new concept developed to bring out the tremendous potential of distributed generation into the mainstream power sector. It is considered an extension of a distributed generation because of its composition, which comprises different distributed generator sources, both renewable and non-renewable.

Microgrids are a localised grouping of electricity generation, energy storage, energy control and conversion, energy monitoring and management, and load management tools, which can operate while connected to the traditional power grid or function independently. The concept of microgrid is referred to as a single electrical power subsystem associated with a small number of distributed energy resources, both renewable and conventional sources, including photovoltaic, energy storage systems, wind power, hydro, internal combustion engine, and gas turbine together with a cluster of loads [10]. For some, microgrid holds the promise of becoming the basic building block in implementing the next-generation intelligent grid infrastructure. However, like most new technologies, there are significant implementation challenges to overcome [11].

Microgrid and distributed generation technologies are developing rapidly, and with the enormous potential of solar resources, these technologies seem to be the most viable if properly harnessed to meet the increasing need for electrical energy in Sub-Saharan Africa.

Also according to [12], regulatory bodies and policies are in place to direct and facilitate loans and grant for microgrid developments in the country. Some of these bodies include: National Electric Power Policy (NEPP) of 2001, and The Nigerian Electricity Regulatory Commission's Mini-Grid Regulation of 2017, Rural Electrification Agency (REA) is responsible for the coordination and implementation of rural electrification strategies and activities under the supervision of the Federal

Ministry of Power, Works and Housing (FMPW&H). Further description of the microgrid supporting policies can be found in the Table 1.1.

Table 1.1: Nigerian Policies Supporting Microgrid Development [12]

2001	2005	2015	2016	2017	2017	2017
National Electric Power Policy (NEPP)	Electric Power Sector Reform Act (EPSRA)	Nigerian Renewable Energy and Energy Efficiency Policy (NREEEP)	Rural Electrification Strategy and Implementation Plan (RESIP)	Power Sector Recovery Programme (PSRP)	Nigerian Electricity Regulatory Commission Mini-grid Regulation	Nigerian Electricity Regulatory Commission Mini-grid Regulation
Provides for the structuring and privatisation of the electricity market	Unbundles and privatises the Nigerian electricity market	Develops renewable energy and energy efficiency (RE & EE) targets and action plans	Coordinates and implements Nigeria's rural electrification policies, target and strategies	Increases electricity access by implementing off-grid renewable solutions	Provides definition, registration and grant of permit for minigrid systems	Provides capital subsidies/grants and technical support to developers of rural electrification projects
Provides for a Rural Electrification Policy, and targets as well as the Rural Electrification Fund	Develops a competitive electricity market	Power roadmap and support for electricity market reforms	Administers the Rural Electrification Fund	Establishes data driven processes for decision making across the sector	Develops contract templates and enforcement of electricity contracts between all parties concerned	Establishes the investor eligibility and the project selection criteria under REF
Promotes research and development in the power sector	Establishes the Nigerian Electricity Regulatory Commission; Rural Electrification Agency	Promotes off-grid renewable development and financing	Promotes low-cost technologies and private sector participation	Develops and implements a foreign exchange policy for the power sector	Describes operation of the minigrid including technical specifications	Outlines the sources and allocation of REF resources
	Consumer protection, licenses and tariffs	Recommends additional regulations and economic instruments		Makes electricity market contracts effective and ensures cost reflective tariffs	Proposes commercial arrangement including tariff setting	Develops a database of possible locations to be targeted by the REF
		Research development and training			Establishes framework for investor and consumer protection	Outlines the REF grant award process, monitoring and evaluation of projects
		Requires bilateral and regional cooperation				
		Implements existing planning and policy				

It is expected that with these policies in place, the Microgrid developments, especially for rural communities, is promoted.

1.4.1 Microgrid Projects in Nigeria

Nigeria is heavily dependent on limited installed available fossil fuel plants for electricity production. The power utility cannot cope with the increasing electricity demand. According to the World Bank [7]press release in February 2021, 85 million people of the Nigerian population are without access to electricity which is about 43% of the Nigerian population. This invariably makes Nigeria one with the most significant deficit in energy access across the globe serving as a constraining factor to private sector growth and development. It is estimated that over 4trillion Naira is spent to power small scale fuel and diesel generator, amounting to 14GW annually [6].

Presently, the majority of the Nigerian population rely on traditional biomass and private generator sets such as petrol and diesel generators to meet their daily electricity demands. However, these generators are costly, expensive to maintain, and are not environmentally friendly. Most of the population that do not have access to electricity in 2018 live in the rural areas, accounting for 64% without access. Due to the poor electrification rate caused by earlier mentioned challenges, some federal, state government and non-governmental organisations in Nigeria initiated the microgrid rural electrification initiatives.

Rural dwellers incur some amount of cost implication on energy alternatives and can pay for microgrid services. Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) estimates that 30 solar microgrids with a total installed capacity of 1MW, serving 6,000 customers currently are in operation in Nigeria [12]. A movement in this direction could meet 14% of the Nigerian population if 100kW sites are put in 10,000 more locations by 2023.

Some of these initiatives gave birth to what is known as the Jigawa State Alternative Energy Trust Fund and Sokoto State energy research Centre, among others. These entities have been using RERs, especially photovoltaic (PV) and Small Wind Turbine, to provide electricity in remote areas. There are a list of pilot PV based and HMG, projects provided by the government agencies in Nigeria [12]. They have provided electricity to thousands of people and health care centres in some rural communities across Nigeria. These projects have slightly improved the national electrification rate in rural communities, mainly in Northern Nigeria. Other existing projects across the country include 50kW Angwan Rina, Shendam LGA of Plateau State, 85kW Gbamu Gbamu, Ijebu East LGA of Ogun State, and 10kW Egbeke, Etche LGA of Rivers State, amongst others as shown in the Figure 1.1.

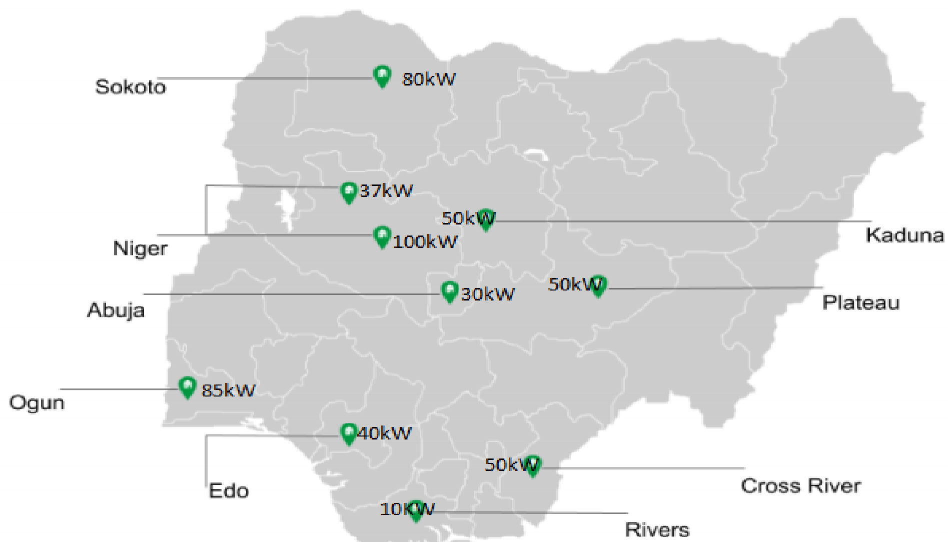

Figure 1.1: Existing Microgrid Sites in Nigeria [12]

Installed microgrid in Nigeria caters for an average population of 2,500 persons living in 300-500 households. Before the inception of microgrids, these community dwellers who primarily engage in farming and fishing relied on candles, kerosene lamps, torch-lights, non-cooking energy source generators, and wood fuels as cooking energy sources. Other commercial activities include welding, grain milling, barbing, retailing, and cash and food crops. On average, the reflective cost of microgrid tariffs is near N200/kWh ($0.57/kWh) [13], which is lower than the cost of running a diesel or petrol generator.

The design of microgrids differ with different applications as they rely on the resources specific and available to the location of the application. As such, knowledge of the renewable energy resource available to Nigeria as a whole is presented in the next section.

1.5 Renewable Energy Resource (RER) Availability and Potentials in Nigeria

Great potential for RER exists in Nigeria that is yet to be tapped. Some of the barriers to RER development include the large oil and gas production down south, the lack of clarity and market information on private government fuel subsidies and independent sector opportunities, and the knowledge gap concerning financial support mechanisms available within the country.

With Nigeria crude oil reserves estimated at over 36 billion barrels, natural gas reserves over 5 trillionm^3, and coal and lignite reserves estimated at over 2.5 billion tons amongst others readily available, it could be difficult switching to RERs, as the bulk of the populations continuous dependence on oil has only increased since late the 19th century [13]. Nonetheless, RER can serve as an alternative energy source to the remnant of the populace not on the national grid. RERs offer possible safe options for clean and environmentally friendly energy.

Nigeria, endowed with vast amount of RERs, has an average daily global horizontal solar irradiation ranging from $4.2kWh/m^2$ in the south to $6.2kWh/m^2$ in the north, experiences 5 to 7 hours of daily sun hours on average, and has moderate wind energy potentials ranging between 2m/s in the coastal areas and 4m/s in northern Nigeria at 10m hub height. Nigeria has an estimated 3.5GW of small hydropower potential, but only 64.2MW has been exploited, while for large hydropower, an estimated potential of 11,250MW with 1900MW exploited capacity. Nigeria's biomass resources include crops, forage grasses, shrubs and animal wastes with daily production of animal waste is estimated to be 227,500 tonnes [14].

The world is evolving, adopting and laying emphasis on the use of renewable energy options as the sure means in attaining energy sustainability and, consequently, environmental sustainability.

Some prosperous countries engaged in promoting Renewable Energy, such as the USA, Japan, Denmark, Germany, and China, a solid and long-term commitment from the government is crucial in realising policies that lead to efficient Renewable Energy development GoN finds challenging. The Government of Nigeria, GoN is faced with suboptimal development of RERs primarily and in part due to policies that are not clear and incentives too weak to attract investors.

About 90% of the Nigeria rural dwellers make use of fuelwood energy. Woodfuel derived from non-fossil and non-nuclear sources which can be replenished while harvesting [14].

Nigeria is among the highest producers of greenhouse gas emissions in Africa [15]. They are emitted into the atmosphere when oil companies operating in the country carry out gas flaring. The Carbon dioxide, CO_2 emissions in the country rank as the second highest in Africa [15].

Environmental degradation, unstable international market oil prices, the social crisis in the Niger Delta area, where the bulk of Nigeria's crude oil is extracted, and global warming makes the choice of alternative energy source unavoidable. The potential of RER in Nigeria is about 1.5times that of fossil energy resources; in energy terms. Hydro, solar, biomass and wind have significant potential to improve and make a difference in the low-level access to electricity in Nigeria.

1.5.1 Solar Energy

Solar energy can be described as the energy gotten from the heat and light rays of the sun through solar concentrators and photovoltaic cells. It is naturally abundant and can be harnessed for powering rural communities. Solar energy in rural and remote areas of Nigeria already serve as an alternative energy source used in drying crops for preservation. Also, with Nigeria located at the equator, it receives abundant solar radiation and sunshine [16].

With a 5% solar device conversion efficiency, it is estimated that the beneficial annual solar energy potential in Nigeria approximates $1.5\times10^{18}J$, equivalent to $4.11\times 10^{10}litres$ of crude oil, corresponding to the fossil fuel annual production currently in Nigeria [17]. Consequently, this amounts to 4.2×10^5GWh of annual electricity production, 26 times the current annual electricity production of 16,000GWh.

Solar energy is a promising RER in Nigeria due to its apparent abundance. The assumed power potential for solar concentrators and PV power is about 427,000MW [18]. According to estimates, designating 5% of suitable land in the central and northern part of Nigeria for solar thermal could provide a theoretical generation capacity of 42,700MW.

Nigeria has an average of $1.804 \times 10^{15}kWh$ of solar energy incident annually on Nigerias' land area of $924\times10^3km^2$ and an average of $5.535kWh/m^2/day$ [19]. Hence, it implies that 3.7% of Nigeria's land is required to collect solar energy equivalent to its available conventional energy reserves.

Solar energy is the primary energy resource driving other RERs such as hydropower, wind, wave and biomass. Although, current Nigerian installation of solar energy is insignificant compared to that of South Africa's, which already have over 200,000 off-grid PV installations [12], Nigeria is hence developing its capabilities to utilise solar energy through its National Energy Policy. Part of the challenges to PV power development can be attributed to ineffective policies in these areas, and GoN commitment in these directions have brought about minimal results.

1.5.2 Hydroelectric Energy

Nigeria has large water bodies and natural falls, including the Benue and Niger rivers, amongst others, contributing approximately 16% of the total installed electricity generation capacity [20]. The total hydropower exploitable in Nigeria is over 14.5GW, above the current total of approx. 13GW. Potential sites exist for untapped small hydropower in the country, estimated at 3.5GW, and water bodies comprising dams and rivers capable of proving 11.2GW exploitable hydropower energy. It follows that if adequately harnessed, small hydropower can address and offer solutions to electricity access to environs within these water bodies proximity.

Hydropower is another form of RERs that can supply uninterrupted electricity as long as their water levels are within range. These water levels can be affected by times and seasons. The higher the rainfalls, river systems and distribution, the greater the generation capacity. Annual rainfall is estimated between an excess of 3500mm in the south coastal areas and reduces progressively to 500mm moving to the extreme Northern part of the country [21].

The Figure 1.2 below shows a representation of the water body distribution, and potential sites for hydropower exploitation in Nigeria.

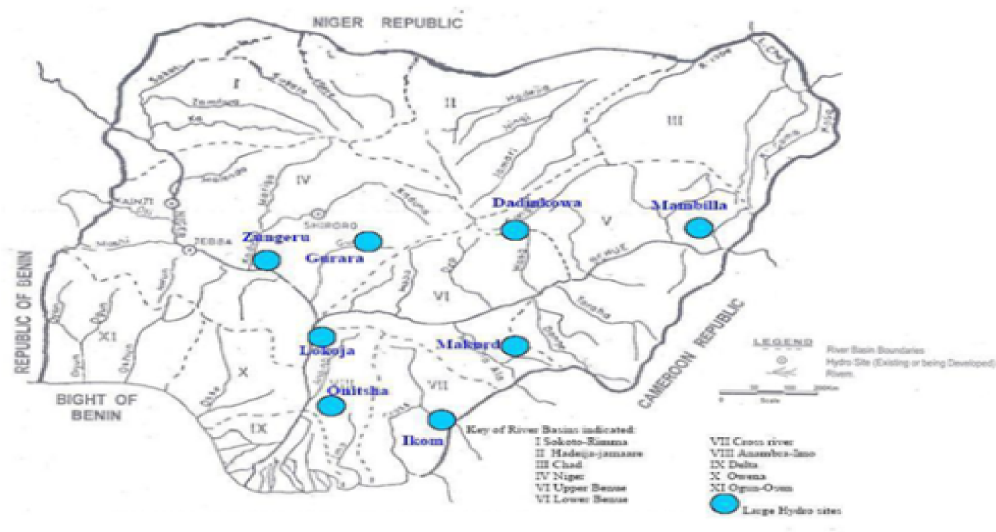

Figure 1.2: Nigeria's Large and Small Hydopower Potentials [21]

Nigeria faces financial challenges in hydropower development as they involve significant investment cost as experienced with the Mambilla plateau. Nigeria plans to increase its hydropower generation by upgrading old hydro plants and installing new ones to generate up to 5.6GW.

1.5.3 Wind Energy

Wind energy is one of the rapid developing RERs around the world, with Nigeria having moderate wind energy potential. Figure 1.3, presents the wind speed distribution in Nigeria. From the figure, it can be inferred that states with wind speeds above 4m/s are considered sites for potential good wind energy exploitation. Many renewable energy grid projects across the country use predominantly solar energy in their designs except for a 10MW land base wind energy project in Kastina State. According to [22], wind energy is not only cheaper and durable, it is does not require high maintenance and environmentally sound. Nigeria has 33.66% of its land mass having over $100W/m^2$wind energy potential.

The estimated wind energy potential exploitable annually at 10m height is 156MWh/yr from Yola, Jos and Sokoto. Studies carried out by [4, 23], show detailed wind energy exploitable potential description for 22 selected states across the country at 25m turbine height and 10m blade diameter. Sokoto ranked the highest state with great potentials with Minna showing the least exploitable potential.

Wind energy can be harnessed for water pumping at wind speeds between 2.5m/s - 4.0m/s and electricity generation at wind speeds > 4m/s.

The development of wind energy in Nigeria is yet to grow when compared to South Africa, which has 30,000 installed systems for water pumping and 3 electricity generating wind turbine plants on its utility grid. Nigeria needs to improve in this regard to meet the shortages across the country.

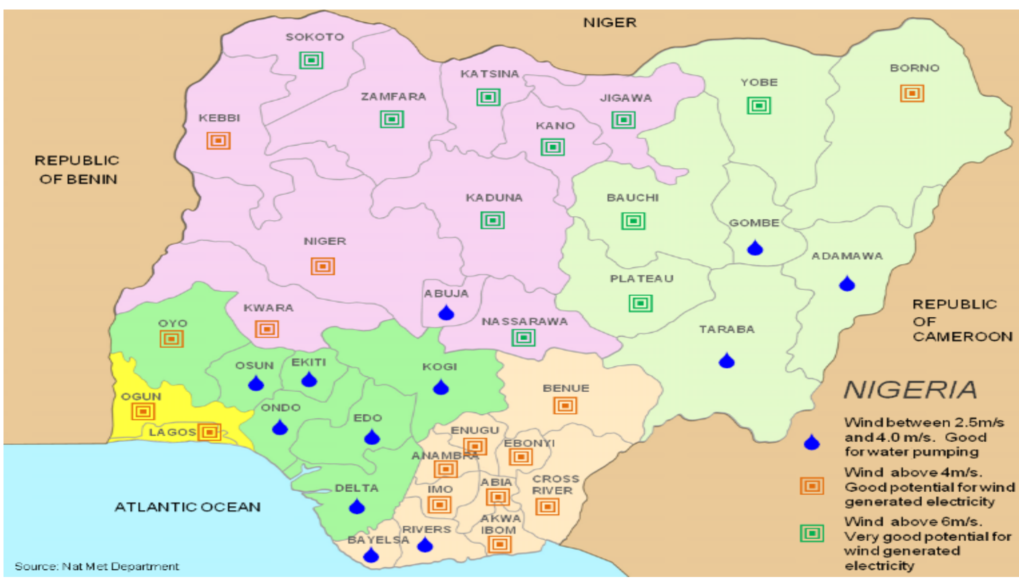

Figure 1.3: Nigeria's Wind Power Potential [22]

1.5.4 Biomass

Biomass are fuels gotten from organic matter for heating and electricity production. Forestry, agricultural, industrial, municipal activities form the primary source of waste used for biomass production in Nigeria. Considerable potential for biomass exists in Nigeria as over 70% of the countries land is used for agricultural purposes. Solid biomass and its waste account for 80% of energy consumed primarily by Nigerians for heating and cooking, especially among the rural area dwellers to meet their daily needs [14]. As at 2019, using the GoN data, Nigeria has about $8 \times 10^2 MJ$ biomass capacity available. Biomass can serve small industries as fuel sources. Wood is not only used as fuel; it is used by construction and furniture industries for erecting electric cables, plywood and paper production, among others. This demand has resulted in shortfalls in the overall biomass capacity from $9.1 \times 10^{12} MJ$ in 1973 [17]. Biogas produced from the fermentation of biomass in anaerobic bacteria.

Dry biomass from shrubs and grasses is estimated to release about $2.28 \times 10^6 MJ$ of energy [24]. Because Nigerians consume a large amount of wood fuel for domestic purposes, about 350,000ha of the country's natural vegetation and the forest is consumed annually, also contributing to the shortfall as only 50,000ha annually afforestation rate is in place to replenish the biomass shortage [25]. Apart from biomass shortages, environmental effects such as soil erosion and desert encroachment are consequences of excessive deforestation.

Consequently, solar concentrators can be developed to reduce the dependence on fuelwood. This will help alleviate the heat waste, preserve the ecosystem, and reduce cooking time and health effects caused by inhaling fumes from wood burning.

Biomass is an RER, and its conservation requires adequate understanding. Nigeria is naturally endowed with biomass energy as countries within the equator with similar weather and vegetation that use municipal waste for paper production, plant residues for biogas production rather than the use of wood fuel.

1.5.5 Biogas

Biogas is a combination of the different types of biomass in the gaseous state used as an energy source for heating, cooling and electricity generation. Nigeria has the potential to generate 169.5GWh (23.53 billion m^3) annual biogas and 88 million tons/year of biofertilizer [26].

Biogas is an RER and can be employed to replace the use of wood fuel, diesel, charcoal and the rest. Also, biogas poses no health hazards, no environmental pollution and burns clean for cooking. Biogas technology is considered feasible in meeting the cooking energy needs of small households with livestock able to produce 50Kg of animal dung per day (3 cow or 6 pigs) and serve as fermented manure for plant food.

In Nigeria, agricultural residues are economically feasible for biogas production though not yet listed among its energy mix. However [27], stipulated that the daily cooking needs of a house of 9 persons can be adequately met using a 6.0m^3 biogas digester, producing 2.7m^3 of biogas in a day at an initial cost of $500 (at current exchange rate = 190,000Naira), $70 annual expenditure and $160 annual benefit. [27], in their conclusion, presented an inexpensive project which could be infeasible for low-income earners dwelling in the rural areas but can be deployed if incentives are made available to reduce the developments initial cost.

For extensive cooking in prisons, boarding schools, hospitals and households, biogas offers a potential substitute if subsidised against the use of wood fuel.

More effort needs to be enacted by the GoN to deploy and encourage the use of single or a combination RERs to generate both electricity and cooking energy required for daily living, especially for those in remote rural areas.

1.5.6 Nigeria's Energy Policies Summarised

The GoN approved the National energy policy in Nigeria in 2003. The policy was called the National Energy Policy (NEP) to exploit the country's energy resources, both fossil and RERs, for sustainable development and active involvement of the private sectors. The NEP stipulated that [28]:

- increasing the reserve base for crude oil, natural gas exploration and development to the highest levels possible.
- exploring other options for power generation and continued improvement in reliable electric power to 75% of the country's population by 2020.

Nigeria Electric Power Authority (NEPA) now the Power Holding Company of Nigeria in the energy policy of 2003, encouraged the development of RERs. Table 1.2, shows the plan for every RER from The Energy Commission of Nigeria (ECN) an agency mandated for developing and promoting RER technologies in Nigeria, includes the whole energy sector coordination of policies, strategic planning and performance monitoring. Also, ECN proffers guidelines for using the different energy types for particular applications and developing recommendations on new RERs.

Table 1.2: Energy Forms and Policies [31]

Energy Form	Policy
Solar	Develop the capabilities to utilize solar energy
Wind	Develop the capabilities to utilize wind energy
Biomass	Promote biomass as an alternative energy source
Woodfuel	Promote the use of alternative energy source to fuelwood De-emphasize fuelwood as part of the nation's energy mix
Hydropower	Promoting rural electrification through SHP, Fully harness the hydropower potential through environmentally friendly means and through the private sector
Other RERs	Will remain interested in other emerging energy sources.

RERs are, therefore, a component of ECNs mandate. The policy's elements of significance in the development and utilization of RERs and their technologies are as follows [29]:

- to develop, promote and harness the RERs of Nigeria and incorporate all viable ones in the national energy mix,
- to promote decentralized energy supple (microgrids), especially in rural areas, based on RERs,
- to discourage the use of woodfuel and promote efficient use of biomass energy,
- to follow up on the international development in RER technologies and application.

1.6 Research Aims

This research aims to develop an optimisation strategy for renewable energy-based HMG systems for rural applications in developing countries.

1.7 Research Objectives

Challenges identified while developing the HMG model include: lack of historical load data as the community has no access to a centralised power supply, and energy use smart meter measuring devices. Language barriers encountered during data collection, which was an estimate of their current use and intended future use based on information gathered; and how to distribute load models to match other corresponding rural communities and determine suitable forecasting methods for application. Thus, the aim of the research is achieved by these objectives:

- Demand profile development: to design a cost-effective and reliable HMG system, significance is paid in getting the load model right. State-of-the-art methods for load profile development and forecasting for unelectrified rural communities are investigated.

- HMG system design: with the need for high renewable energy penetration to design a comprehensive state-of-the-art HMG system, investigation into the resource availability and component selection suitable for use with low cost, integrating DG back-up are researched.

- Algorithm development: considering the stochastic nature of RER and for optimal operation of designed HMG system, an investigation into metaheuristic optimisation strategies and their performance in operating the HMG system is done. This understanding establishes the effects of algorithm parameters on the different strategies developed.

1.8 Research Contributions

1. In this research, significant contributions are made in the design and forecast of load profiles for microgrid applications in rural electrification, particularly in load estimation and indices considered in forecasting loads over a ten-year period. The study employed the bottom-up simulation approach for demands in houses, schools, worship centres and commercial businesses combined with physical and behavioural approaches, which is validated using energy consumption pattern of similar communities as found in the literature.

2. This research also shows existing load forecast methods and their suitability for different applications. Results obtained showed that no single forecast methods fit all data types. Developed forecasting models using socio-economic components are compared with literature for similar applications to validate models employed.

3. HOMER design tool is employed for the HMG design, comprising RERs, diesel generator and energy storage systems as backup. System analysis are investigated over varying indices to decide system suitable for application.

4. Also, three metaheuristic optimisation methods are adopted and evaluated to improve the HMG operations for varying load profiles for a year. Effects of parameter tuning on the optimisation strategies are considered. The optimisation strategies minimize the DG operation through the year at different levels in the HMG design system, considering constraints on the system components and reliability of meeting the load demand at all times and constraints for DG operation and battery charging of the system. The results show that parameter

tuning is significant to avoid constraint violation and performance of the HMG design.

1.9 Research Organization

The chapters following the thesis are organised as Chapter 2 introduces the concept, inception, research, and applications of microgrids. It discusses the available microgrid technologies, design methods, load forecasting methods, optimisation methods applicable to microgrids. Chapter 3 gives a background to the location under study. It presents the demand profile developed and forecasting implemented to suit community demand. Chapter 4, the available RERs are gathered and component selection established. The HMG is modelled in Homer and compared with a DG only base model, and RERs only model. Chapter 5 defines the optimisation problem formulation with characteristic constraints on the system, HMG components are modelled in Matlab, three metaheuristic optimisation methods are developed, and the system simulated under different load conditions and parameter settings. Chapter 6 presents the main conclusions to all aspects considered in the research, including recommendations and future work.

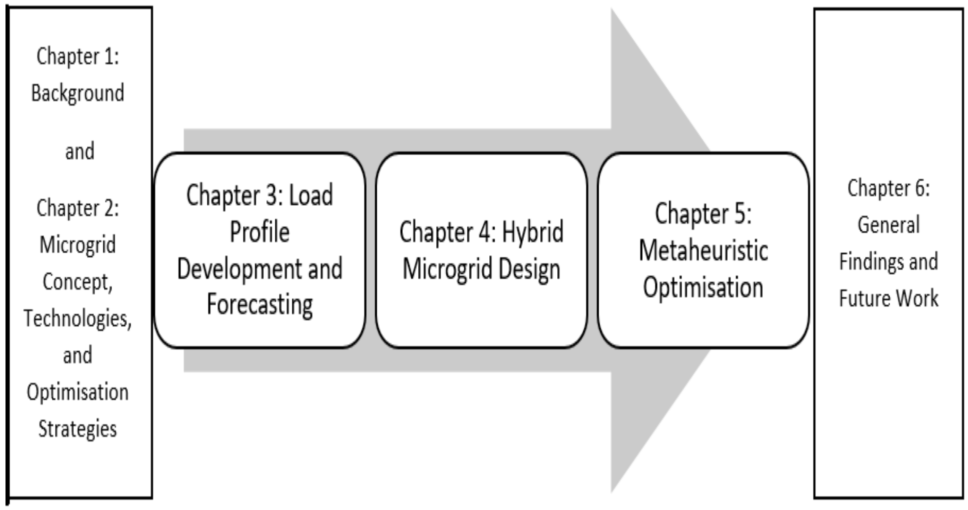

Figure 1.4: Research Organisation

Chapter 2

Microgrid Overview

2.1 Introduction

Research into microgrids has been carried out by many institutions and individuals around the world. These studies have considered the design make-up, control, operations and safety concerns of microgrids. However, these studies have not fully explored the potentials and benefits of microgrids regarding efficient power generation and energy management. In this chapter, the review of microgrid research as carried out by several countries is presented, which considered the microgrid operational, management and control features. The microgrid types, benefits, characteristic, and concept of microgrids are considered as it pertains to load estimation and forecasting, component selection and sizing, design models, and optimisation.

2.2 Microgrid Definitions

Several definitions and well-designed scheme of classification for microgrids exist in the literature. A broadly cited description, developed by the US Department of Energy [30], defines a microgrid as a group of organised loads and Distributed Energy

Resources, DERs within clear defined electrical boundaries, able to act independently as a single controllable entity from the grid. A microgrid can be connected and disconnected from the grid and operate efficiently in grid-tied or island modes. It, therefore, implies from the above that.

1. A microgrid can either be island or grid-tied
2. Microgrids are identifiable in the distribution system
3. Microgrids may include a number of complementary resources in its configuration.

Microgrid benefits have led to an increasing introduction and development of policy and regulatory incentives for its growth and applications. These include

- Subsidies to reduce the initial cost of investment and operational costs of implementing a microgrid [31].
- Financial support policies to secure finances for rural electrifications at reduced rates [32].
- Tax incentives to provide exemption or reduction on renewable energy equipment taxes [33].
- Concession policies which seek to minimise competition among investors by assigning geographical areas to that region's sole providers of electricity services [34]. It encourages investors to devote themselves to microgrid projects to protect their investments from competition medium to long term.

2.2.1 Microgrid Inception and Research

Microgrids continue to be a key topic for research in rural electrification, power systems, distributed generation, and sustainable energy. Several countries are involved in microgrid research for remote communities, and have published papers in this area [35]. Part of the focus of this study is microgrid planning aspects for remote rural communities.

Consortium for Electric Reliability Technology Solutions (CERTS), in the US and the European MICROGRIDS project began the research and development into microgrids. Microgrid description in developed[1] (US, Spain, Japan) and developing[2] (China) [36] countries are discussed further below.

2.2.1.1 US Research

CERTS anchored the grid-tied concepts of microgrids. Its microgrids allowed island operation, supplying sensitive and some adjustable loads at events of any main-grid disturbances. In its architecture, the microgrid consisted of loads(sensitive, shed-able and adjustable), micro sources with capacities less than 500km connected to the adjustable and sensitive loads supplying feeders connected via static switches to the leading network. The power electronic control method technology enabled the microgrid's island operation, allowing the micro sources to supply essential loads during unplanned events by isolating the load-carrying feeders. The CERTS microgrid had room for expansion, and all its micro sources had individual storage at their busbars. An idea was tested at Wisconsin University with success [37, 38].

2.2.1.2 European Research

The power supply security, electricity market, and environmental protection were essential considerations when the European research proposed and developed the smart grid technology. The European study also focused on, increasing high penetration

[1] A country having an effective rate of industrialization and individual income is known as Developed Country.

[2] Developing Country is a country which has a slow rate of industrialization and low per capita income.

of RERs and DERs, improving power quality, minimizing power losses and encouraging islanding to increase the reliability of the microgrids. Its architecture comprised of micro sources, controlled low voltage loads and flywheel energy storage systems. Spain, Greece and Germany formed the experimental platforms for the fundamental communication, control, protection, security and operation theories [39]. In Spain, University of Seville microgrid configuration consisted of the photovoltaic, fuel cell, and lead-acid batteries. An electrolyser was placed in the in the distribution line to overcome the intermittent nature of the photovoltaic system, excess power generated used to produce hydrogen stored in lead-acid batteries used by the fuel cells to produce electricity that served external grids.

2.2.1.3 Japan's Research

Japans research and development into microgrids reduced environmental pollution, met consumer needs, and energy supply diversification. They focused on balancing intermittent generation and fluctuation, employing controlled generation and energy storage systems in their microgrid architecture from optimal renewable energy generation. Photovoltaic and wind power systems having lead-acid batteries for storage were mostly considered to meet residential loads and serving as a support to the grid in existence as in Kythnos Island microgrid. Remote monitoring and control were used to maintain load demand, with standards used to build their centralised control systems. In addition, it broadened the CERTS microgrid definition to include traditional power supplied by independent power systems. Japan focuses on deploying new energies, RERs and their applications sponsored by The New Energy and Industrial Technology Development Organisation [40].

2.2.1.4 China's Research

China microgrid research undertaken by many institutes involved developing an experimental platform comprising of loads, RERs, and energy storage systems, distributed generation function system, integration and control technology of power systems with distributed pluripotent complementary energy microgrid, and also a PV-Wind system built to provide to electricity to HeFei University campus during power outages [41]. The microgrid system had photovoltaic systems and inverters, wind power systems and inverter, active and passive loads, and lead-acid batteries. The system employed the master-slave structure for smooth transitioning issues of microgrids. The configuration had one inverter as the master inverter with island mode voltage control and grid-tied mode current control operating selection modes, and others as current sources slave inverters.

[42] mentions microgrids, a critical part of the future of smart grids to offer a better quality of power, flexibility control and improved reliability. [43] further stresses [42] view in which a review of microgrid experiments and tests are presented. The results confirmed that microgrids play a significant role in smart grid evolution. Nevertheless, it identified the need for more research into dependable control strategies to improve system reliability and develop a generic simulation tool to ease further research in transient stability performance, control and protection strategies, and development of design guidelines standards for microgrids [43].

From the study, the microgrids discussed had in common lead-acid batteries for storage, photovoltaic systems and wind turbine power systems implying their popularity in use. Storage systems are important to help stabilise microgrid operations and where absent, grid-tied connections are essential. Due to the intermittent nature of renewable power source, power quality is a problem with microgrid deployment. As such, more work is needful to improve stability and reliability issues affecting performance and power quality of microgrids.

2.3 Microgrid Technologies

Microgrids constitute DERs, Energy Management System, EMS, power converters, controllers, and communication systems to obtain flexible energy management [44, 45]. The consumer is an essential component for microgrid implementation and promotion [46].

- DERs consists of distributed generator and storage and supplies power to meet energy demand.
- Energy management systems are employed to control, monitor, optimise, and evaluate the power system [47]. It is utilised for renewable energy power prediction and planning and load forecasting.
- Power converters are equipment used for electrical energy conversion, which can either be simple or complex depending on the operational frequency and voltage. They are utilised to detect the microgrid running state. Also, the DERs produce either DC or AC voltages at varying frequency and amplitudes than the grid; thus, a power electric converter interface is essential [48].
- Controllers are vital in microgrid implementation for maintaining power quality, voltage and frequency parameters by managing DERs and load in power systems [49].
- Communication systems convey, monitor, manage, and controls the operations in microgrids. It interconnects the different parts within the microgrid and ensures control and management [50, 51].

- Customers can also be energy suppliers and affect the choice technique selected, load operation and control of the microgrid considering cost and efficiency. A microgrid can have a consumer-driven demand response arrangement [52]. The involvement of consumers is fundamental to intelligent grid development and strongly promotes developers engagement [53]. The consumers function in user behaviour change, interaction needs, resource management and community schemes [54].

The capacities of DERs referred to in microgrids are somewhat small scales, although without worldwide agreement. It is mentioned to be less than 100kW by [55, 56], micro-generation having even smaller capacities of 30kW thermal and less than 3kW electrical were considered, EU standard defines micro-generation capacities reaching 50kW depending on the scale of the residential load. [48] considered micro sources less than 500kW. By and large, the power generators should have comparable capacities as the energy demand within the microgrid and located close to final consumers.

Emerging technologies like photovoltaic arrays, wind-power generators, combined heat and power, including small hydro and internal combustion driven generators, make up the distributed generators for microgrid applications [44, 57, 58]. Due to either main-grid disturbances or intermittency in RERs, a microgrid response to sudden load changes or disturbances causes instability. Thus Energy Storage Systems (ESS) are essential for microgrid deployment, particularly in architectures with RERs, few energy generation options are available, and the microgrid is typical in island operation. ESS are advantageous in reshaping peak demand and energy storage during times of surplus for later use [59].

Because of the intermittency experienced in deploying RERs, integrating DERs into the microgrid is optimally beneficial. When varying generator types are accessible they compensate for each other and the energy storage offers energy stability and quality, enabling high penetration of different distributed generators [60].

2.3.1 Microgrid Optimal Design and Planning

Microgrid studies can be classified into microgrid design and microgrid operational planning [61]. They are critical for the successful development of microgrid for real-time system applications [62]. System design for microgrids involves long term optimal selection and sizing of DERs whilst considering some objectives: energy security issues, minimum cost, and environmental issues [47]. The design of DERs is vital to maintain the power grid reliability, power flow, level of short-circuit current, and node voltage [63]. The load demand, technology information, weather conditions, utility tariffs from different tariff schemes, and operation and maintenance cost limit the microgrid component selection technique deployed. An optimal capacity sizing is a trade-off between investment cost minimisations and peak load satisfaction.

Furthermore, with given DERs, capacity operation planning deals with short term optimal microgrid planning ranging from one to seven days, having a time interval of one hour or less. Microgrid planning embraces all aspects of microgrid management. Its goal is to achieve attractive economic performance during power demand fluctuations and uncertain disturbances resulting from the variability in RERs.

The optimal microgrid operation consists of two primary functions, demand-side and supply-side management (DSM and SSM).

DSM entails modifying the energy demand, controlling the condition of the energy system, changing the load shape and generation optimisation, end-use and delivery processes [64, 65]. Also, DSM allows all the flexible loads and power-consuming devices for rescheduling. DSM promotes peak load reduction and profile reshaping, overall emission, and cost reductions.

The SSM decisions include the DER operations, ranging from the fuel types, production output or switch on/off and the buying and selling of electricity to the grid [66]. Generation scheduling refers to the organised dispatch of power produced from generation sources over a specific time horizon whilst satisfying system and technology constraints. DERs generation scheduling achieves cost savings under operational constraints of each DER over given periods [67].

In Nigeria, microgrid development can play pivot roles in combating electricity challenges by coordinating the use of RERs from the rooftops PV arrays or wind turbines with intelligent technologies and devices. Microgrids can operate on either island or grid-tied in the event there is an electric grid within proximity. However, for study purposes, the microgrid considered allows for grid connection in future. This kind is applicable for off-grid designs in remote rural areas, academic institutions, hospitals, isolated communities, or commercial purposes to supply their power demand whether or not connected to the grid or having grid problems.

Microgrids can also serve as part of the central grid providing support for peak hour loads, grid failures and poor quality instances. DERs microgrid systems can offer solutions to the electrification crisis in rural Nigeria to match modern intelligent grids. Several forms of RERs power generation projects are in operation in different parts of the country. These projects comprising single RERs are developed for application in schools, health centres, rural communities, street lighting, communication industries. Some potential sites have been identified for solar, wind and small hydropower development.

Already existing microgrid applications can serve as an experience to improve better practice in new microgrid deployments in off-grid rural locations. Instead of building massive centralised power stations with enormous investment, lengthy construction periods, the GoN can invest in using RERs for microgrid development. Research offers many business models of microgrids that are applicable for remote rural communities off the grid. Microgrid clusters are possibilities where neighbourhood by neighbourhood, their local demands and distributed generation systems balanced amongst themselves. These clusters can allow Nigerian off-grid remote communities to interconnect with each other, enabling national grid connection. Private investors find the microgrid interconnection idea an economic venture when compared to isolated grid systems. The advantages of exploiting Nigeria's RERs cannot be overemphasised as it is required to ease its current energy crisis. At most times, remote power access as a result of cost is not feasible.

However, after many years, Nigeria cannot deliver electricity to rural communities due to low load factor, area topology, and cost inhibiting socio-economic development. Depending on load type and resource availability, adopting a mix of RERs sources and energy storage systems, and backup power sources can serve. This combination can provide a reliable electricity supply, is economical and environmentally friendly than a single power source supply.

A Hybrid Microgrid (HMG) system can cater to connected load demands with appropriate coordination and control and make it more suitable for remote rural applications. HMG models can be developed and optimised to suit applications considering the locations topology, socio-economic status, type of load demand and availability of RERs to the area. RERs are cost-effective for investment, operations and maintenance, environmentally friendly, create jobs and allow for decentralised systems in communities. They also serve the communities with power supply for their homes, farms, small commercial businesses, water pumping and irrigation. Independent operation necessitates a stable micro-grid that can, without help from the grid, supply power to its consumers load demand. These applications require some distributed generators to give the necessary reliability. As such, the sizing of the HMG components for autonomous operation becomes a significant consideration.

2.4 Microgrid Design

Microgrid design involves different microgrid facets such as load modelling, generation component selection, sizing and modelling, storage option, and control strategy determination. System cost, operation and reliability are significant concerns when designing the microgrid.

[68], presented microgrid evolution worldwide, proposed a standard microgrid for better power quality, and optimised energy generation aiding designers in optimising green distributed system efficiency for reliable supply. [43] presented a review that described what a microgrid is and provided a multidisciplinary portrait of the present microgrid real-world applications, challenges, drivers and prospects. It brought forward that because of the dropping cost for RERs and ESS, parity in cost is evident with the traditional energy sources, causing more RERs adoption.

[69], a review of microgrid issues and studies carried out in microgrid-related areas were discussed. The study areas presented include the benefits of microgrids, microgrid value propositions, distributed generation, power electronic applications, economic issues, control and operation in microgrids, microgrid clusters, and protection and communications issues. Microgrid technologies, [70], presented an overall microgrid description and typically distributed generation technology and described microgrid control methods with pros and cons, providing insight into future grid evolution. [71] presented a review of microgrid architectures, providing the benefits of grid-tied and island microgrids with energy storage.

A study on microgrid village design with DERs and its economic feasibility evaluation is presented in [72]. Five steps are provided for the microgrid village design, which includes;

1. The annual demand and location climate conditions estimation

2. The selection of the DERs and RERs,

3. Optimization of the selected facility,

4. System operational stability analysis,

5. Fixed and variable costs economic evaluation.

[73], carried out another study on the design and operation of a remote microgrid. The results showed that remote microgrids, optimal ESS and RERs and an optimal unit dispatch mechanism lead to a significant reduction in the lifetime cost and emissions. Similar results were obtained in [74], which considered the optimal design and operation of a grid-tied microgrid.

In designing microgrids, it is essential to note that microgrids can be AC or DC. [75] suggests considering the DC/AC load ratio before choosing either an AC or DC microgrid design. A change in the ratio affects the total cost. It makes it a practical way for defining the economic point for either DC or AC microgrid selection. The DC microgrid is economical when the ratio is greater than the threshold ratio, and if less, the AC microgrid is considered more economical. The costs considered include the investment cost, operation cost and reliability cost.

HMG include loads, DERs (fuel cells, Solar PVs, microturbines, wind turbines, diesel generators), ESS (flywheels, batteries, superconductor inductors). Loads are the energy demand of the consumers that must be met by the HMG design throughout the project life. DERs can be divided into two groups:

1. DER grid-tied with the inverter (Solar PVs, fuel cells)

2. DER direct-tied conventional rotating machines (an induction generator driven by a fixed-speed wind turbine).

ESS can be charged with excess power and discharged during power deficits, enhancing microgrid reliability and rendering it economical and efficient. Furthermore, energy storage used for fast responses prevent transient instability and participate in voltage and frequency control of the microgrid by delivering the balance reserve extending from a short time. Figure 2.1 represents the diagram of a microgrid which includes many systems: load demand, Solar PV, wind power generator, diesel generator and battery storage. DERs interface with the corresponding bus through a power-electronic converter where needed. The diesel generator serves as a backup when the power from RERs and ESS are insufficient to meet the load. Thus, the microgrid continues to operate, providing a reliable power supply at all times. The microgrid operates in the island mode.

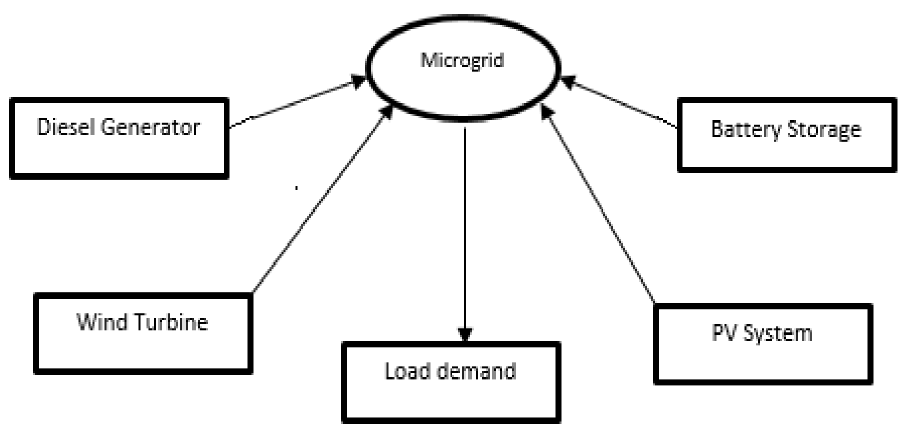

Figure 2.1: Microgrid

2.4.1 Load Estimation and Forecasting

2.4.1.1 Load Profile Estimation

Two common approaches are used for demand profile modelling, namely the statistical and the bottom-up method. The statistical method aims at characterising the input data description based on measured demand profiles, with a forecast done on the extracted character [76, 77]. In contrast, the bottom-up approach focuses on developing the load profile from each terminal appliance [78, 79]. Looking at the statistical modelling approach, [80] suggested a multiple linear regression model for maximum demand forecasting and total energy usage, taking into account social-economic aspects (bedroom number, home composition and dwelling type). [81] recommended dividing historical time series into components based on weekdays and seasons to model the trend energy demand, termed decomposition approach. [82] designed a time-varying multiple regression model for load forecasting, looking at utility production and consumer behaviour efficiency for every hour.

[83] introduced a structure that analyses local energy consumer usage practices, assuming that load demands follow a non-stationary multivariate Gaussian distribution. [84] suggested a functional vector autoregressive state-space model for predicting energy demand for application between local and national grids. Though the bottom-up approach involves significant data relating to household appliance consumption behaviour, its accuracy is high. Data acquisition challenge has impaired the bottom-up approach development in the past. However, in recent years, intelligent infrastructure developments in homes have made energy load prediction attention in the bottom-up prediction method [85]. For instance, the use of intelligent sockets to gather and upload information about the energy use of every appliance to the Wi-Fi communication data centre, in turn, contributes to the load forecast accuracy and efficiency.

[86] suggested a bottom-up approach by adding up each appliance consumption to form household load profiles. [87] presented a model of both statistical and measured data combination using the 1-min power cycle and using single appliance qualities as the primary building block. [88] recommended a stochastic bottom-up design to predict demand for domestic lighting; a three-state non-homogeneous Markov chain was employed to illustrate the occupancy patterns of lighting demand. [89] developed as random processes each appliance start, depending on social and seasonal factors.

[90] developed a predicting model to examine occupant behaviour, appliance

efficiency and stock effects on each household demand profile. [91] experimented utilising real-world smart meter datasets from used energy behavioural analysis got from big data mining technology designed. [92] introduced a high-resolution design for household energy usage based on appliance use and occupant activity. It follows from the research that various appliances exist in households, and family structure, behaviour, and environment influence how they are used. In the bottom-up research approach, some studies considered the extraction process of historical days; there are many historical days where days differ in terms of weekday type and weather condition from the forecasted day. The forecast accuracy decreases if days without high historical similarity are used to forecast the demand. The use of energy varies with changing human behaviour and ambient conditions; the energy demand profile for every hour demonstrating the dynamic problem nature is applied to microgrid designs [93, 94].

Therefore, in this study, considering the limited data available, and lack of smart metering for better accuracy, a bottom-up demand profile model is formulated and replicated to represent a year for the community based on analysing energy use behaviour for each appliance. In order to extract the consumption behaviour precisely, load variability is introduced to depict real-life scenarios.

2.4.1.2 Load Forecasting

Load forecasting is necessary for the decision-making process to deal with consumer demand changes and seasonality carried out by energy management systems. In recent times, the complexness and quality of forecasting methods have developed rapidly, using artificial intelligence algorithms, which give room for carrying out energy management activities from low-level forecast uncertainties. It is common practice for different purposes to employ varying forecast methods as no single methods fits all purposes.

The accuracy in electricity demand forecasting helps in the decision on power production and infrastructural development. Its inaccuracy can result in both social and economic consequences. Underestimating the forecast for energy demand results in forced outages and shortage in power supply, while over-prediction could result in over-investment in power generation and possible spiked electricity prices.

Nevertheless, accuracy on load forecasting is a complex parameter to achieve, primarily because certain factors influence energy consumption factors such as weather (temperature, rainfall, humidity, wind), holidays, economic status, and human behaviour in electricity use. Many methods have been utilised over the years, which can be classed as either short-term and long term forecasting. These are also approached on different aggregate levels.

- A top-down scheme from the utility side
- A bottom-up scheme from the user side by analysing consumer activities.

1. Short-term forecast: This type of forecast ranges between an hour to a week. It is relevant in generator scheduling and maintenance, security analysis, and economic dispatch of power systems. Methods used include trend and same-day approach.

2. Long-term forecast: This type of forecast covers periods over a week and is vital to policymaking, supply capacity expansion, and design/adoption of advanced technology power systems. Methods used include end-use methods and econometric models.

Load forecasting techniques are typically classified into two groups: statistical techniques and artificial intelligence techniques, though the boundary between the two is becoming more and more ambiguous due to multidisciplinary collaborations in the scientific community. A review of load forecasting techniques are presented in Table 2.1 below.

The selection of a forecasting technique depends on several factors ranging from

- Context of forecasting,
- Available and relevant historical data,
- Desired degree of accuracy,
- Expected forecast period,
- The value of the forecast to the forecaster, and
- The time available for making the analysis.

These factors must be considered continuously and on a variety of levels. In general, a technique that makes the best use of available data and acceptable accuracy is widely preferred when forecasting.

A forecasting method that considers factors significantly influencing energy consumption, such as human behaviour, is designed to predict energy demand over ten years. The forecasting process considers a continuous assumed increasing load factor, transmission and distribution losses to reduce the influence of under design of the HMG system to meet the predicted demand profile.

2.4.2 Distributed Energy Resources (DERs)

DERs are a combination of RERs and conventional energy generating sources.

Renewable energy refers to those naturally occurring energy resources that are self-replenishing. They are distributed naturally, enabling power generation in remote areas and reducing the need for transport systems investment [98]. Examples of

Table 2.1: Load Forecasting Review

Forecasting Techniques	Model Used	Strength	Weakness	Reference
Regression	Multiple Linear Regression, Simple Linear Regression	Previous forecast load and factors such as time of the day and weather are relatable. Useful in non-real time forecasting.	Not accurate for real time load and unable to handle nonlinear load consumption. Adding parameters make it unstable	[95]
Time Series Analysis	Auto Regressive Moving Average, Auto Regressive Integrated Moving Average, Deterministic decomposition	Capable of accommodating seasonal component effects	Suffer numerical instability	[95, 96]
Artificial Neural Networks	Multilayer Perceptrons, Back Propagation Algorithm, Steepest descent Error Back Propagation	Adjusting the weights during the training process allows for better handling of nonlinear relationships in load consumption	Large amounts of data are essential to train models and complexity in the training of such data	[97]
Fuzzy Inference System	Defuzzification Method using Centre of Area, Middle of Maxima, Last of Maxima and Centre of gravity	Fast and accurate in performance including ease in formating rule	Based on trial and error the membership fuction rule is selected	[96]
Support Vector Machine	Support Vector Regression using Incremental Learning Algorithm Support Vector Regression	It enhances higher feature space dimensionality by using ε-insensitive loss for linear regression computation and reduction in model complexity.	major concerns are in selecting suitable kernel and interpretation difficulties	[97]

RERs was introduced in Chapter 1, to include solar, wind, hydro, biomass geothermal and tidal energy.

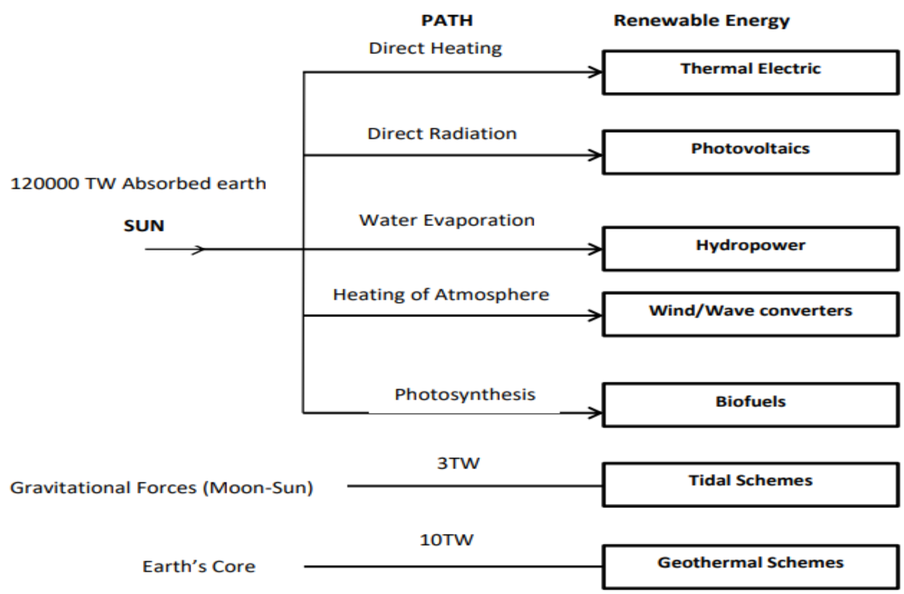

Figure 2.2: RERs Flow Paths

Figure 2.2 shows the primary paths for obtaining RERs from the earth. PV and Wind applications offer potentials in the study location, implying the sun is the primary source for accessible RERs in these regions [98]. Other advantages of RERs are:

- They are natural/infinite.
- Because of their low greenhouse emissions, they are referred to as clean energy.
- RERs maintenance could be less expensive compared to conventional generators.
- RERs proffer reliable energy with proper planning and infrastructure.

RERs support the needed flexibility in power generation reducing fossil fuel dependence [99].

2.4.2.1 PV Cell

A PV cell converts sunlight into DC electricity. Cells are connected and positioned in a glass layered supporting material cover known as a module. The PV module can operate connected to the grid or isolated through inverters.

The PV cell (monocrystalline or polycrystalline) have two silicon semiconductor layers (n-type silicon and p-type silicon) sandwiched and doped to allow for electricity flow [100]. The resultant is a p-n junction. The concept is illustrated in Figure 2.3 below.

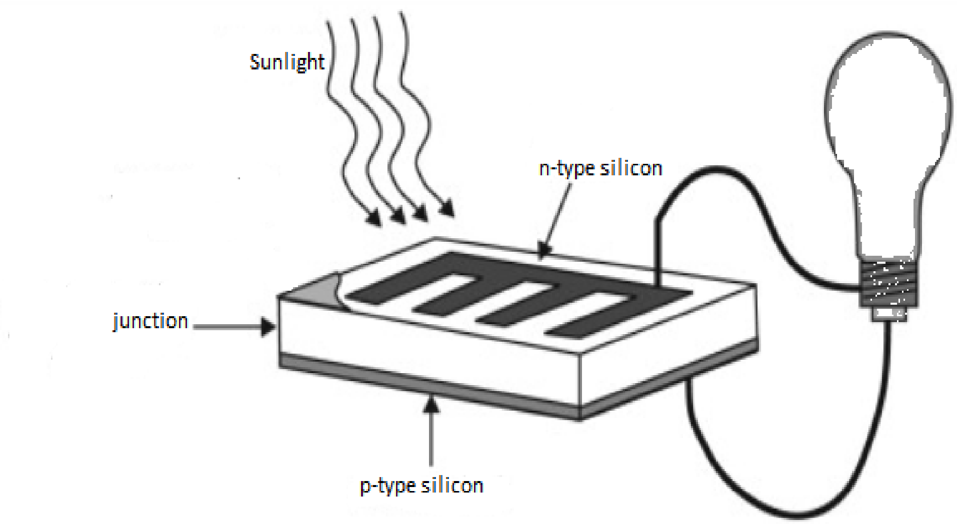

Figure 2.3: PV Cell Concept

Electrons are produced from the n-type layer in the presence of solar radiation. The electric field repels these electrons at the p-n junction.

A connected external circuit allows electrons to move to the p-layer from the n-layer. Current then flows from the positive-negative terminal. The equivalent solar cell electrical circuit is represented in Figure 2.4.

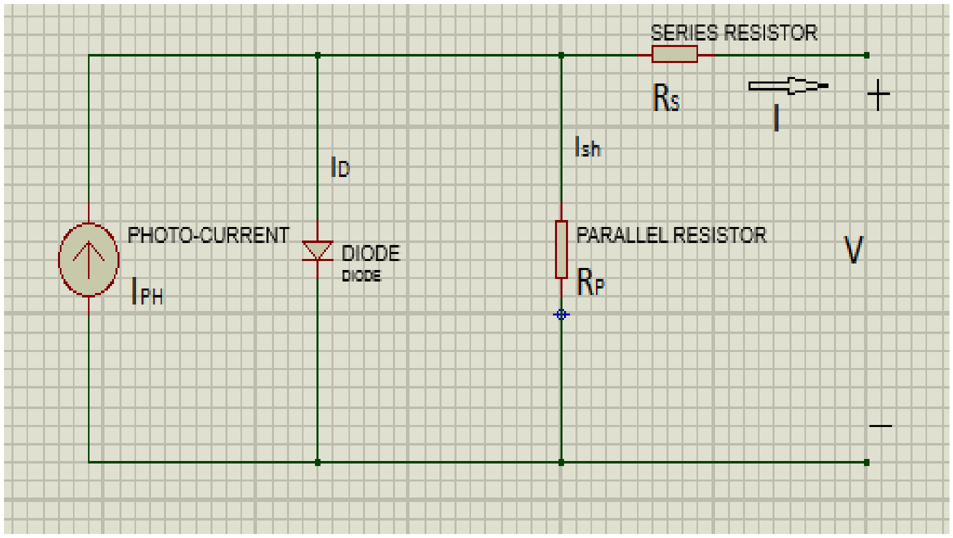

Figure 2.4: PV Equivalent Circuit [102]

It consists of a current source in parallel with a diode. The series resistor, R_s and the shunt resistor, R_{sh} are included in catering for any losses that are likely to occur in the PV cell [100].

The current to the load from the connected PV cell is given by

$$I = I_{PH} - I_D - I_{sh} \tag{2.1}$$

Where, I_{PH} is the light-generated current in the cell, I_D is the voltage-dependent current lost to recombination, and I_{sh} is the current loss due to shunt resistances.

$$I_{sh} = \frac{V + IR_s}{R_{sh}} \tag{2.2}$$

In this single diode model, I_D is modelled using the Shockley equation for an ideal diode:

$$I_D = I_0 \left[\exp\left(\frac{V + IR_s}{nV_T} \right) - 1 \right] \tag{2.3}$$

where n is the diode ideality factor (unitless, usually between 1 and 2 for a single-junction cell), I_0 is the saturation current, and V_T is the thermal voltage given by:

$$V_T = \frac{kT_c}{q} \tag{2.4}$$

where k is Boltzmann's constant $(1.381 \times 10^{-23} J/K)$ and q is the elementary charge $(1.602 \times 10^{-19} C)$.

Writing the shunt current as $I_{sh} = \frac{V+IR_s}{R_{sh}}$ and combining this and the above equations results in the complete governing equation for the single diode model:

$$I = I_{PH} - I_0 \left[\exp\left(\frac{q(V+IR_s)}{nkT_c} \right) - 1 \right] - \frac{V+IR_s}{R_{sh}} \tag{2.5}$$

The parameters in equation (5) are primary to all single diode equivalent circuit models:

I_{PH}: light current (A)

I_0: diode reverse saturation current (A)

R_s: series resistance (Ω)

R_{sh}: shunt resistance (Ω)

n: diode ideality factor $(unitless)$

In an ideal PV cell, R_{sh} is infinite and $R_s = 0$; therefore, the current delivered to the load is represented as equation.

$$I = I_{PH} - I_0 \left[\exp\left(\frac{q(V+IR_s)}{nkT_c} \right) - 1 \right] \tag{2.6}$$

The I-V curve of the PV cell is represented by the Figure 2.5 below.

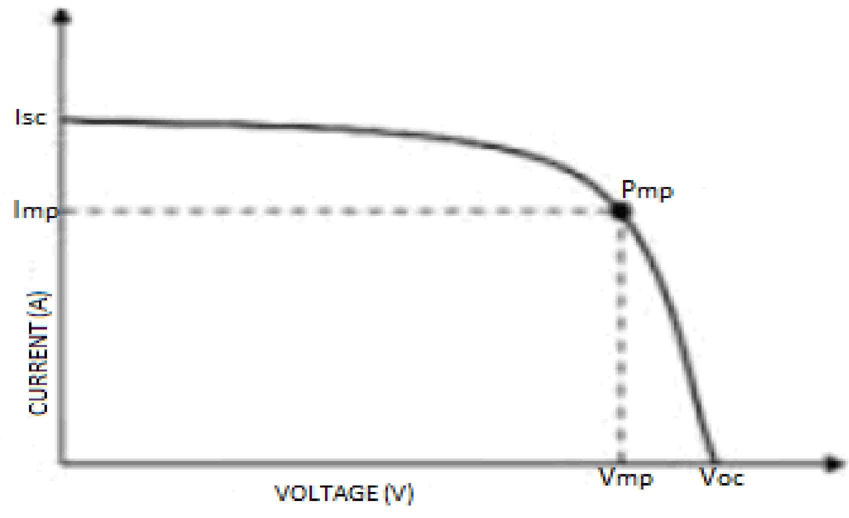

Figure 2.5: PV cell I-V curve [102]

The characteristics of the PV cell, as shown in the Figure 2.5 above has a short circuit current, I_{SC} the open-circuit voltage, V_{OC}, and the maximum power point, P_{mp}, which is a product of I_{SC} and V_{OC}.

PV Module The PV module consists of parallel and series connection combinations of PV cells [101]. The cell number in parallel determines the current output from the module, and the voltage output depends on the number of cells in series. If the number of cell in parallel, N_p and N_s the number of cell in series, a cell current I_c, and cell voltage output, V_c respectively, then the current and voltage from the given module will be:

$$I_M = N_p \times I_c \tag{2.7}$$

$$V_M = N_s \times V_c \tag{2.8}$$

[101]further explains that the PV module current output is directly proportional to the solar irradiation. Nevertheless, as the temperature increases, the voltage and

power outputs reduces. The modules cell temperature depends on irradiation and the voltage-temperature relationship that will be addressed later.

2.4.2.2 Wind Turbine

Wind turbines are systems that include a generator, a rotor, turbine blades, and a drive. As the wind blows through the blades, air utilizes aerodynamic forces that make the blades turn the rotor. When the rotor turns, the turbine speed is adjusted to match the operating speed of the generator. Most wind turbines systems have a gearbox and generator in a single unit at the rear of the turbine blades. Like photovoltaic (PV) systems, the wind generators output is processed by an inverter that changes the electricity from DC to AC to be used.

The working principles of the wind turbine are illustrated with two processes carried out by its main components: the generating system, which converts mechanical torque into electricity and the rotor, which gets kinetic energy from the wind through its blades and converts it into mechanical torque.

Figure 2.6 illustrates the working principles of a wind turbine.

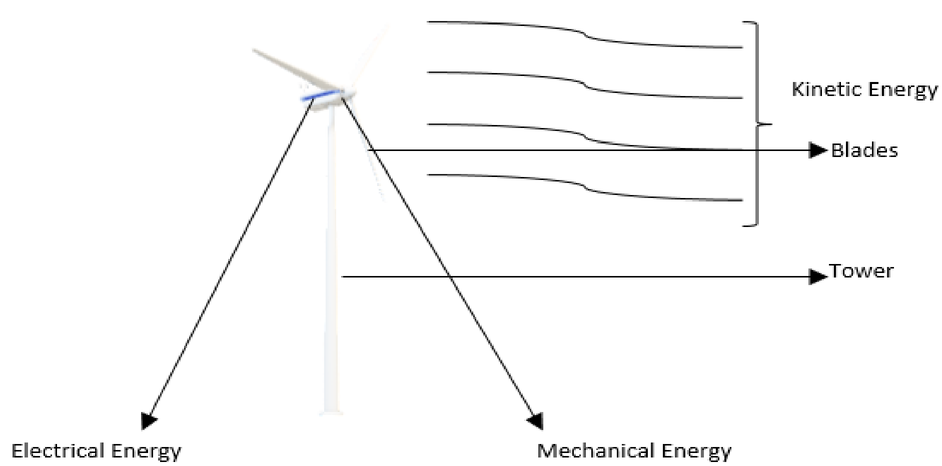

Figure 2.6: Wind Turbine Operating Principle

A wind turbine is equipped with any three-phase generator. Several generator types are used in wind turbines [102], but three types of wind turbine generators typically used:

- Squirrel cage induction generators,
- Direct drive synchronous generators,
- Doubly fed (wound rotor) induction generators,

Wind Turbine Modelling In this section, an overview of the developments in wind turbine modelling is presented. The first wind turbines were centred on a direct grid coupled synchronous generator with pitch-controlled rotor blades to restrict the mechanical power in high wind speeds. Hence, the first modelling efforts were devoted to this wind turbine concept [102, 103]. The direct grid coupled synchronous generator was followed by a direct grid coupled asynchronous squirrel cage induction generator. This type of generator has a more favourable torque versus speed characteristic than the synchronous generator, thus reducing the mechanical loads, and it is also cheaper. This concept is still applied nowadays by some manufacturers. To curb the power extracted from the wind at high wind speeds, either stall control or pitch control is used. Many papers on modelling a wind turbine with a direct grid coupled squirrel cage induction generator can be found in the literature, with both stall control and pitch control combination of the mechanical power [103–106]. A modern variable speed wind turbine with a doubly fed induction generator has replaced the conventional constant speed wind turbine with a direct grid coupled squirrel cage induction generator. The manufacturers have also started to apply a direct drive synchronous generator grid coupled through a power electronic converter of the total generator rating.

Therefore, modelling efforts have been given to these wind turbine concepts as well. Because the variable speed wind turbines are complicated systems, most papers addressing their modelling cover one subsystem; the electromechanical conversion system, the drive train, the control of the generator currents and the DC link voltage or the rotor speed controller, [105, 107]. As the power created is proportional to the cube of the wind speed, it is imperative to locate any electricity-generating turbines in locations with high annual mean wind speeds, and the available wind resource is a vital factor in determining where the wind farms are sited [108]. High wind speed areas will often be away from the habitation and the associated well-developed electrical distribution network, leading to a requirement for careful consideration of the integration of wind turbines to relatively weak electrical distribution networks. The difference in the working fluid density (water and air) illustrates clearly why a wind turbine rotor of a given rating is much larger than a hydro-turbine [108].

Wind turbines operate by obtaining kinetic energy from the wind passing through their rotor. The wind turbine power generated is given by [103]:

$$P = 0.5 C_p \rho V^3 A \tag{2.9}$$

where

$P =$ power in watts,

$C_p =$ power coefficient,

$V =$ Wind velocity in meters per second,

$A =$ swept area of rotor disc in meter square,

$\rho =$ density of air ($1.225 kg/m^3$).

The force obtained on the rotor is proportional to the square of the wind speed; hence the wind turbine must be developed to withstand bad storms. Most modern designs are three-bladed horizontal-axis rotors as this gives a good value of peak Cp and an aesthetically pleasing design [108]. The power coefficient, Cp, measures the amount of wind energy extracted by the turbine.

2.4.2.3 Diesel Generator

Diesel Generators (DGs) were developed over 100 years ago, forming the first among distribution generator technologies. The Otto (spark ignition, SI) and Diesel cycle (compression ignition, CI) engines have gained extensive recognition in almost every economic sector. Because of their high reliability and efficiency, they are utilized on many scales, ranging from small units of 1 KW to numerous MW power plants. Smaller engines are mainly designed for transportation and can be converted to power generation with slight modification. Large engines are frequently designed for mechanical drives, power generation, or marine propulsion. As sudden changes occur in load demands by the consumers, the diesel generators prime mover must have a fast dynamic response and good disturbance rejection capabilities.

The Diesel Engine model describes the fuel consumption rate as a function of speed and mechanical power at the engine's output and is usually modelled by a simple first-order model relating the fuel consumption to the engine mechanical power [109].

The power outputs of the engine and generator are varied with the changing load to meet the consumer demands. The governor's task is to adjust the fuel flow and then regulate the inputs of the engine and generator, and hence provide the necessary power to meet the change in the load.

DGs are the most common type of microgrid technology in use today. The role of DGs has been the provision of standby power and peak shaving. The fuel cost of a power system is expressed mainly as a function of its actual power output and modelled by a quadratic polynomial [110]. The total diesel fuel consumption rate L/hr for the DG can be expressed as:

$$GEN = \alpha_{DG} + \beta_{DG}.P_{DG-nom} + \gamma_{DG}.P_{DG-out}^2 \tag{2.10}$$

Where, α, β, and γ are cost coefficients of the particular generator, P_{DG-nom} is the nominal power of the diesel generator in kWassumed to be known and P_{DG-out} is the power produced as a result of the DG being ON. The constants cost coefficients α, β, and γ are gotten from the manufacturers manual.

2.4.3 Energy Storage System (ESS).

The microgrid concept integrated with ESSs has gained interest and acceptance because it stores energy during surplus energy generation hours and supplies energy at peak load hours and energy deficit periods.

[59], a study was carried out on the optimal sizing of energy storage for microgrids. Lithium-ion (Li-ion) batteries were the focus of the study in which the cost-benefit analytical technique was used to estimate the economic feasibility of the battery storage for both the grid-connected and island modes.

ESSs are classified based on the usage of energy in a specific form. ESSs can be categorised as Mechanical Energy Storage (MES), Electrochemical Energy Storage (EcES), Chemical Energy Storage (CES), Electrical Energy Storage (EES), Thermal Energy Storage (TES), and Hybrid Energy Storage Systems (HESS). Also, these systems can be classified depending on the formation process and materials used.

Table 2.2 and Table 2.3, presents a detailed ESS classification.

Table 2.2: ESS Classification

Category	Operating Principle	Modes	Examples	Advantages	Disadvantages	References
MES	deliver the stored power when required for mechanical work .	pressurized gas, forced spring, kinetic energy potential energy.	flywheel, pumped hydro storage, compressed-air Gravity ESS	operate flexibly to convert, store energy from sources .	high capital cost, negative environmental impact, reduced geological implementation	[37] [111]
TES	store energy in the form of heat or ice	low-temperature TES, high-temperature TES	liquid (water, molten salt, and thermal oil), solid (stone, concrete, metal, and ground), or liquid with a solid filler material (molten salt/stone) .	alternative technology to replace the use of fossil fuels and can meet the demand of sustainable energy regulations, low capital cost (\$3–60/kWh), low self-discharge rate (−0.05%−1%), secured energy, environment - friendliness, and acceptable energy density	life expectancy remains low (−30%–60%)	[112] [113]
CES	released through electron transfer reactions to produce electricity directly	energy is stored in the chemical bonds of atoms and molecules	coal, gasoline, diesel, propane, ethanol, hydrogen, liquefied petroleum gas.	stores significant amount of energy for long periods, desired environmental impact of , Due to available raw material resource, per unit cost is reduced.	efficiency is the most critical criteria to develop this technology .	[114] [115]

Table 2.3: ESS classification continued

Category	Operating Principle	Modes	Examples	Advantages	Disadvantages	References
EESS	Energy can be stored by modifying the electrical or magnetic fields with the help of	capacitors, super-conducting magnets	Super-capacitor SS, Super-magnetic ESS	used as short-term storage devices in case of high flow current given that the capacity of the conventional capacitor is limited. Integrating the transmission and distribution system with renewable energy sources.	high self-discharge rate (up to 40% per day) and costs (6000 dollars/kWh).	[115] [116]
HESS	integration of two or more ESSs	combines the characteristics of high power and high energy storage system to improve the stability and reliability of the system with the reduction of the power quality problems .	battery/SC , battery/SMES , battery/ FC , FC/ SC , and SC/ RFB is possible.	system efficiency and life expectancy of the battery have been improved. the extension of life cycle up to 75% through peak shaving and related thermal burden reaction		[117] [118] [119] [120] [121] [117] [122]
EcSS	chemical energy in the active material is converted into electrical energy	Conventional rechargeable batteries, flow batteries	Lead-acid SS, Lithium-ion SS, Nickel-cadium, redox flow battery SS, Sodium Sulphur SS.	minimal maintenance is needed, storage devices are available in different sizes	chemical reaction reduces the life expectancy and energy of battery	[123]

Flywheel energy storage (FES) [124], Batteries [119], compressed air energy storage (CAES) [122], SCs [120,125], superconducting magnetic energy storage (SMES) [126], hydrogen storage [127], with hybrid energy storages (HESs) [122], are commonly used storage technologies for microgrid applications.

In [127], an investigation was carried out to determine the impact of electrical storage and grid upgrades on the optimal design and operation of a microgrid under different carbon emissions constraints. The trade-off between storage and grid upgrade was examined and compared to those of a reference case.

[128], presented ESS technology comprehensive review, structure, configurations, features, classification, energy conversion and evaluation processes. The paper also identified vital factors, issues, and challenges with possible recommendations for further developing ESS in future microgrid applications.

However, ESS technologies face energy storage challenges such as charging/discharging, life cycle, safety, size, reliability, cost, and overall management. Thus, accurate selection and design of ESSs are required regarding capacity, energy management protection, and characteristics to enhance the performance of ESSs in microgrid applications.

Battery storage is one of the major options for energy storage in systems using either solar PV and wind energy or their combination [126]. For study purposes, the battery energy storage systems are considered in detail because of their use and availability in the region.

2.4.3.1 Battery Energy Storage Systems (BESS)

BESS is widely applicable in the power systems generation, transmission, and distribution sectors, benefiting consumers [129]. [130, 131] carried out a comprehensive review on battery storage technologies, such as lithium-ion, lead-acid, redox flow, and nickel-cadmium.

Figure 2.7 illustrates for one day the power profile of BESS. From the power curve Figure 2.7, the horizontal axis (time) denotes the discharging characteristics of the battery to compensate for the power deficit. Power below the time axis depicts the charging state of the cell during excess generation [132].

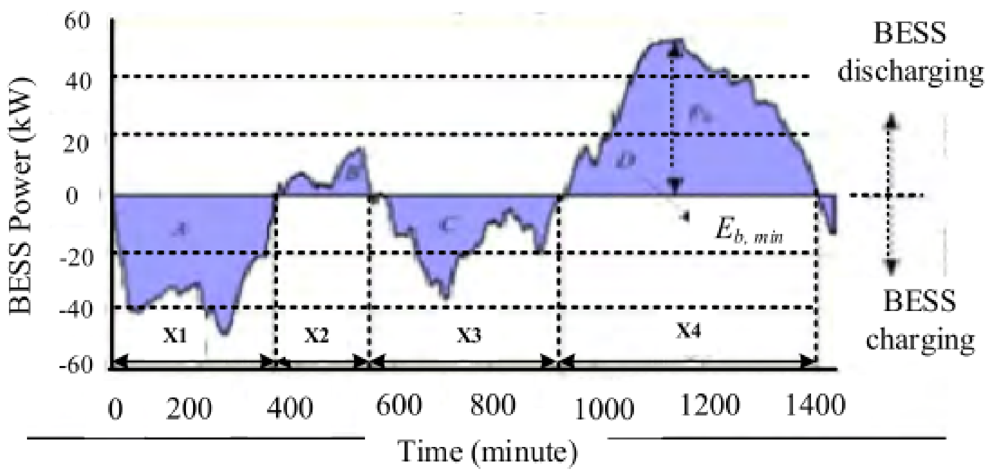

Figure 2.7: Charging and Discharging of BESS [134]

Battery capacity is a vital contributing factor when selecting a storage device. Battery capacity is the total quantity of electrical charges delivered in a single discharge by the cell. The State of Charge (SoC), is the ratio of remaining capacity to the nominal capacity. Separate studies show that a quasi Z-source inverter is a suitable technique for parallel battery operation, [133] proposed a quasi Z-source inverter for BESS for microgrid applications. The study results proved that microgrid voltage remains balanced in the unbalanced load conditions. Examples of BESS are Lead-acid, lithium-ion and sodium-sulphur storage systems are discussed in [128]. For study purposes, the Lead-acid battery technologies are considered practicable and available storage technology and discussed further.

Lead-Acid Storage Systems Lead-acid (PbA), batteries are well-used rechargeable storage devices with various designs and sizes for different applications [134]. The PbA battery shows high efficiency (70%–80%) and possesses the highest cell voltage among all electrolyte batteries [135].

The cathode is made of PbO_2 and anode Pb, with sulphuric acid as the electrolyte. According to [82,90], they are less expensive than other battery technologies and suitable for large-scale microgrid applications. Other PbA advantages are, it provides tremendous charge holding and energy density with fast response and long life cycle (5–15 years) [112]. Nevertheless, the traditional PbA battery has a short cycle lifetime (500–2000 cycles), periodic water maintenance, low specific energy, and premature failure due to sulphonation. Sophisticated PbA batteries have been developed that addresses the above limitations, possessing nine times higher capability for handling power and four to ten times increased life cycles [136].

The development of lead-acid batteries has focused on innovative materials for improvement in the performance and implementation of PbA for applications in the integrated wind, PV power, and automobile sectors. Reference [137] investigated an islanded renewable energy microgrid emulator with a PbA battery. The proposed method can be applied in different microgrid configurations using the combinations of available generating units.

The cost of the energy storage option is crucial in deciding what storage technology to use. A comprehensive study on the costs of various storage technologies is detailed in [138]. The findings are summarised as:

1. Though energy storage technologies are becoming attractive for microgrid use, their high costs and are not competitive enough as anticipated by renewable energy advocates.

2. Energy storage are expected to reduce essentially in few years due to increased

use of RERs. Enforcement of government policies that support energy storage, the call for a reduction in fossil fuel usage, and numerous changes are expected as the power grid evolves.

2.5 Microgrid Optimisation Methods

In Microgrid constrained optimisation, the general practice is to convert the problem into more manageable subproblems that can be solved and used as the basis of an iterative process. Various optimisation techniques for microgrids can be found in the literature, revealing various heuristic optimisation techniques described to solve the constrained problems, which are nonlinear. These techniques mainly focus on microgrids and also define the operational settings of the non-dispatchable distributed energy resources and dispatchable distributed energy resources.

2.5.1 Optimal Planning in Microgrid

The optimal planning of microgrids has attracted much attention over the years. Above and beyond the microgrid design, microgrid operation planning over the short term is a branch addressed by several pieces of research. [139] described energy management systems and optimal scheduling of microgrid. The optimal decisions, including generators for power and heat production, proper load management, storage system scheduling, and local grid power selling and purchasing for the next day, are decided by maximum profit.

[140], a general formulation to establish the optimal strategy and cost optimisation scheme for a microgrid is described accounting for emission cost, start-up costs, operation cost and maintenance costs.

The mixed-integer linear programming model in [141] obtains optimal economic operation scheduling of a microgrid in an isolated load area, and a virtual power producer is used to operate the generation units optimally. The methodology is applied to an actual microgrid case study. Also, [142] presented a framework for the energy production planning problem to minimise the total cost and heat interchange within subgroups of the overall microgrid using the mixed-integer linear programming methods.

[143], a short-term DER management methodology in smart-grids is presented as short as five minutes ahead of schedule, and the earlier achieved schedule is rescheduled; thus, the Genetic Algorithm, GA approach is used for optimisation. [144] investigate the operational planning of an independent microgrid with solid oxide fuel cells, tidal power generators and PV. The microgrid supplies heat and electricity to the surrounding towns and harbour facilities.

[145] proposed a probabilistic energy management system to optimise the microgrid operation based on an efficient point estimate method. [146] proposed an intelligent energy management system to optimise the operation of DERs in a combined heat and power-based microgrid over a 24-hour time interval with a modified bacterial foraging optimisation algorithm. Both operation cost and emissions were considered for minimisation. [147] investigated the optimal operation management of DER in a renewable microgrid for a 24-hour time interval, and it considers the uncertainties from load demand forecasting error, grid bid changes and non-dispatchable generator output power variations. [148] propose a functional architecture for an island microgrids real-time operation, and day-ahead scheduling and real-time scheduling are considered. A chaotic quantum genetic algorithm is applied for the environmental, economic dispatch problem for DERs in an intelligent microgrid [149]. Operation planning of an independent microgrid is obtained from the genetic algorithm, where solar cell, heat pumps, fuel cells and water electrolysers are applied.

[89] formulated an optimisation problem based on consumer demand and RERs

modifications and uses an imperialist competitive algorithm to calculate the cost function. [90, 91] included the sizing and operational analysis of a standalone hybrid microgrid in the formulated objective function, then resolved using ant colony and a multiobjective algorithm. [92] overcomes the stability problem of a hybrid microgrid with the harmony search-based hybrid firefly solver. [93] employed a particle swarm-based solver to search for the setting for microgrid control parameters.

[95, 96] suggested that overall power generation costs for the microgrid owner, fuel consumption by DGs, BSS life cycle characteristics, and power losses are significant factors in their formulated fitness functions. [97] a genetic algorithm is applied simultaneously, with the mixed-integer linear programming to solve a two-stage optimisation problem for a multi-microgrid network considering utility profits and consumer satisfaction. [98] used a non-dominant sorting genetic algorithm-II, a fast and elitist type of genetic algorithm, used to solve a multiobjective optimisation problem of microgrids by controlling the load imbalance in the microgrid.

Similarly, various types of genetic algorithm, such as the actual coded genetic algorithm, hybrid-Fuzzy genetic algorithm, and floating-point genetic algorithm, are used in [99, 101] to solve the optimisation problem for standalone microgrids and power systems. Contrary to most genetic algorithm-based techniques that consider binary numbers in their genes and chromosomes, a floating-point number is used in each gene and chromosome of a floating-point genetic algorithm [102]. Hence, floating-point genetic algorithms have more advantages than binary genetic algorithms. The main reasons are more efficiency, less memory utilisation, and increased precision. Moreover, different operators can be utilised for greater flexibility [103]. The operation of a genetic algorithm-based solver can be improved by considering the scaling operator and the traditionally used crossover and mutation operators [104]. The scaling operator can be applied in the form of a different function. Using an appropriate scaling function can reduce the problem complexity and speed up identifying a solution [105].

2.5.2 Operation Management of Microgrids

[150] formulated an economic load dispatch problem of a microgrid using four different optimisation algorithms. The generating cost of the dispatchable DGs present in the microgrid is taken as the objective function. In [151], authors have inspected the effect of these constraints on two different test systems. Simulation results show that the lambda logic technique had the fastest computational time.

[152] proposed the optimal generation scheduling problem for a microgrid consisting of conventional generators, PV systems, WT generators, electric vehicles and BSS. Application results of the optimal generation scheduling of the microgrid with and without EVs and battery storage are attained for comparison. Simulation results reveal that the optimum cost incurred in microgrid with the electric vehicles and BSS is minimal.

[153] proposed a new model for optimal microgrid operation comprising wind turbine, microturbine, energy storage system and loads. Particle Swarm Optimization, PSO algorithm was used to optimise the operation of this microgrid. Alternatively, the Monte Carlo simulation method has been applied to model the uncertainties of wind generation, power consumption of uncontrollable loads, energy price of the upstream distribution network, and the disconnection probability from the network and failure probability of units. This method encompassed all probabilistic conditions and at last presented a probability distribution function for all the decision variables. Simulation results showed that using a deterministic method in the optimal operation of microgrids with non-dispatchable resources was not appropriate and stochastic methods must be applied.

[154] proposed a multiobjective and stochastic problem for optimal scheduling

of microgrid comprising electrical and thermal loads, conventional energy sources (microturbine and boiler), non-conventional energy sources (PV and WT), combined heat and power, energy storage systems (electrical and thermal storages) and series flexible alternating current transmission system devices. In order to attain a higher power transfer to the upstream grid, a dynamic voltage restorer is incorporated in the line between the leading network and the microgrid. In the proposed optimisation technique, solar radiation, wind speed and loads are considered uncertain parameters based on a stochastic approach. The proposed stochastic and multiobjective optimisation problem was solved using the augmented Epsilon-constraint technique. The proposed optimisation technique simulation results were compared with results attained using other heuristic algorithms to reveal the efficacy and viability of the proposed optimisation technique simulation results.

[155] proposed a probabilistic unit commitment model for the optimal operation of plug-in electric vehicles in a microgrid. The microgrid considered here comprises wind turbines, microturbines, plug-in electric vehicles, boiler, battery storage and thermal storage. The usual unit commitment schedule total profit was taken as the objective function. PSO algorithm is applied to minimise the fitness function. Even though probabilistic UC-Vehicle to Grid, V2G cannot represent the indeterminate nature of load, wind and vehicles, the attained values are nearer to reality in association with the deterministic ones. Comparing the simulation results of deterministic and probabilistic UC-V2G reveals that the probabilistic method does not overrate the total expected profit.

In [156], an optimal management strategy of WT/PV/DG independent hybrid systems for supplying required energy in autonomous microgrids is proposed. Guaranteed convergence PSO with Gaussian Mutation, GPSO-GM is developed to solve the optimisation problem of demonstrating the effectiveness and validity of GPSO-GM. Results obtained were compared with results obtained by using particle swarm optimisation and genetic algorithm. Simulation results demonstrate that the design of hybrid energy systems based on using both battery banks and diesel generators to support non-conventional energy sources is more efficient than the design, which only battery banks or diesel generators exclusively.

Optimal operation of microgrids considering the uncertainty of non-conventional energy generation was presented by [157]. Simulation results reveal that stochastic methodology can be applied successfully for optimal microgrid operation with uncertainties through the case study. In [158], near-optimal operation/allocation of Grid-level battery energy storage system has been investigated with the deliberation of lifetime characteristics. Simulation results reveal that the ADP can optimise the system operation under various scenarios. In [159] has proposed an optimisation-based MG framework for optimal microgrid operation. The proposed optimisation framework comprises three optimisation components to carry out unit commitment, consumer load scheduling and power balancing. The optimisation problem is developed considering transmission constraints, ramp-up/ramp-down constraints.

[160] proposed an economic operation model of isolated community microgrid comprising micro-gas turbine, wind turbine, heat pump and energy storage battery. The optimisation problem is solved using the hybrid PSO technique. Simulation results reveal that temperature adjustment of temperature controlling devices can lessen charge-discharge cycles of the energy storage system and enhance microgrid schedulability besides improving the economic efficiency of the microgrid. [161] proposed an improved bat algorithm and a point estimate method to optimise the operation of microgrid comprising wind turbine generator, solar photovoltaic system, microturbine, fuel cell and battery. [162] proposed an optimal scheduling strategy for microgrid operation considering constraints of island capability. A new concept called the probability of successful island is developed. The proposed chance-constrained model has two advantages when compared to the deterministic model.

[163] proposed a multiobjective bi-level optimal operation model for distribution network with grid-connected microgrids to obtain operation benefits of both distribution network and microgrids. The simulation studied was carried out in the IEEE 33-bus distribution network with Europe's typical microgrid and a real system with 128 nodes and seven microgrids in Shandong, China. In [164], a cost-effective hybrid power system in a coastal area of Bangladesh is proposed, which minimises gas emission by a substantial amount owing to reduced fuel consumption. HOMER software is used to determine the reduction in gas emission.

[165] formulated an optimisation model based on the day-ahead forecasted power of non-controllable loads at each time interval of the day (the load profile for the equipment of a greenhouse) in addition to the weather forecast based estimation of the solar energy availability. The optimisation time period is one day (24 hours) that is divided into hourly slots. The optimisation model aims to optimise three non-conventional energy sources (biogas, photovoltaic, geothermal), reducing the daily costs necessary for the dispatchable generators. In order to validate the results obtained, an experimental system equipped with intelligent metering instruments is introduced.

A load control algorithm is developed to consider PV generation operating in island mode [166]. LABVIEW software is used to design the load control algorithm. [167] presented two mixed-integer linear programming models for complete microgrid planning under uncertainties in solar irradiance, electricity demand and wind speed. To demonstrate and compare the effectiveness of the RO and 2SSIP model, the author presented a case study in which the two models are applied to plan a standalone microgrid in Singida, Tanzania. In [168] proposed optimal economic dispatch of a grid-connected microgrid. The microgrid comprised wind, solar photovoltaic and diesel power sources. Simulation results reveal that lower costs are attained in the microgrid when the grid operators DR benefit is maximised at the outlay of minimising transaction/fuel costs.

[169] presented optimal operation management of microgrids using the point estimate method and firefly algorithm considering uncertainties in probabilistic energy management systems. Simulation results revealed that if the uncertain parameters considered can be calculated or projected, the distributions of all of the optimal costs and state variables can be precisely and proficiently evaluated utilising Hong's point estimate method.

[170] presented an efficient algorithm based on PSO for energy and operation management of a microgrid comprising various distributed generation units and energy storage devices. PSO is applied to sort out the optimisation problem. The obtained simulation results substantiated the efficiency of the proposed approach to sort out both probabilistic and deterministic energy and operation management problems under various equipped scenarios of the microgrid.

[171] proposed an optimal day-ahead scheduling model for a microgrid system with wind turbine units, photovoltaic cells, battery storage systems and diesel generators. Simulation has been performed on three different IEEE standard bus systems. Simulation results reveal that the proposed optimisation technique is consistent under normal and fault operation conditions for the optimal day-ahead scheduling of microgrids. [172] presented a comparative study between three different configurations for supplying an irrigating pumping system and a farmers house with the required electrical demand in two different regions. Hybrid Optimisation by Genetic Algorithms simulation software tool is utilised for optimal sizing and cost-effective analysis of a hybrid standalone photovoltaic-wind system.

[173] presented a model predictive control based optimal operation approach for a residential microgrid considering forecast uncertainties. The control accomplishment at each sampling time is attained by solving a novel mixed-integer linear programming optimisation problem. Simulation results specify that the operation cost of the model

predictive control approach is appreciably lower than the conventional day-ahead programming approach under a perfect forecasting situation. In [174], a cuckoo search algorithm was implemented for solving the environmental, economic dispatch problem of a microgrid.

[175] presented a parametric programming based approach for energy management in microgrids. The optimisation problem is solved offline on a flexible time-scale basis, permitting online realisation to be attainable on real-time system state updates. By using operational and design boundaries on the renewable energy systems, renewable resource inconsistency is captured as different parametric apprehensions of solar and wind power, which results in the conversion of the problem from a nonlinear to a linear form. The algorithm was tested using various electricity pricing information to construct two case studies for the system's incentivised and open market operations. Both cases studies are applied to the same renewable energy apprehensions to optimise the decisions of a microgrid over a one-week operational period. Simulation results reveal that under the incentivised program, the storage system is almost not utilised, and the power production extras to local demand are sold to the main grid.

A direct current microgrid with improved maximum power point tracking algorithms for solar and wind energy systems is developed in [176]. A two-model maximum power point tracking technique is implemented to improve the PV system power generation.In addition, an Optimal Power Control maximum power point tracking algorithm is included for the wind energy conversion system with the pitch angle controlling method to improve the supply to the grid. [177] presented optimal operation planning for an isolated microgrid comprising PV, WT, DG, and BSS. This optimisation problem is solved using PSO. Simulation results reveal that the operation cost of the operation planning attained with an indeterminate cost model is more significant than that with an indiscriminate cost model.

In [178], the microgrid stochastic economic load dispatch problem is devised based on the wait-and-see approach. Simulation results reveal that the new mechanism in IPSO adds to the optimisation capability. [179] developed a PI controller based voltage controller on improving the voltage profile of island microgrid. In [180], a power allocation approach for storage batteries and diesel generators is proposed by the overall deliberation of system operations financial and ecological benefits. The non-dominated sorting genetic algorithm solves the optimisation problem. The model is analysed by solving a problem on a realistic island, and the sagacity of the proposed model and the power allocation approach is confirmed. [181] presented the instantaneous scheduling of electric vehicles and receptive loads to minimise operation cost and emission in the occurrence of PV and WT in a microgrid. Simulation results revealed that electric vehicles integration and reactive loads reduce system emission and operation costs.

The Integrated Renewable Energy System (IRES) by [16] considered PV arrays, solar thermal, wind-power, biomass and small hydro as RERs and discussed methods developed to design IRES using linear programming (LP) approach to minimise total annual cost and subject to some energy and power constraints. Another research utilised the idea based on appropriately combining wind-power, solar, and biomass systems and demonstrated that IRES is reliable and a practical concept from the energy deployment and generation standpoint. Therefore, it established that IRES plays a vital role in meeting the energy demands of rural dwellers and improving their living conditions. An optimal renewable energy model, OREM developed and considered 38 various RERs options in trying to minimise the cost ratio with resource restriction, social recognition, reliability and demand factors used as constraints.

2.6 Optimisation Strategy Selection

From the sections above, many optimisation techniques have been applied to the study of microgrids for different applications. To decide what algorithms are employed in the research carried out, the different techniques are considered and demonstrated in the Figure 2.8 below.

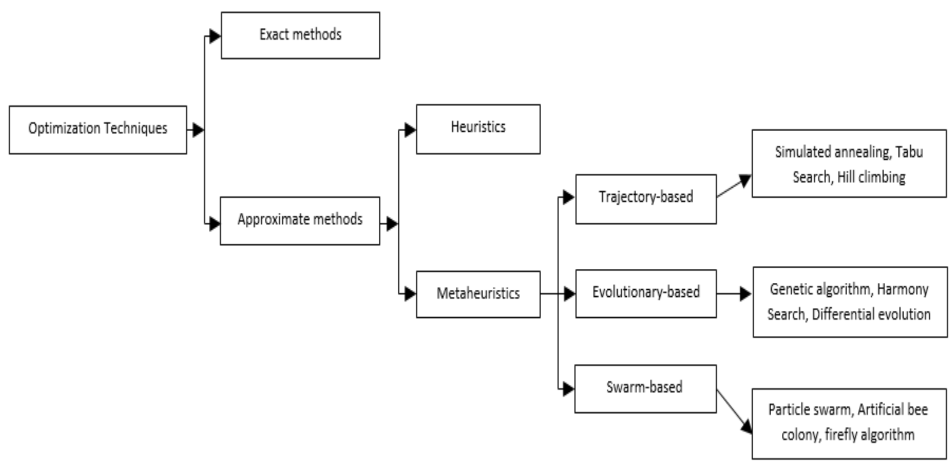

Figure 2.8: Optimisation Technique Description.

Exact methods These are methods used to find the optimal solution to an optimisation problem. These methods include dynamic programming, linear programming methods. They are restricted to the kind of problems they solve (NP-complete problems), and more time is required to solve real time problems.

Approximate methods These methods do not guarantee optimal solutions but are suitable for more complex, stochastic, and demanding exponential effort (NP-hard problems).

Heuristics Heuristic designates a computational procedure that determines an optimal solution by iteratively trying to enhance a candidate solution considering a provided measure of quality. Examples are black-box optimisation techniques and direct search.

Metaheuristics A metaheuristic is a higher-level heuristic designed to find and generate a suitable solution to optimisation problems with little or no information and limited computation capacity. Its stochastic nature easy recovery from the local minima, deal with objective uncertainties and handle multiple objectives with minimal changes required. Metaheuristics can further be divided into Trajectory-based algorithms, Evolutionary-based algorithms and Swarm-based algorithms. Figure 2.8, one method each is selected, and their performances are evaluated further.

2.6.1 Design and Optimisation Software Tools

Different software is used for microgrid design and optimisation. The widely used software options available are detailed in the Table 2.4 below:

Table 2.4: Design and Optimisation Software Tools

Tool/Components	Free	Hydrogen load	Wind	Mini - hydro	Fuel-cell	Control strategies	PV, DG, BSS	Simulation	Thermal load	Economic opt.	GA	Ref
SOLSIM			$\surd$				$\surd$	$\surd$				[182]
RAPSIM			$\surd$				$\surd$	$\surd$				[183]
INSEL			$\surd$				$\surd$	$\surd$				[183]
SOMES			$\surd$				$\surd$	$\surd$				[184]
ARES							$\surd$	$\surd$				[185]
HYBRIDS			$\surd$				$\surd$	$\surd$				[184]
HOGA	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$		$\surd$	$\surd$	[183]
HYBRID2	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$				[183]
HYDROGEMS		$\surd$	$\surd$	$\surd$	$\surd$		$\surd$	$\surd$	$\surd$	$\surd$		[184]
HOMER PRO	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$		[183]

Table 2.4, presents different tools and achievable components of available microgrid design tools. Amongst all tools listed, HOMER PRO, HYDROGEMS, and HOGA tools are comparable with HOMER PRO selected because of the control strategy component absent in HYDROGEMS, and free component absent with HOGA as seen in Table 2.4.

2.7 Conclusion

The concept, research inception of microgrids has been established to be an electrical entity able to operate independently, grid-connected or in clusters. The different technologies in application described as consisting broadly of loads, generating sources, and controls. The different methods of load forecasting is established and finally, optimisation of the microgrids in term of optimal planning and various operational strategies as seen in literature are described.

The deployment of microgrids with RERs is common with its configuration as they have self replenishing power sources that are environmentally friendly. Though with issues of power quality due to their intermittent nature, and continuous load demand variations, ESS becomes essential to improve reliability and stability of the the network. Microgrid planning, operational management, and optimisation offers strategies to efficiently curb excess power losses, minimise design cost, manage power demand and supply.

Several factors impact the advance in microgrid research and development. These include:

1. The availability of RERs and harvestable local clean energy.

2. Energy cost, reliability and power quality. It means meeting the sensitive load requirement by high-quality power local provision and exploiting the use of

DERs assets via embedded intelligence, minimising power disturbances.

3. Energy efficiency. The improved understanding of energy use, knowledge on efficient energy appliances and appliance switch-off. Increased control of demand offers evidence that leads to energy use efficiency.

Depending on the objective (economic, environmental, and energy performance) of study, an optimisation strategy is adopted. Common features of these optimisation strategies include the objective function (single or multiple), decision variable, and constraints. The robust nature of metaheuristics informed its selection for the economic performance of the microgrid considered in research.

The various optimisation strategies require separate tuning of their specific parameters. Parameter tuning is a critical issue, as it directly affects the performance of selected strategies. Improper tuning could result in achieving local optima solutions or increased computation time which will be addressed in study.

In determining the load estimation approach, data type available, and the need to improve accuracy informed the choice of the bottom-up approach requiring questionnaire development to best suit research problem and with the absence of smart metering, the data gathered is replicated to form a years worth for design and simulation purpose. This also affects the choice of forecasting technique deployed to include population growth and appliances assumed to be reasonable added over the forecast period as indices considered.

The benefits of microgrids include; reduction in gaseous emissions (mainly CO_2), energy efficiency or rational use of energy, deregulation or competition policy, growing increase in demand for power, diversification of energy sources, national and global power requirements, modular generating plants availability, reduced construction time and capital costs of smaller plants, ease of finding sites for smaller generators, and generating may be sited closer to load, which may reduce transmission costs.

Chapter 3

Load Design and Forecasting

3.1 Introduction

In this chapter, the methods employed for the load estimation and forecast is presented. The current load demand based on each household, school, worship centres and commercial businesses are considered in developing the community's demand profile developed in Excel. An improved community load profile is developed, taking into account the use of energy-efficient appliances, and assumptions are made in order to shift the base loads from points of zero demands to base loads > 0kW. Refer to Appendix A.1 and A.2, for sample questionnaires.

Furthermore, a forecast is carried out on the maximum load demand over ten years, and the 5th years forecast is used for the design of the hybrid microgrid.

Excel is a spreadsheet from Microsoft which allows data organising, formatting, graphical representation and calculations. The graphs plotted in excel shows the load demand flow in every hour over a 24 hours for individual load demand categories considered.

3.2 Load Estimation

Kogi state located in Nigerias' middle belt area, popularly called the confluence state because of the coming together of the Niger and Benue river which meets at the state's capital Lokoja (the first administrative capital of modern-day Nigeria). Agriculture and natural minerals are the central part of its economy, (agriculture: cocoa, coffee, palm oil, cashew, groundnut, maize, cassava, rice, melon, and minerals: coal, limestone, iron, petroleum and tin). Its coordinates are 7.73370N, 6.69060E. Kogi State has 21 local government areas. Igah community under Olamaboro local government is considered for research purpose.

The resource gathered was for Igah community, Figure 3.1 ($7^0 10.4' N, 7^0 32.4' E$) is a pictorial representation of the selected community. Sixty houses are considered with an average population of 240 people, increasing during the festive periods to over 300 people. Igah community spans an area of 1,132km^2.

Figure 3.1: Igah Community

The people of Igah are not connected to the national grid; hence, they rely on kerosene lamps, torch lights, solar rechargeable lamps, wood fuel and mini fuel generators to meet their daily electricity demand. The populace, including children, are known for farming, and as such, their day to day activities (Monday - Saturday) involves walking long distances to their farms and carrying harvest to the markets in neighbouring villages. Igah community is made up of a couple of worship places, a primary and secondary school, a barbing saloon, a blacksmith, a food milling site, and mini grocery sites located in private homes.

Education is not free; only those who can afford it are able to attend. Those unable to afford to accompany their parents to the farm and the elderly are left at home. It is observed that on a typical Monday to Saturday from 4:30 am, Igah dwellers start their day heading to their farm sites, where most of the day is spent on-farm activities (planting, weeding, harvesting). At 05:00 pm,they start returning home. Schools operate between 08:00 am - 04:00 pm, the blacksmith and barbing saloon operate between 09:00 am - 05:00 pm. When the dwellers are at their farm sites, they have their generators Off and back On when they are home. In the day times, it is mostly the barbers, blacksmith, school, and milling machines that tend to run their generators in other to carry out their activities. On a typical Sunday, the Igah dwellers spend the day in the worship centres, visiting neighbours and engaging in different village meetings.

In order to design accurate and efficient power systems, a good knowledge of the expected power demand for applications is required from the study area. For research purposes, this was estimated through interviews of the village head, school teachers, farmers, and rural dwellers. These indices were considered during the load demand survey of the study area for the proposed HMG.

- Population
- Number of houses
- Number of house occupants

- Average daily electrical energy consumption
- Number of schools, churches, and their energy Demand.
- Commercial businesses and their energy consumption.

The data obtained are based on the results obtained from the electrical load survey conducted in Igah by the researcher in December, 2018. The primary load is residential with some load for commercial, churches and school. During the survey period, there was no health centre available. The load is composed of household devices such as lighting points, fans, rechargeable lamps and radios. Note that refrigerators, ironing devices and other heavy electric equipment were included in the calculation but considered extras because not every house during the survey had these appliances. The actual energy consumed by each of the categories is shown in Table 3.1.

Table 3.1: Basic Inventory

Basic Load Demad						
Appliance	**Quantity**	**Power Rating(W)**	**Hours**	**Energy consumed (Wh/day)**	**Total Individual Energy (kWh/day)**	**Total Community Energy (kWh)**
Residential Houses						
Bulb	3	40	8	960		
Fan	1	75	8	600		
Radio	1	5	8	40		
Phone	2	7	8	112		
Rechargeable lamps	1	23	8	184	1.90	113.76
Church						
Bulb	4	60	5	1200		
Fan	2	75	5	750		
Microphones	2	48	5	480		
Sound system	1	95	5	475		
Keyboard	1	73	5	365	3.27	6.54
School						
Bulb	5	60	7	2100		
Fan	2	75	7	1050	3.15	3.15
Extras						
MP3	1	20	5	100		
Fridge	6	100	10	6000		
TV set	18	80	8	11520		
Electric stove	1	800	3	2400		
Washing machine	1	500	2	1000		
Pressing iron	3	1000	2	6000		
Blender	2	300	1	600		
Microwave	2	1000	1	2000		
Air conditioning	3	1200	8	28800	58.42	58.42
Commercial						
Clippers	2	11	3	66		
Bulb	4	60	4	960		
Grinder	1	1000	4	4000		
Welding machine	1	3600	3	10800		
Grinding machine	1	1500	5	7500	23.33	23.33

Table 3.1 shows an estimation of each appliance's rated power, quantity, and average hours of use by the categories in a single day. The data collected aimed to understand the general behaviour of the people regarding the use of electricity as

shown in Figure 3.2, their current usage and future usage if constant electricity was made available.

Energy consumed (Wh/day) is a product of each appliance quantity, power rating and hours of use in a day. The total individual energy (kWh/day) is the sum total energy consumed by each category of user in kWh/day [186], while the total community energy is the cumulative sum for all members of the different categories under study described as:

$$EnergyConsumed = Quantity \times PowerRating \times Hours \tag{3.1}$$

$$TotalIndividualEnergy = Sum(EnergyConsumed)/1000 \tag{3.2}$$

$$TotalCommunityEnergy = TotalIndividualEnergy \times NumberOfUsers \tag{3.3}$$

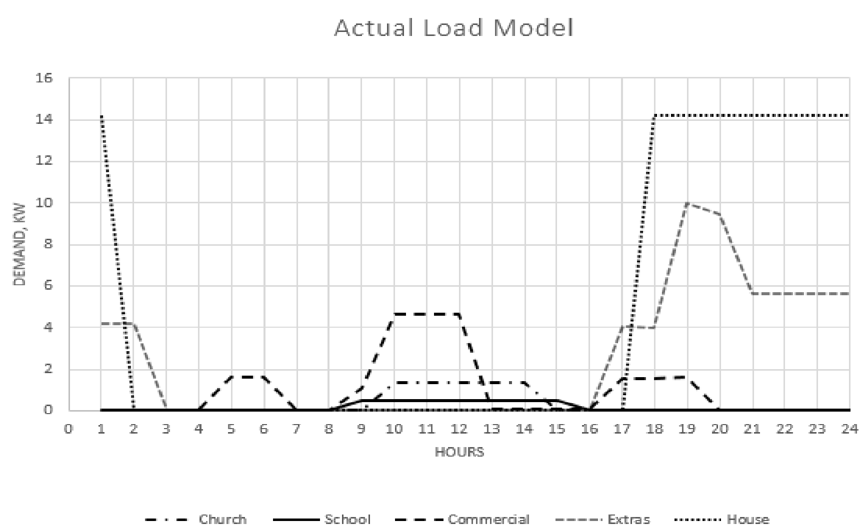

Figure 3.2: Basic Graph of Current Load Model

Figure 3.2 is a plot showing the demand of each load category against each hour in a day.

It was gathered that no generators were in use in the residential houses between the hours of 6:00 am - 3:00 pm, as they were mostly in their farms or market. Their mini generators started coming on after 05:00 pm, electricity use peaking between 7:00 pm-midnight. The school had its generator ON between 8:00 am - 4:00 pm during term time weekdays only. The barbing saloon, welders shop, grinding/milling machine and worship centres had their generators at different times of the day depending on their activities. From Figure 3.2, it can also be inferred that at a particular time of the day, the whole community is in blackout with zero, 0kW of energy generated.

Also from Figure 3.2, the demand for the houses has the highest demand of 14kW between 1700hrs and 0100hrs when compared to other entities considered, with schools having the lowest demand between 0800hrs and 1600hrs. At all other times, the demand is 0kW when the school is closed. The church, commercial load demand are also represented. The Extra load profile represents appliances not common with every household as seen in Table 3.1.

An improved load curve was assumed considering every house had the essential appliances (bulb, fan, radio, phone, television and fridge) and based on the possible constant power supply to the community to make up a daily baseload $\simeq$ 14kW, to be able to carry out system design, and predictions with ease and shown in Table 3.2.

Table 3.2: Improved Load Demand

Appliance	Quantity	Power Rating(W)	Hours	Energy consumed (Wh/day)	Total Individual Energy (kWh/day)	Total Community Energy (kWh)
Assumed Residential Demand						
Bulb	3	20	12.67	760.02		
Fan	1	75	8	600		
Radio	1	5	8	40		
Phone	2	7	8	112		
Fridge	1	100	24	2400		
Television	1	80	8	640	4.55	273.12
Church						
Bulb	4	60	5	1200		
Fan	2	75	5	750		
Microphones	2	48	5	480		
Sound system	1	95	5	475		
Keyboard	1	73	5	365	3.27	6.54
School						
Bulb	5	60	7	2100		
Fan	2	75	7	1050	3.15	3.15
Commercial						
Clippers	2	11	8	176		
Bulb	2	60	3	360		
Grinder	1	1000	8	8000		
Welding machine	1	3600	8	28800		
Grinding machine	1	1500	6	9000	46.34	46.34

From Table 3.2, it can be seen that energy savings is achieved by using lower power rated appliances (e.g bulb). Comparing Table 3.2 and Table 3.1, improved hours of use from 8 to 12.67 hours for residential bulb demand, 8 to 24 hours for residential fridge demand assuming constant electricity supply.

Figure 3.3 is a load curve generated based on the data gathered and the improved load demand containing assumed loads. It shows that differences exist between the actual and the improved load profiles. A notable difference is seen in the profile load peaks. This results from using energy-saving types of equipment in the improved load demand development. Also, we assume commercial businesses operate on a regular 09:00 am - 05:00 pm steady power supply, and every residential house has a fridge ON for 24hrs, causing a shift from the 0kW loads.

As with Table 3.1, same calculations apply to Table 3.2, with the use of energy saving appliances and variations in the daily running hours considered.

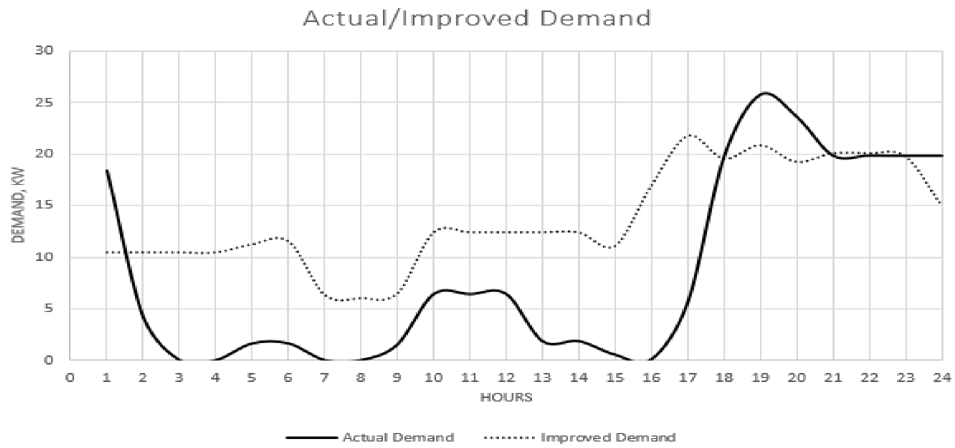

Figure 3.3: Load Curves

The total hourly demand of the community on Y-axis is plotted against 24 hours on X-axis shown in Figure 3.3. It can be seen that the actual demand starts at 18kW, peaks at 1900hrs with 26kW load demand and comes to an end having 20kW load demand. The peak occurs at 1900hrs resulting from more people using energy at this time after returning from the farms and school.

The improved demand starts at 10.5kW, peaks at 22kW (1700hrs) and ends at 15kW. The improved demand was derived by assuming the community had steady power supply and using energy saving appliances. These assumptions improved the profile by shifting the profile point from the 0kW points and also decreasing the demand at the peak point. The rise and fall in plots depicts more appliances switched ON and OFF by users.

The nature of human activities in the community gives rise to the Figure 3.4, showing a lower demand during the daytime on Sundays and the evenings and night, having similar demand. Also, no change in energy use is experienced over the year. Day/Night hour changes due to seasons are assumed negligible as the average sun hours during the summer (Apr-Oct) months was found to be 12.19hrs of daylight, and for winter (Nov-Mar) months, 11.57hrs of daylight.

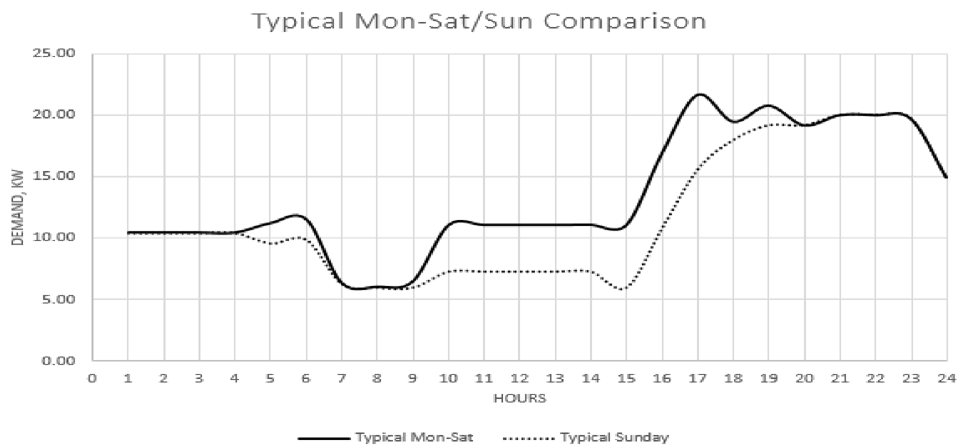

Figure 3.4: Typical Mon-Sat and Sun Load Profile

Figure 3.4, is a representation of the improved load profile showing the profile behaviour Monday - Saturday and Sunday. The difference exist as businesses are closed on Sundays. A combination of the load profiles in Figure 3.4, gives the improved load profile in Figure 3.3.

3.3 Load Forecasting

A bottom-up approach is considered using a combination of both end-use and econometric methods for the microgrid design. They are suitable for the long-term and allow for varying demand pattern simulation alongside introducing new and advanced technologies, and also considers the changes in consumer activities. This approach relies on the accuracy and amount of information provided by the end-user, economic and behaviour indices. Table 3.3 shows the factors considered for load forecasting.

Table 3.3: Consumer Load Demand

S/N	Consumer Type	Average Daily Consumption Per House	Current number of consumers	Per Annual Increase in Consumption (%)	Number of New Consumers Per Year
1	Residential	4.55	60	5	3
2	Church	3.27	2	5	-
3	School	3.15	1	5	-
4	Commercial	46.36	1	5	1

The study adopted a 5% increase for annual increase in consumption from questionnaire data gathered and interacting with the rural dwellers, and 1 new addition to commercial load to include all the different businesses within it.

In forecasting the load, the load factor is important, and it is referred to as the ratio of the average load to the maximum demand during a certain period of time. The load factor is always < 1since the maximum load is expected to be greater than the average load [187].

$$LF = \frac{Demand_{Average}}{Demand_{Maximum}} \tag{3.4}$$

Where LF = load factor (assumed values)

$$Demand_{Maximum} = \frac{ActualUnits_{Total}}{LF \times 8760} \tag{3.5}$$

where

$Units_{Total}$ = Total number of units supplied in a year

8760 = Total number of hours in a year.

The following equations are used for the yearly forecast with values from Table 3.3.

Year 1. For S/N 1 - 4.

$$Consumer\,Type = \frac{Total\,Individual\,Energy * Number\,of\,Users * Days\,in\,a\,year}{1000} \tag{3.6}$$

Year 2 - Year 10 For S/N 1 - 4.

$$Consumer\,Type = \frac{((Total\,Individual\,Energy * 365) + 5\%\,of\,Total\,Individual\,Energy * Days\,in\,a\,year)) * (Number\,of\,Users + U_{New})}{1000} \tag{3.7}$$

where

U_{New} = Number of New Consumers Per Year (assumed from interaction with community dwellers).

Table 3.4, shows the results for the load forecast.

Table 3.4: Ten Year Load Forecast

S/N	Consumer	Yr1	Yr2	Yr3	Yr4	Yr5	Yr6	Yr7	Yr8	Yr9	Yr10
1	Residential	99.60	109.86	120.57	131.78	143.49	155.70	168.40	181.60	195.30	209.50
2	Church	2.39	2.51	2.63	2.75	2.86	2.98	3.10	3.22	3.34	3.46
3	School	1.15	1.21	1.26	1.32	1.38	1.44	1.49	1.55	1.61	1.67
4	Commercial	16.91	17.76	20.30	24.53	30.45	38.06	47.36	64.27	84.57	100.64
5	Miscellaneous	5.00	6.50	7.00	8.00	9.00	10.00	11.00	12.00	13.00	14.00
6	Sum 1-5	125.10	137.83	151.76	168.37	187.18	208.17	231.36	262.65	297.83	329.27
7	10% T&D losses	12.51	13.78	15.18	16.84	18.72	20.82	23.14	26.27	29.78	32.93
8	Demand at 6+7	137.61	151.62	166.93	185.21	205.90	228.99	254.49	288.92	327.61	362.20
9	Demand approx.	138	152	167	185	206	229	254	289	328	362
10	Assumed LF	0.5	0.55	0.6	0.65	0.7	0.71	0.72	0.73	0.74	0.75
11	Maximun Demand, kW	31.42	31.55	31.76	32.53	33.58	36.82	40.35	45.18	50.54	55.13

From Table 3.4, the categories load demand (S/N 1 - 4), Miscellaneous demand is introduced to take care of uncertainties with demand increase by users and 10%

losses for transmission and distribution losses that may be experienced in moving power from the microgrid to the consumer locations.

Reasonable electricity usage is achieved with load factors > 0.75 with limited demand control benefit. For load factors < 0.5, periods of high demand use and low utilisation rate is experienced. As such, for possible benefit in the demand control, load factors between 0.5 - 0.75 were considered.

Preceding years of interest that will be used for further research are Yr1, Yr5 and Yr10, having maximum demands of 31.42kW, 33.58kW and 55.13kW, respectively.

Figure 3.5, shows the maximum energy use expected over ten years.

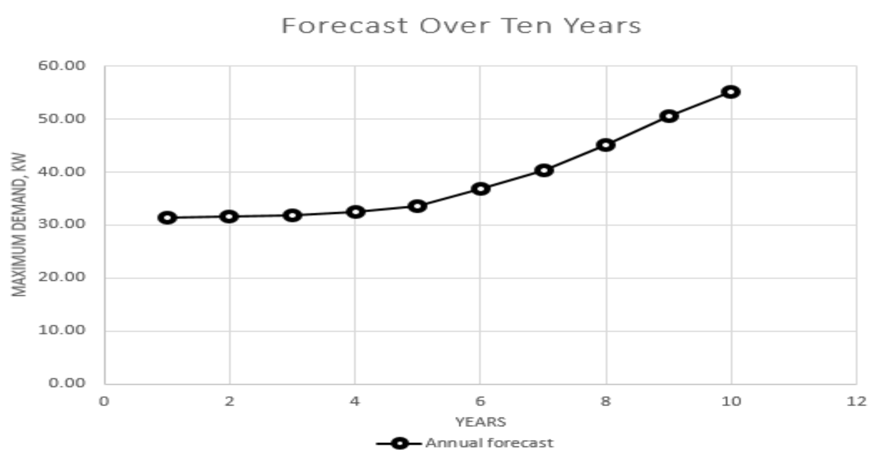

Figure 3.5: Ten Year Load Forecast

From Figure 3.5, for every year, assumptions are made on the load profile that changes its pattern. This is because it is expected that with available power supply, the behaviour, social status and engagements tend to shift slowly as seen in Year 1 - 5. Then power supply becomes steady, there is significant change in their lifestyle (need for comfort), people purchase more appliances for their homes, businesses and farms..

Year 1 - 5 is seen to have a slow increase in the maximum yearly demand from 31.42kW - 33.58kW resulting from a 0.05 increase in the load factor and for year 5 -

10 experienced an exponential increase from 33.58kW - 55.13kW due to a 0.01 load factor increase.

Figure 3.6 below gives a presentation of these effects on the load profile's daily load profile for the 1st, 5th-year and 10th-year load forecast.

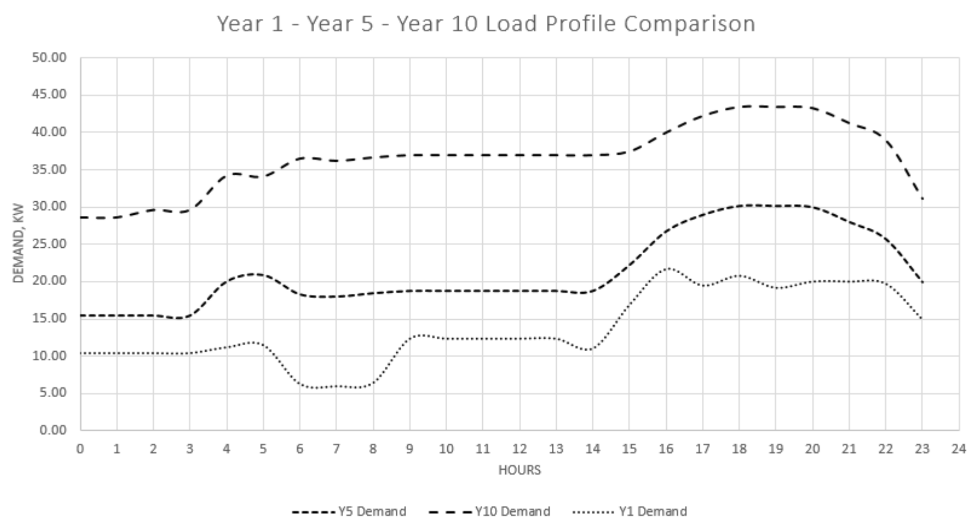

Figure 3.6: Year 1, Year 5 and Year 10 Average Daily Load Profile

As with the improved load demand profiles in Figure 3.3 represented as Y1, Figure 3.6 demand profile is further improved to accommodate the changes resulting from the load forecasting causing the shift in Y5 and Y10 demand respectively. Y5 load curve starts with a demand of 15.44kW at night when the light bulbs and fans are in use, then increases to 21kW when some commercial loads (grinding machines) start coming ON. The load is seen to remain flat between the 0600 - 1400 hours, by this time the grinding machine businesses have gone OFF and community dwellers gone to their farms, schools and other businesses in operation. From 1400 - 1800 hours, the curve is seen to rise to 30kW because schools close about this time and more appliances come ON. The curve remains flat for the next 2 hours when farmers return and begins to drop as businesses shut down and user retire to bed.

Y10 load curve is similar to that of Y5 in terms of the pattern but differ in the demand value. Between 0300 - 0600 hours, the curve increases and flattens because the grinding business is assumed to operate for longer periods as a result of growth experienced.

3.4 Variable Demand

The system is bound to face variability in consumer demand as a result of changes in daily human activities, which need to be considered to show the robustness and reliability of the microgrid design application. Random variability is introduced to the load data, making it more realistic. Day-to-day and Timestep are the random variability inputs to HOMER. HOMER puts together a year-long array load data from specified daily load profiles, then steps through the time series. In each time step, it multiplies a perturbation factor, α by the value in that time step [188].

$$\alpha = 1 + \delta_d + \delta_{ts} \tag{3.8}$$

where

δ_d = daily perturbation value

δ_{ts} = time step perturbation value

The variable load can then be defined as any event that causes spikes to the baseload demand. The microgrid must meet these spikes within certain limits. A proposed load model is developed to show uncertain events that are likely to occur at different times throughout the year due to changes in peoples consumption behaviour. The system designed is robust enough to meet uncertainties. A variable load curve to demonstrate more realistic events through a year is shown as Figure 3.7, for the 1st year.

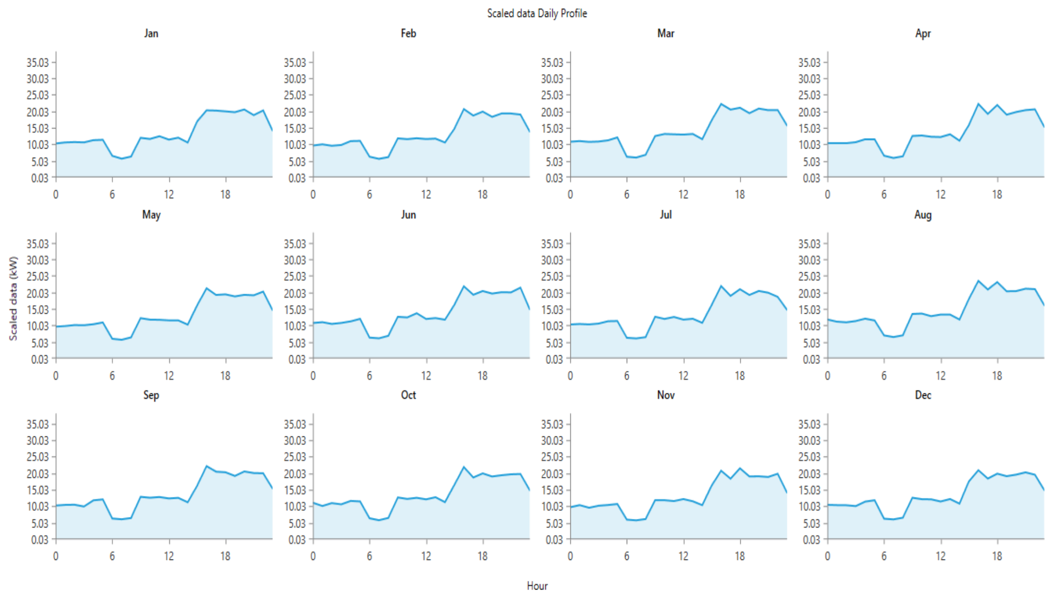

Figure 3.7: Variable Load Curve for Year 1

Figure 3.7 is a representation of the monthly load demand profile developed in HOMER and showing the effects of random variability through the year. The random variability inputs are 20% day-to-day and 15% timestep. HOMER randomly draws the daily perturbation value once per day from a normal distribution with a mean of zero and a standard deviation equal to the daily variability (Day-to-day) input. It randomly draws the time step perturbation value every time step from a normal distribution with a mean of zero and a standard deviation equal to the time-step-to-time-step variability (Timestep) input value.

3.5 Conclusion

In this chapter, the load assumptions, design and forecast is considered. A 10yr forecast was carried out on the load developed from data gathered. It is also observed that the type of data available limits the type of forecasting methods utilised for demand prediction. The forecast carried out considering both end-use and econometric indices showed a progressive increase in the load demand over the years. This is expected as growth and development happen with power availability. Also, the essential lifestyle is likely to improve with people acquiring more gadgets to make a living more convenient.

The Maximum load demand, assumed load factor, percentage increase on the end-user sides, including system losses, are considered in predicting the load demand. The load for Yr5 is further employed for HGM system design in the following chapter.

Chapter 4

Microgrid Design using Homer

The HMG is designed using Homer Pro software, six microgrid designs are presented, and the results are discussed.

Homer Pro (HOMER), created by the National Renewable Energy Laboratory (NREL) USA, is employed to develop a hybrid renewable energy system [188]. It is, among others, a global software tool for designing optimised microgrids in varying sectors, ranging from grid-tied microgrid systems, island system designs and rural system designs.

4.1 Simulation Process

In HOMER, the location for the study is defined and selected. HOMER contains up to 30 years of historical meteorological data from NREL for different locations around the globe. The average daily load characteristics are also inputted. HOMER uses the load data provided to estimate and develop year-long load information. The desired microgrid components are selected, and the characteristics of the cost of each component stated. Desired constraints and sensitivity variables consideration are finally selected for the simulation process to commence. HOMER simulates multiple microgrid design combinations based on the chosen components selected and simulates the microgrid system's operation for an entire year in one hour time steps. HOMER also examines the different microgrid combinations for a run, and based on variables considered for optimisation, it provides the system configurations.

4.2 Sensitivity Analysis

Sensitivity analysis can be carried out in HOMER, allowing comparison amongst multiple simulation results for particular variables/options of interest to see their impact on system designs. Worthy of note is that HOMER provides the fuel cost and cost of the components, which can be modified to fit specific design considerations. It also provides cost for grid extension for the proposed location of consideration, which allows for decisions on the viability of the system design installation or grid extension.

The resulting output after a complete simulation presents a number of microgrid combinations with different Net Present Cost (NPC) component capacities and system performance characteristics. The base case configuration for meeting the load is considered a system consisting of only a diesel generator. Decisions on the microgrid configuration selected are assumed to be a system design with the desired component selected, sensitivity variables, and the least NPC.

The system proposed is designed to have a photovoltaic system, wind turbine system, an energy storage system, a converter, and a diesel generator. Furthermore, it consists of 2 load buses, a DC bus connecting the photovoltaic system and energy storage systems, an AC bus connecting the diesel generator, and the wind turbine system.

The optimised system and variables used in HOMER are imputed into MatLab for further optimisation using some optimisation strategies to evaluate the system's operation at a reduced cost.

4.3 Inputs and Component Selection

In simulating real-life scenarios, a realistic load profile must be proposed for areas without historical user data. Basically, in rural areas, electricity consumption is mainly for domestic lighting and entertainment, community schools, and small-scale commercial activities (food processing and blacksmithing). Therefore, a carefully assumed load demand is proposed for use.

4.3.1 Load Data

The load demand carefully developed in Chapter 3 is used as input to HOMER. A community of 60 residential houses, a school (secondary and primary), two worship centres, and commercial loads (blacksmith and food processing) is analysed. In determining the daily usage of the rural dwellers, the load curve seeks to explain the consumption pattern of the community. Bearing in mind that energy saving and carbon reduction components are introduced, the electricity usage equipment includes lighting, television and radio sets, table or ceiling fans, fridges, sound appliances, food processors and other electrical pieces of equipment. Other sources (microwave, washing machine, pressing iron, electric stove, air-condition) of usage are not considered in the load profile development. Also, the building types and sizes, occupant number, behaviour and exact activities are considered not in detail but assumed where necessary. Note that all appliances implemented are not all simultaneously in use during the 24hr period, as can be seen in Figure 3.4. 8760 hourly electrical load value for one entire year using the load profile with some added random variables such as day-to-day and time-step-to-time- step is then generated by HOMER. During the simulation process of the synthetic 8760 load data to depict a real life scenario, a 20% day-to-day randomness and 15% time-step-to-time-step randomness are used to implement the variable load curves as shown in outliers presented in Figure 4.1, Figure 4.2, and Figure 4.3. The outliers shows the extremely low and extremely high load demand points relative to the nearest load demand point and the nearest of the neighbouring co-existing values in the load demand dataset considered.

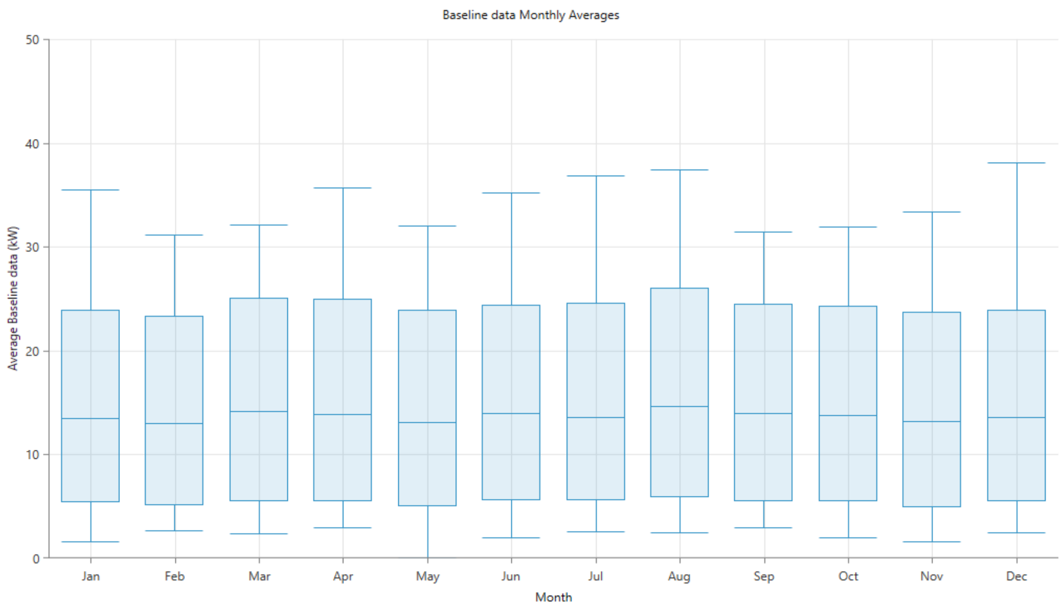

Figure 4.1: Monthly Variable Load Curves for Year 1

The 1st year load forecast, as shown in Figure 4.1, for each month, the top line corresponds to that month's overall maximum load demand with the least demand value 32kW in February and highest demand value of 48kW in December. The bottom line corresponds to the overall minimum load demand with lowest value experienced May. The top of the blue box is the average of the daily maximums of all of the days in the month with August having the highest value 26kW, and the bottom of the box is the average daily minimum load demand. The middle line is the load demand overall average for the whole month.

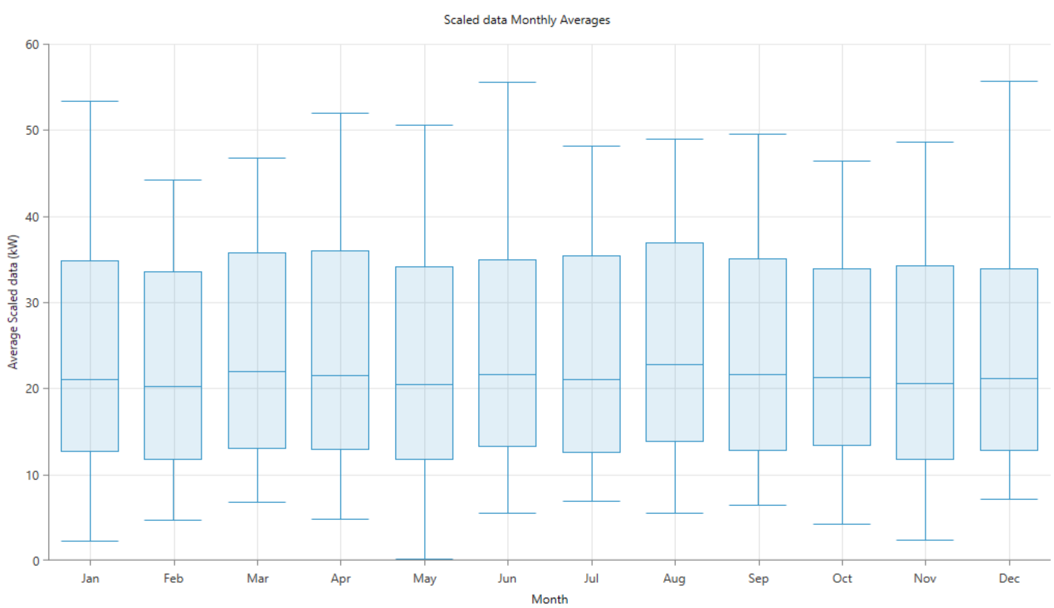

Figure 4.2: Monthly Variable Load Curves for Year 5

For the HOMER HMG design, the 5th year load forecast was utilised. Figure 4.4, The overall highest maximum and lowest minimum, average daily maximum and average daily minimum, and least average monthly load demand have the load demand values of 57kW, 0kW, 48kW, 12kW and 20kW occurring in the months of December, May, August, May and February respectively.

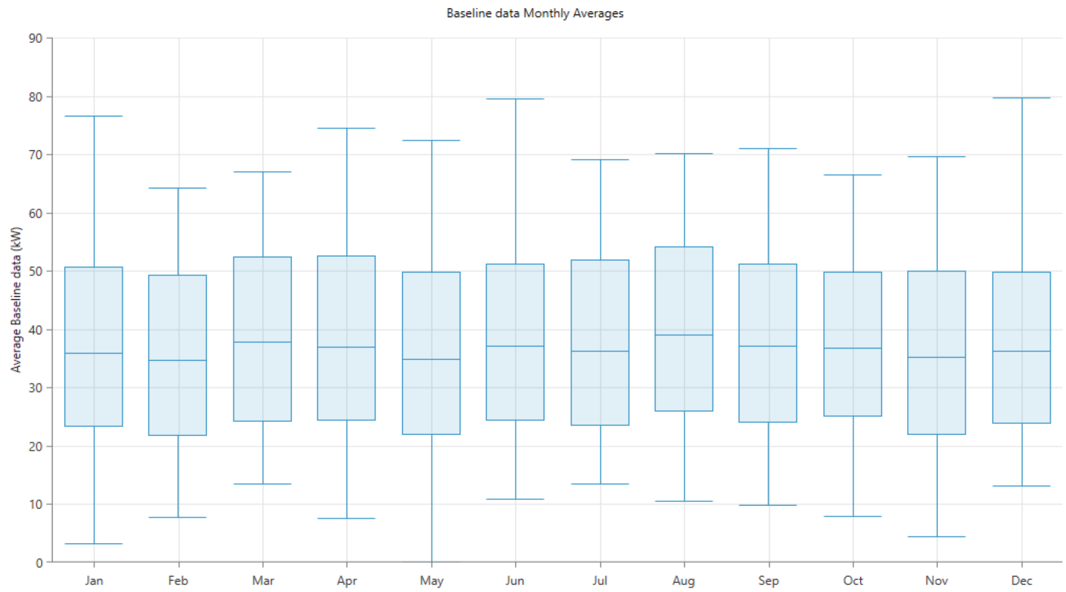

Figure 4.3: Monthly Variable Load Curves for Year 10

The 10th year load forecast, as shown in Figure 4.3,The overall highest maximum and lowest minimum, average daily maximum and average daily minimum, and least average monthly load demand have the load demand values of 80kW, 0kW, 54kW, 22kW and 35kW occurring in the months of December, May, August, May and February respectively.

Figure 4.1, Figure 4.2, and Figure 4.3 all have similar outlier patterns with variations seen only with their respective load demand values and common values for the overall minimum load demand experienced in the month of May.

Figure 4.4 shows the load demand input into HOMER.

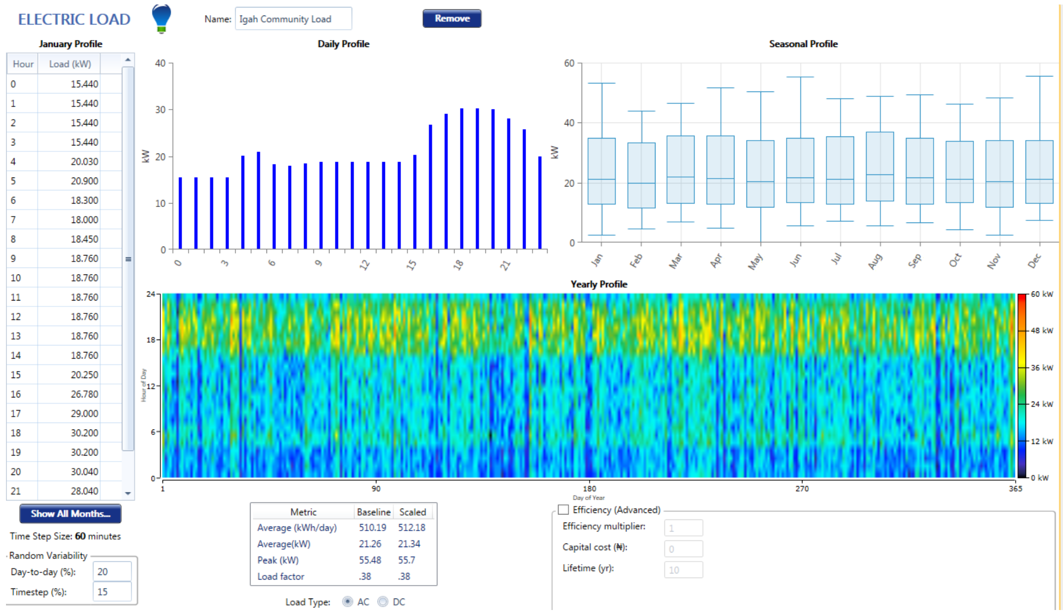

Figure 4.4: Year 5 Load Profile

The load demand for every hour is specified alongside the random variability of 20% on day to day basis with a time step of 15%. Then HOMER generates the results as shown in Figure 4.4.

4.3.2 Meteorological Data

The proposed system design for Igah community needing meteorological data comprises PV, WT. With average annual wind speeds > 4m/s, the site has wind potential to produce power for the system. No potential for small hydro and ready to use biomass, hence not considered. Nevertheless, the HMG system offered the potential to generate electricity with up to 80% degree of the renewable fraction. Solar availability in the study location obtained from NASA surface meteorology available in HOMER tool software.

Based on the available RERs common within the study area, solar and wind resource selected for the location coordinates in HOMER are discussed further.

4.3.2.1 Solar Radiation

Solar radiation values for Igah, $7^0 10.4' N, 7^0 32.4' E$, as earlier said, was obtained from the NASA website. It shows a 22yr average monthly solar radiation data at 1hr intervals represented in Figure 4.5. The clearness index seen on the right axis of the Figure 4.5 is generated by HOMER after imputing the daily radiation data.

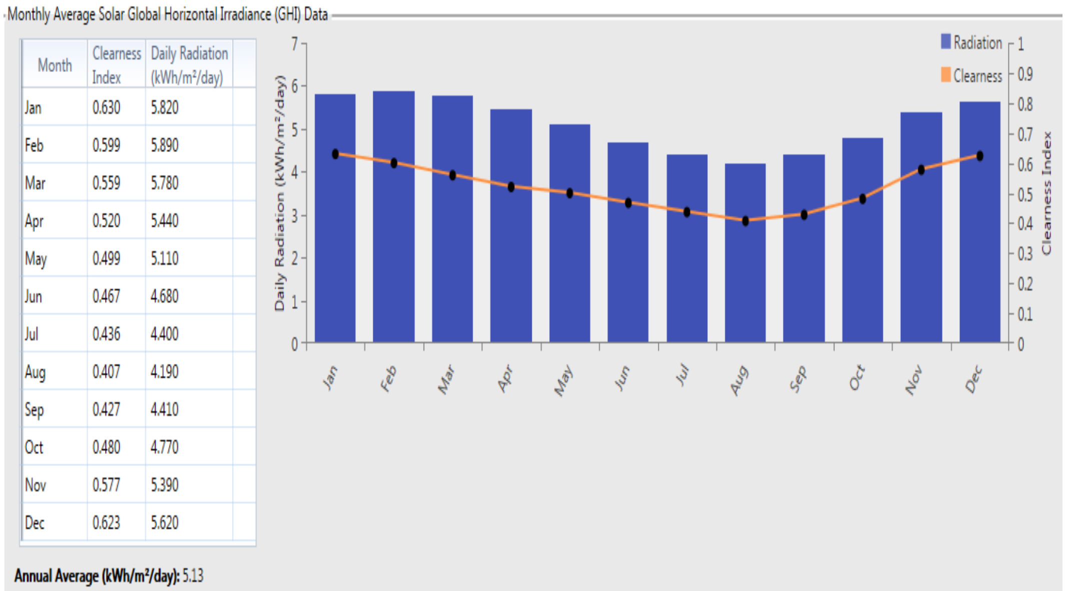

Figure 4.5: Average Monthly Solar Radiation

The solar radiation ranges between $5.89kWh/m^2/day$ in February and $4.19kWh/m^2/day$ in August with an average clearness index[1] of 0.519 and a scaled annual average of solar radiation estimated to be $5.13kWh/m^2/day$. Solar radiation was observed to be high for the months of November to May with readings $> 5kWh/m^2/day$, and low for the months June - October, where there is a slight drop due to seasonal variations representing the dry and rainy seasons respectively.

[1] A measure of atmosphere clearness, and calculated as the fraction of the actual total solar radiation on the surface of the Earth during a certain period over the theoretical maximum radiation during the same period. It is a dimensionless quantity and vary from 0 to 1.

4.3.2.2 Wind Speed

The wind speed data were obtained from the same NASA website for same study location. It is a 30yr average monthly wind speed and was measured at 50m above the surface of the earth in the interval of 1hr represented in Figure 4.6.

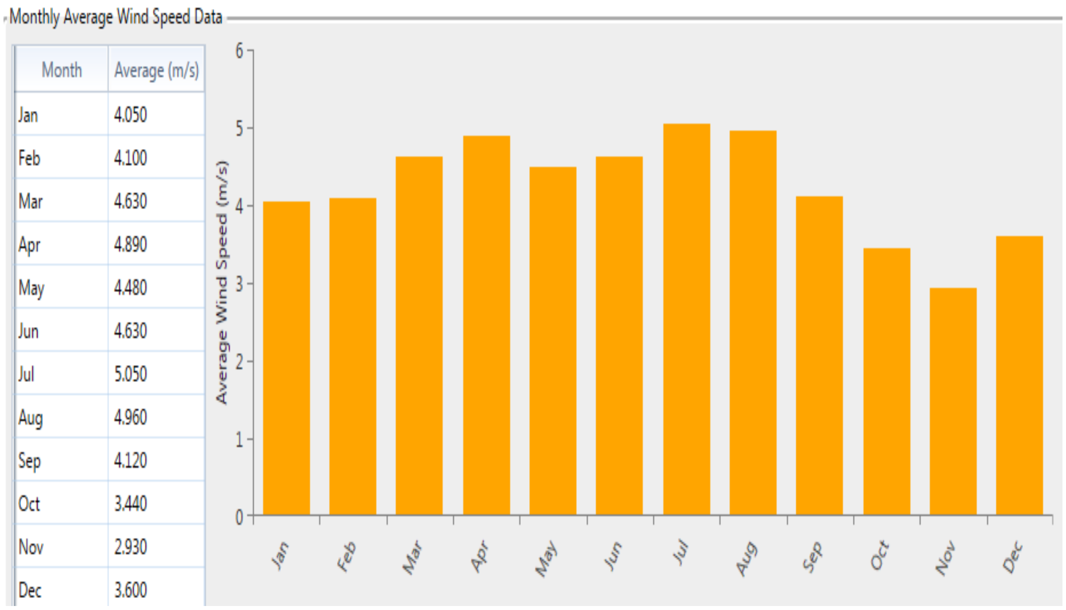

Figure 4.6: Average Monthly WindSpeed

From Figure 4.6, the monthly annual average wind speed is 4.24m/s, and wind speed ranges from 2.93m/s to 5.05m/s. The high wind speed above 4m/s occurred between January and September, peaking in July and the low wind speeds noticed between October and December with the least wind speeds in November. For design purposes, the wind and solar systems are expected to compensate for one another throughout the calendar year because of their seasonal availability.

4.3.3 System Components, Cost and Design Specification

Component costs were gotten from live online prices, market surveys and open literature. Import taxes, transportation, and installation expenses are not included in the calculations.

PV, WT, lead-acid batteries, and diesel generators were selected from the HOMER component library. With the diesel generator included in the design as back-ups. The batteries are charged when there is excess power generated from the renewable sources and discharged when the available renewable sources do not meet the load demand. The diesel generators come ON when both the renewable and the energy storage systems are unable to meet the load demand.

4.3.3.1 Photovoltaic Panels

The annual average solar radiation for the proposed location is $5.13kWh/m^2/day$ shown in Figure 4.5 above. Central HMG installation is proposed for the location in an open field, where design and planning for the position of PV module surface are not affected by shading.

Refer to Table 4.1 for further specifications of the HMG components, (N = Naira).

Table 4.1: System Components, Cost and Design Specification

S/No	Component	Cost (N/kW)	O&M	Lifetime
1	Generator[2]	35,600.00	11.430/hr	15,000hrs
2	Photovoltaic Panel[3]	215,00.00	860.00/yr	20yrs
3	Wind Turbine[3]	175,600.00	1,317.00/yr	15yrs
4	Battery[3]	56,250.00	562.50/yr	10yrs
5	Converter[3]	168,000.00	1,680.00/yr	15yrs

[2]https://ade-power.com/generators/cummins/62kva. Accessed 2020/08/17

[3]https://shop.vesselnetsolar.com/?_ga=2.1539638.60783952.1652902511-387653600.1605849321 Accessed 2020/08/17

4.3.3.2 Wind Turbine

A generic wind turbine selection is made, with a capital cost of N175,600/kW. See Figure 4.7, for the wind turbine power curve and Table 4.1 for other wind turbine specifications.

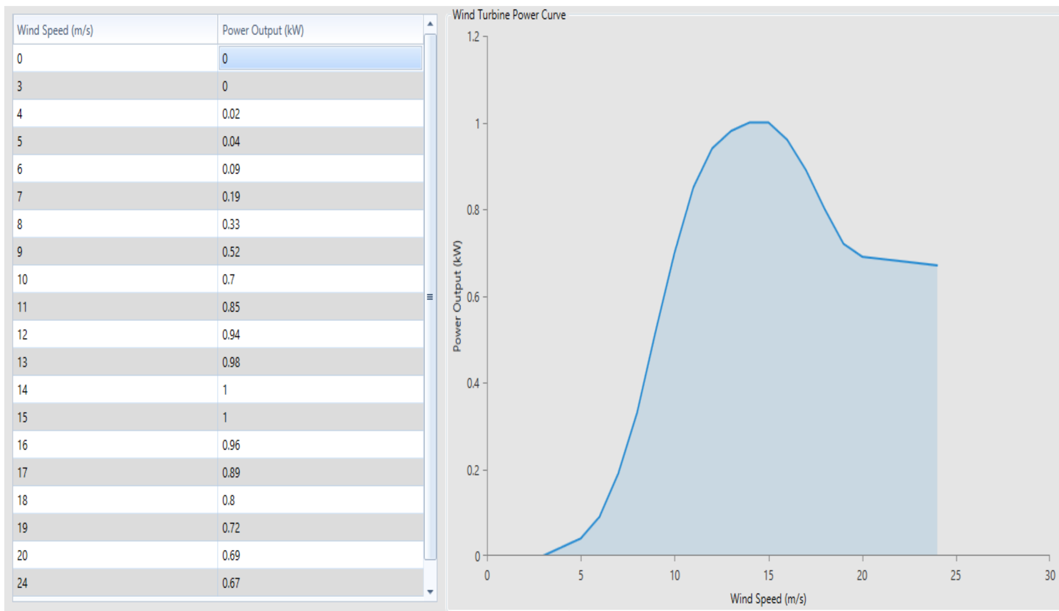

Figure 4.7: Wind Turbine Power Curve

From Figure 4.7, at wind speeds 0m/s to 24m/s, the respective power output is presented. It can be seen that the wind turbine starts to produce power at 3.5m/s wind speeds and increases progressively with increased wind speed, attaining maximum power output at wind speeds 14m/s-15m/s. For wind speeds >15m/s the output power decreases, and shuts down for wind speeds greater than 24m/s for safety. This is because the wind turbine systems (blades, and mechanism) are put under stress causing excess friction and damage when operating at excessive wind speeds. From Figure 4.6, it can be said that the wind turbine produces power throughout the year except for the months of October, November and December.

4.3.3.3 Battery Storage Systems

A generic Lead Acid battery is selected for study purposes. It has a nominal capacity of 83.4Ah and a voltage of 12V. One battery has 1kWh of energy stored, maximum capacity as restricted with HOMER. Refer to Table 4.1 for the cost of the battery and Figure 4.8, for battery properties.

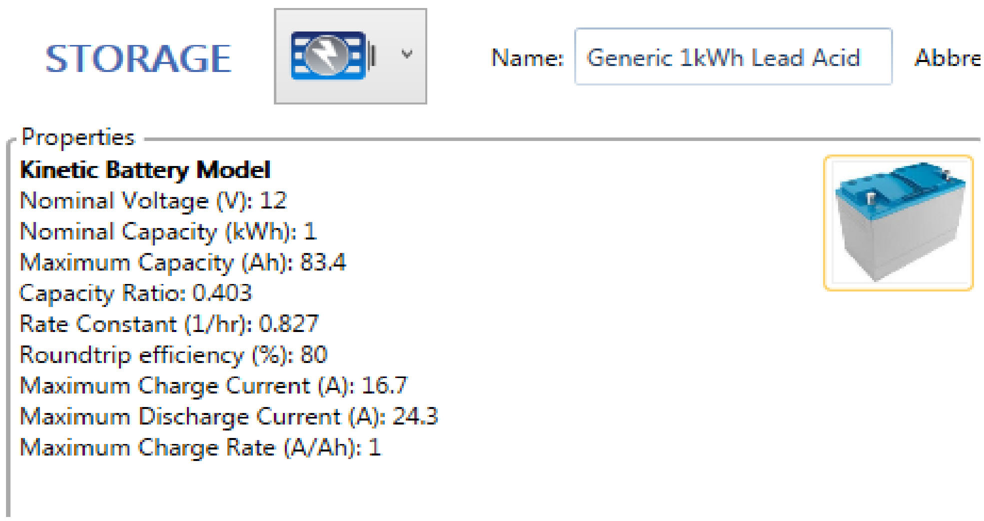

Figure 4.8: Lead-Acid Battery Properties

The cost of each battery is considered as N56,250.00 for a working life of 10 years. The minimum SoC is considered as 20% and 100% initial state of charge, this means the battery is able to charge to full capacity but stops discharging when it is 20% full capacity. After 10 years, the batteries are due replacement.

4.3.3.4 Power Converter

The converter is used as a coupling between DC and AC system so that electrical power can flow in a bidirectional way. It also acts as an inverter and rectifier depending on power flow direction. In this study, the converter used is a generic system converter. For simulation purpose, the inverter efficiency is considered as

95% [189] for a life span of 15 years and the rectifier efficiency is considered 95% for a relative capacity of 100%. Higher inverter efficiencies lower associated losses in the inverter and efficient at full load. The selected converter for this study has a rating of 35.9kW with capital and replacement cost of N168,000.00 each. See Table 4.1 for details of the converter.

4.3.3.5 Diesel Generator

For the study purposes, the peak demand is considered when selecting a generator for microgrid design. In the study, the peak load demand is 55.70kW, and a generator with a capacity of 62kW was selected by HOMER to achieve minimum cost. A Cummins manufactured generator that operates on a 4-cylinder turbocharged engine at 1500RPM is selected. Other generator specifications are seen in Table 4.1. In addition, the diesel price in Nigeria when the study was carried out was N225/ltr in urban areas. Based on an exchange rate of N412.56 to $1, the dollar equivalent will be $0.54/ltr. Due to the values of the global market and variations between countries, diesel prices constantly fluctuate. HOMER simulates three different diesel prices per litre, which accounts for deflation and inflation of fuel prices. Refer to Figure 4.9 for the resultant fuel curve for the diesel generator.

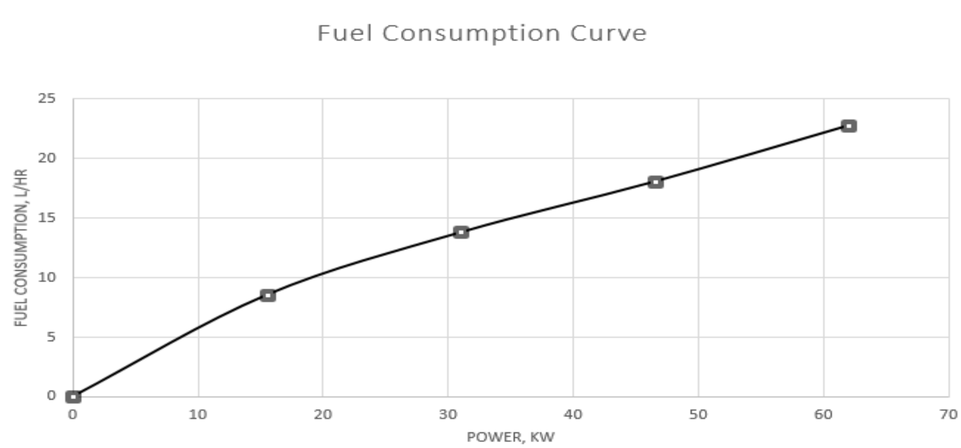

Figure 4.9: Fuel Curve

The Y-axis and X-axis are the fuel consumption in litres per hour, and amount of power generated respectively from the selected DG. It can be seen that no power is generated when the DG starts running even though fuel is consumed and maximum power is achieved at a fuel consumption rate approximately 22L/HR.

4.4 Dispatch Strategy

The dispatch strategy explains the principles for charging the energy storage system. For isolated microgrids with power generation from 100% RES, the energy storage systems are charged by excess renewable energy. While for systems that consist of the diesel generator and energy storage systems, managing the charging operation of the system as it regards how the diesel generator charges the battery systems is of critical significance. For research purposes, the cycle charging dispatch strategy is used. It involves operating the generator at total capacity to meet the load and also charge the batteries with the excess power produced. During the operation, the battery's minimum SoC of 20% stimulates the generator to come ON. A set-point SoC of 80% was selected for this study to enable the generator to continue charging the battery until it reaches the chosen set-point SoC.

4.5 Economic Analysis

The economic parameters utilised by HOMER are the annual Interest rate and Project lifetime. The software ranks all systems according to the net present cost and considers the Levelized cost of energy. These parameters are discussed below:

Annual Interest Rate It is the discount rate and is calculated as [13]:

Annual real Interest rate,

$$I = \frac{i' - f}{1 + f} \tag{4.1}$$

Where,

i' =nominal interest rate

f = annual inflation rate

Net Present Cost (NPC) It is the cost for installing and operating the system for the estimated project lifetime. It is referred to the lifecycle cost of the project. HOMER simulation results are ranked and based on total NPC, and it is calculated as follows [12]:

$$C_{NPC} = \frac{C_{AnnualTotal}}{CRF(i_R, N)} \tag{4.2}$$

$$CRF(i_R, N) = \frac{i_R(1 + i_R)^N}{(1 + i_R)^N - 1} \tag{4.3}$$

Where,

$C_{AnnualTotal}$ =The total annualized cost (N/yr) and includes capital, replacement, annual operating and maintenance and fuel cost.

CRF =Capital Recovery Factor is used to calculate the present value of a series of equal annual cash flow.

i_R = real interest rate

N =project lifetime

Levelized Cost of Energy It is the average cost per kilowatt-hour N/kWh of used electrical energy produced by the system. It is calculated as [12]:

$$COE = \frac{C_{AnnualTotal}}{E_{AC} + E_{DC}} \tag{4.4}$$

Where,

$C_{AnnualTotal}$ = The total annualized cost

E_{AC} = AC primary load served, kWh/yr

E_{DC} = DC primary load served, kWh/yr

4.6 Results and Discussion

HOMER considers the various factors such as technical feasibility, climate, load consumption and diesel prices, the net present cost of developing a particular system and the cost of energy. Then, depending on all these factors, the HOMER system picks the best feasible solution by trying various combinations from the primary proposed system consisting of PV, WT, DG, BSS.

Based on the input parameters in the sections above, a simulation was performed with a 6% annual real interest rate [190], 5th-year load forecast. Three configurations were selected from HOMER simulations for comparing the optimal configuration of the entire system.

Two categories of simulations are considered.

1. The load Without Variability, WoV HMG design.

2. The load With Variability, WV HMG design.

Year 5 Load WoV HMG Design. Figure 4.10 presents the load model fed in HOMER.

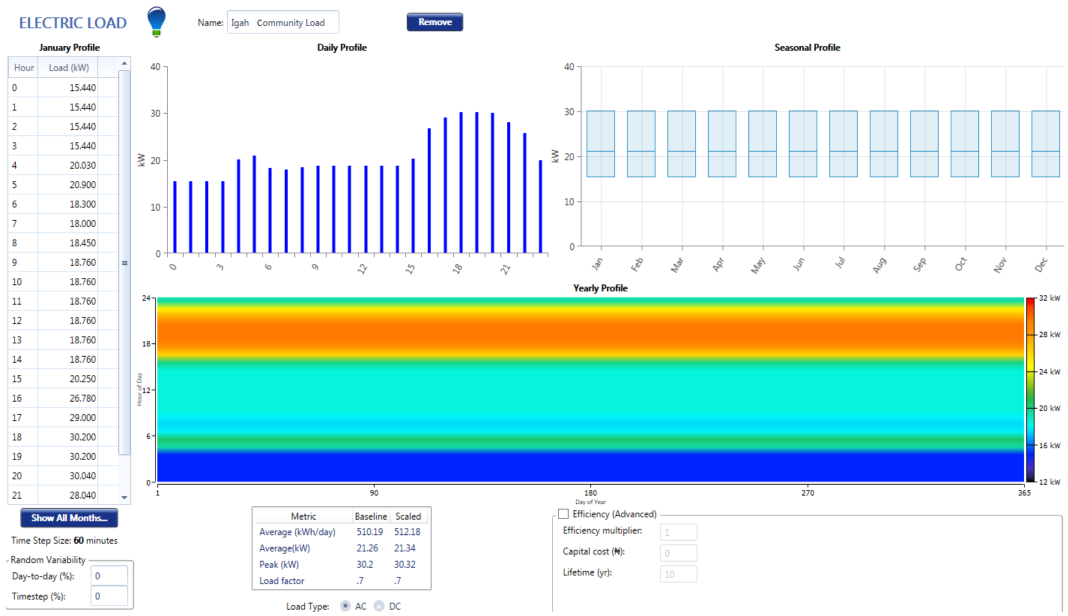

Figure 4.10: Yr 5 Load WoV

From the Figure 4.10 above, the Day-to-day and Timestep random variability are set at 0%. This gives give no room for the system to operate during load fluctuations beyond the designed load and in event of increase in load demand the system is likely to fail and therefore unreliable for use.

The simulation of the Year 5 load without considering variability in the load model produced the system specifications for different design technologies as presented in Table 4.2 below. The base case is having only a DG, 34kW.

Table 4.2: Load WoV HMG Design Model Results.

Component	DG only	HMG Capacity	PV-WT-BSS	Unit
DG	34	34	-	kW
PV	-	58.8	123	kW
WT	-	92	107	kW
BSS	-	168	536	-
Converter	-	21.6	40.7	kW

	DG only	Lowest Cost System, HMG	PV-WT-BSS	Unit
NPC	N185	N133	N143	Million
Initial Cost	N1.21	N43.1	N82.2	Million
O & M	N14.4	N7.0	M4.8	Million/yr
LCOE	N77.27	N55.48	N61.94	/kWh

The HMG presented a 66% RERs fraction and has a DG running time of 3,266 hours in a year. With the DG running almost half of the year, the lifespan is reduced, having a considerable cost for its operation and maintenance. Also, implying the DG would need replacement after 4.5 years and approximately 7 times through the project life. The PV-WT-BSS technology had unmet electrical loads, making it unreliable.

For the three technologies evaluated, the emission results are presented in Table 4.3 below.

Table 4.3: DG, HMG and PV-WT-BSS Model Emission Results for Yr5 Load WoV.

	DG only	HMG	PV-WT-BSS	
Quantity	Value	Value	Value	Units
Carbon Dioxide	159,052	55,483	0	kg/yr
Carbon Monoxide	1003	350	0	kg/yr
Unburned Hydrocarbons	43.7	15.3	0	kg/yr
Particulate Matter	6.08	2.12	0	kg/yr
Sulphur Dioxide	389	136	0	kg/yr
Nitrogen Oxides	642	329	0	kg/yr

Load WV HMG Design The variable load is employed in the HMG system design, and the results presented in Table 4.4. The simulation is performed by comparing the optimal configuration of HMG systems. The simulation was performed for a project lifetime of 25years. HOMER software simulated 33,981 solutions in a time span of about 22 minutes and found 35,692 feasible solutions based on the geographic location, technical feasibility and Economics.

Table 4.4: Load WV HMG Design Model Results

Component	DG only	HMG Capacity	PV-WT-BSS	Unit
DG	62	62	-	kW
PV	-	78.8	136	kW
WT	-	101	132	kW
BSS	-	299	516	kWh
Converter	-	21.6	39.2	kW

	Base Case, DG	Lowest Cost System, HMG	PV-WT-BSS	Unit
NPC	N221	N144	N147	Million
Initial Cost	N2.21	N58.4	N88.0	Million
O & M	N17.1	N6.71	N4.65	Million/yr
LCOE	N92.65	N60.37	N63.75	/kWh

HOMER results show cases for optimised results and sensitivity analysis. The scenarios are as shown below:

1. The first scenario simulates a base case system configuration having just a diesel generator as the power source.

2. The second scenario simulates a system configuration having a diesel generator, wind turbine, PV system, and an energy storage system.

3. The third scenario simulates a system configuration having only RERs without the diesel generator.

4.6.1 Diesel Generator System

A 62kW diesel generator only system design as shown in Figure 4.11

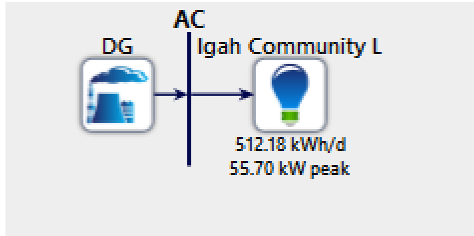

Figure 4.11: DG only Configuration

From the results:

1. The DG only system gives the cost of energy of N92.65/KWh, a net present cost of N221.41Million, an operating cost of N17.2Million/yr and an initial cost of N2.21Million.

2. The renewable energy fraction for this system is about 0%.

3. Maximum energy is supplied to the load using just the DG

4. The CO_2 emissions is 185,078kg/yr, fuel consumption/yr is 70.705Ltr, excess power of 5,400kWh/yr.

The gases emitted in the atmosphere during the project life cycle of 25 years due to burning diesel is shown in Table 4.5.

4.6.2 Diesel Generator - Wind Turbine - Solar PV - Energy Storage System

The optimal design and component capacities for this configuration are represented in Figure 4.12 and Table 4.4. The HMG system considered in HOMER for optimisation consists of PV modules, Wind, Batteries and converters, Diesel generator sets. This system is islanded.

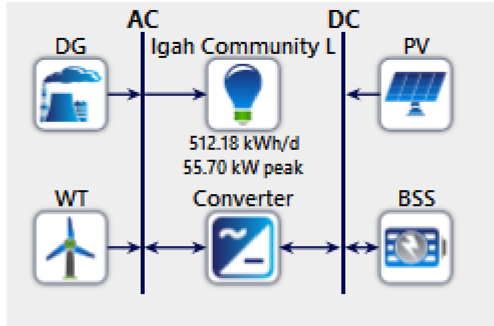

Figure 4.12: HMG Design

From the results of simulating scenario 2:

1. The HMG only system gives the cost of energy of N60.37/KWh, a net present cost of N144.3Million, an operating cost of N6.7Million/yr and initial cost of N58.5Million. DG O&M is found to be N3,391,595/yr

2. The renewable energy fraction for this system is about 77.3%.

3. 85% of energy is supplied to the load using RERs, and the DG supplies 15% of the total energy supplied with running hours of 1,735hrs.

4. The CO_2 emissions is 39,419kg/yr as seen in Table 4.5, reduced to a great extent as most of the energy utilized by the load is drawn from renewable energy resources implemented in the system. Fuel consumption is 15,059L/yr, excess power of 79,032kWh/yr.

4.6.3 Wind Turbine - Solar PV - Energy Storage System

In this scenario 3, a 100% RERs penetration is simulated. The design and configuration of the system are as shown in Figure 4.13, Table 4.4 and results summarised below.

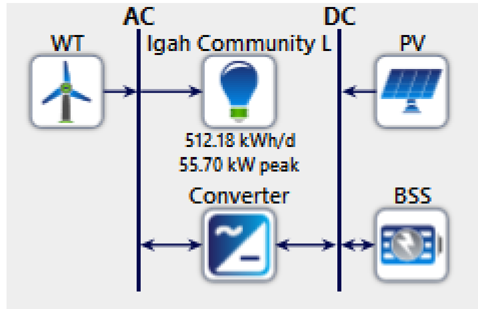

Figure 4.13: RERs Microgrid Design

From the results of simulating scenario:

1. The HMG only system gives the cost of energy of N63.73/KWh, a net present cost of N147.4Million, operating cost of N4.7million/yr and initial cost of N88Million.

2. The renewable energy fraction for this system is about 100%.

3. Maximum energy is supplied to the load using RERs.

4. The CO_2 emissions is 0kg/yr, Fuel consumption is 0L/yr, excess power of 154,540kWh/yr, and 6,146kWh/yr unmet electrical load.

Table 4.5 presents the emission results from the three scenarios considered.

Table 4.5: DG, HMG and PV-WT-BSS Model Emission Results for Yr5 Load WV.

	DG only	HMG	PV-WT-BSS	
Quantity	Value	Value	Value	Units
Carbon Dioxide	185,078	39.419	0	kg/yr
Carbon Monoxide	1,167	248	0	kg/yr
Unburned Hydrocarbons	50.9	10.8	0	kg/yr
Particulate Matter	7.07	1.51	0	kg/yr
Sulphur Dioxide	453	96.5	0	kg/yr
Nitrogen Oxides	1096	233	0	kg/yr

As expected, PV-WT-BSS produced 0kg/yr of harmful emissions, HMG had significant emission production with DG only configuration producing the highest amount of emissions resulting from burning diesel fuel used for its operation.

4.7 Conclusions

In this chapter, the predicted load for year five is utilised in homer for the HMG design. In order to design a robust system, the design considers load variability, making the system cope with uncertainties that may occur. After that, a survey on available resource to the study location for the feasibility of RERs development is done. It is observed that the average annual wind speeds through the year were 4.24m/s, with average solar radiation of $5.13kWh/m^2/day$. Lead-acid batteries and a backup diesel generator are included in the HMG design. Different configuration scenarios are then simulated, depending on the performance in terms of meeting the load, cost and emissions, and the desired HMG is selected for further optimisation using three metaheuristic techniques in MatLab to improve the system operation improving the overall system efficiency.

Scenario 2, having the HMG simulation, offered a preferable result for a reliable system always able to meet the load presented in Table 4.6 below.

Table 4.6: Result Summary and HMG Design Specifications

Component	DG	RERs	HMG
Diesel Generator	62	-	62
Solar PV	-	136	78.2
Wind Turbine	-	132	101
Battery Storage System	-	516	299
Converter	-	39.2	29

Measured Indices	DG	RERs	HMG	Unit
NPC	N221.41	N147.4	N144.3	Million
LCOE	N92.65	N63.75	N60.37	/kWh
O & M	N17.2	N4.7	N6.7	Million/yr
Initial cost	N2.21	N88	N58.5	Million

Measured Indices	DG	RERs	HMG	Unit
Fuel Cons	70,705	-	15,059	ltr/yr
DG Hours	8760	-	1,753	Hrs
Total Energy Produced	192,346	359,290	282,231	kWh/yr
Excess Energy	5,400	154,540	79,032	kWh/yr
Unmet Load	-	6,146	-	kWh/yr
CO_2Emission	185,078	-	39,419	kg/yr

From Table 4.6, it is clear that the HMG model offers more economic benefit when compared to other microgrid designs. The HMG offers almost 79% CO_2 gas emission compared to the DG only system. According to the research conducted by scientific America's energy and environmental editor, David Bello, when a trillion tons of carbon is released into the atmosphere, the temperature increases by CO_2, which is dangerous. As such, carbon emissions must be kept below a trillion tons to minimise global warming effects. HMG system subsequently reduces fuel consumption and carbon emissions enormously.

Though the RERs microgrid model has no emissions, the system fails to meet 6,146kWh/yr of electric load every year, making the system unreliable. Consequently, the cost of electricity for the favourable systems is N60.37/kWh (0.15/kWh), having the least COE among all configurations and having the least NPC of N144.3Million.

With HMG clearly offering better options to power generation, RERs suffer a number of factors limiting its deployment in Nigeria which include the significant costs of RERs components, costs installation and maintenance, non- involvement of the private sector, inadequate investment in the energy sector; lack of technological know-how, the subsidies granted to generators of energy from fossils, and political instability.

Recall from the load forecasting carried out in Chapter 3, Year 5 calculations assumed a load factor of 0.7 corresponding to that produced by HOMER and the DG system estimated by HOMER of 34kW was designed able to meet the maximum demand of 33.58kW of the forecasted load without considering variations in the load to achieve minimum cost.

Chapter 5

Microgrid Optimisation

5.1 Introduction

This chapter introduces the three algorithms used for the DG running hours minimisation. The literature on various optimisation techniques have been considered in Chapter 2, where metaheuristic strategies are selected for implementation. The genetic algorithm, particle swarm and simulated annealing optimisation methods are described, and the problem formulation is described, an objective function developed that describes the DG operation, including its maintenance. The RERs are not considered in the objective function equation but are included in the simulation process as constraints on the HMG system. MatLab is used to carry out the HMG system optimisation. The input data (meteorological and component specifications) are the same as those used in Homer. The results are further discussed for each algorithm and scenarios considered.

The HMG optimisation proposed in this study was implemented using MatLab software. MatLab has been chosen as the preferred software for simulating the HMG model because of its freedom to define its parameters to achieve the desired design. The amount of data to be handled in this research such, as weather data, load data, also necessitates using a fast computing platform that MatLab offers. MatLab also allows for flexible manipulation and fine-tuning of parameters for the control of algorithms.

5.2 Algorithm Design

5.2.1 Genetic Algorithms

In 1975 [191], Holland developed the genetic algorithms for the survival of the fittest based on the Darwin's theory of evolution. It involves creating a group of candidate solutions represented as strings of a point in a search space, an objective function that evaluates the solutions, a set of genetic operators generating new solutions from old ones while adhering to some genetic rules. Each candidate solution is weighed by its objective function until the best solution is achieved. Tasks carried out by GAs are:

- Choice of string representation,
- Selection of genetic operators,
- Determine the Fitness function,
- Determine the probabilities for controlling the genetic operators

The standard GA operators include Selection, Crossover, Mutation, and Elitism.

1. Selection: Here, the next generation parent is selected to give more reproductive chances to the population members with better fitness.
2. Crossover: This is the random process of recombining parents. Depending on the crossover probability, an exchange of characters between strings are performed. The process involves selecting two mating parents, selecting a

crossover point, and exchanging the chromosomes between the two strings. This operation enables the GA to acquire information from the generated individuals. The genetic search space is thus extended and more complete.

3. Mutation: This process involves periodic arbitrary modification of the string bits. In binary representation, this implies flipping the state of a bit from 1 to 0 or vice versa.

4. Elitism: At this stage, the best solutions found are preserved by retaining a selected number of them in the next generation. Elitism is essential to prove the convergence to the optimum through a Markov chain analysis. Elitism also prevents the event of losing the best individual in each generation. Fig 5.1gives a representation of the GA operators.

Population	Chromosome 1	1	1	1	0	1
	Chromosome 2	0	0	0	1	1
	Chromosome 3	1	1	0	1	0
	...	0	1	1	1	0
	Chromosome n	1	0	0	0	1
Crossover	Chromosome 1	1	1	1	0	1
	Chromosome 2	0	0	0	1	1
	Chromosome 1	1	**0**	1	0	1
	Chromosome 2	0	**1**	0	1	1
Mutation	Chromosome 3	1	1	0	1	0
	Chromosome 3	1	1	0	1	1
Elitism	Chromosome n	1	0	0	0	1

Figure 5.1: GA operators

An outline of GAs basic principle is described below:

Randomly generate a population with chromosomes and their objective functions. The chromosome in this research are DG ON/OFF states with different sets of DG energy production and represent the quality of each plan. Generate a new population-based on Darwin's theory of evolutionary using the four genetic operators described in Fig 5.1 and perform

Selection: Select two chromosomes from a population with a probability based on their objective functions;

Crossover: Elements of two-parent chromosomes are crossed over based on a specific rule to create two children chromosomes;

Mutation: Elements in an arbitrary chromosome is mutated with a mutation probability.

Elitism: Carryover elites to the next generation

The four operations are repeated until a new population is generated. Then, keep generating a new population until the stop criterion is reached and the chromosome with the minimum objective function is considered the optima.

GA flowchart can be seen in Fig 5.2.

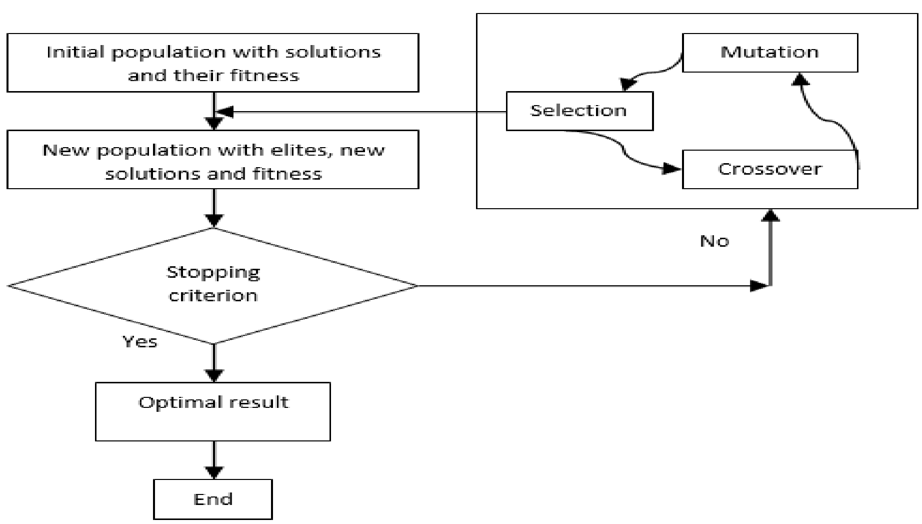

Figure 5.2: GA Flowchart

5.2.2 Simulated Annealing

In 1953 [191], Metropolis et al developed the simulated annealing optimisation technique. As from the algorithm's name, SA mimics the annealing process in metallurgy, a technique that involves the heating and regulated cooling of a material to enhance the size of its crystals and lower defects in the materials. SA simulates the reordering of particles in a body to crystalline state followed by temperature decrease, thus exposing a solution to heat and slow cooling, delivering a more optimal solution (lower energy state). SA is applied to complex computational optimisation problems where particular algorithms fail; even though it usually attain approximate solutions to the global minimum, it could be sufficient for various fundamental problems. SA solves problems having an objective function of many variables and subject to many constraints. The idea of slow cooling employed in the SA algorithm is explained as a gradual decrease in the chance of accepting worse solutions while exploring the solution space. Accepting worse solutions gives room for a more general search for the global optimum.

Generally, SA algorithms work as follows. The temperature gradually decreases from an initial positive value to zero. At each time step, SA selects at random a solution close to the current one, measures its fitness, and moves to it according to the temperature-dependent probabilities of selecting better or worse solutions, which during the search respectively remain at 1 (or positive) and decrease towards zero. Simulated annealing: mimics annealing in metallurgy that involves the slow and controlled cooling of a material to increase crystal sizes and reduce defects in the material. Cooling is controlled by a temperature-like parameter that is closely related to the Boltzmann Probability Distribution (BPD) concept. Which is [191],:

$$P(E) = \exp^{\frac{-E}{kT}} \tag{5.1}$$

For

k =Boltzmann constant, $1.38x10^{-22}J/K$

T =Temperature

E =Energy

SA begins with an initial solution at a relatively high temperature. A second point is created within the vicinity of the initial point, and ΔE is calculated. If ΔE is negative, the new point is accepted; otherwise, the point is accepted with a probability of $\exp\frac{-\triangle E}{kT}$. This completes one iteration. In the next generation, T is reduced and the process repeated. Before every temperature reduction, all solutions generated are tested.

The concept of SA follows the Monte-Carlo iterative method described as follows

1. Choose an arbitrary initial solution X^0, a stopping criterion ε. Set T sufficiently high, decide on n and set $t = 0$.

2. Determine the neighbouring point $X^{(t+1)} = N(X^t)$. Normally, a random point in the neighbourhood is created.

3. If $\triangle E = E(t+1) - E(t) < 0$, set $t = t+1$. Else create a random r in the range (0,1). If $r \leq \exp\frac{-\triangle E}{kT}$, set $t = t+1$. Else go to 2.

4. If $|X^{t+1}-X^t| \leq \varepsilon$ and T is small, stop. Else reduce T according to cooling schedule and go to 2.

SA flowchart can be seen in Fig 5.3.

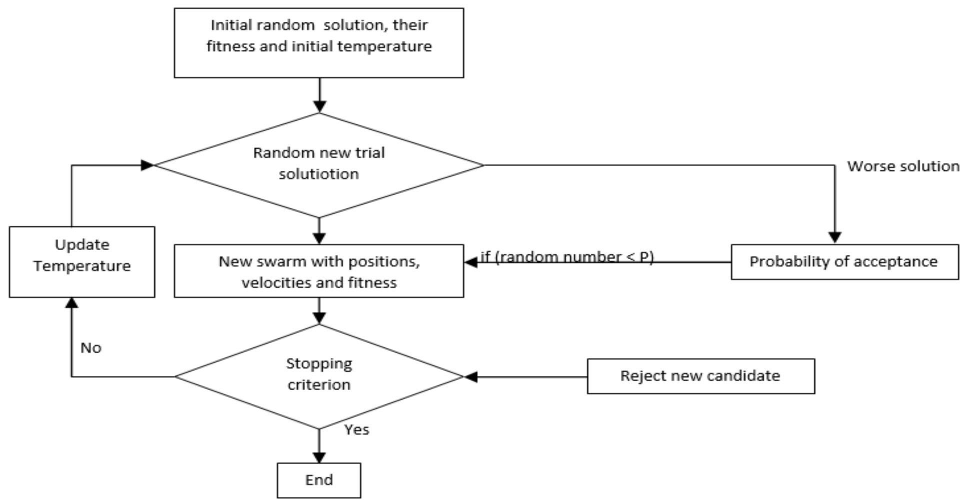

Figure 5.3: SA Flowchart

5.2.3 Particle Swarm Optimisation

Particle swarm optimisation designed in 1995 [192] by Kennedy and Eberhart is a metaheuristic technique that uses computer programming to model the swarming behaviour of naturally occurring instruments (birds, bees or fishes) referred to as particles. PSO involves replicating the social behaviour among individual particles flying through a defined search space, with each particle representing a single interaction of all search dimensions. The particles evaluate their positions on every iteration relative to the objective function, and neighbourhood particles share their best position memories. Based on their memories, they adjust their velocities and positions afterwards. In so doing, the particles converge towards a global solution.

PSO makes little or no assumptions about the optimisation problem and can search a multidimensional search space of possible solutions. Furthermore, as with other classical optimisation techniques, a problem does not need to be differentiable as PSO does not require the gradient of the optimisation problem.

In 1998, Shi and Eberhart [192] made improvements to the overall PSO technique performance by introducing the inertia, w parameter. The inertia weight was introduced to regulate the influence of the previous velocity histories on the current velocities, consequently influencing the trade-off between the local and global explorative capabilities of particle flying points. Small inertia weights tend to facilitate local search, while large inertia weights enable global search to fine-tune current exploration area. The appropriate selection of the inertia weight provides a balance between the local and global exploration abilities and consequently reducing the number of iterations required to reach optimum. Thus the inertia weight aids non-dominated solution generation and maintains diversity.

Many challenging engineering problems are optimisation problems which can be stated as min/max of f(x). Some simple functions f for which problems of the sort are solved. For other functions, just one method exists to solve the problem, which is evaluating the function at numerous points, hoping to find the best one. PSO offers explorative abilities that involve selecting points at which to evaluate the fitness within the computer program.

The investigations carried out by Kennedy and Eberhart suggested that particles benefit from both individual and collective memory of the swarm, which is the concept behind the PSO technique. PSO starts with an initial velocity matrix of the form [192]:

$$V_{ij} = X_{min,j} + r_1 * [X_{max,j} - X_{min,j}] \tag{5.2}$$

where,

i = the population size,

j = the number of decision variables,

$X_{min,j}$ = the minimum value of an individual in the population,

$X_{max,j}$ = the maximum value of the individual in population.

Further, new particle positions are expressed using the following equation:

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \tag{5.3}$$

where X is the particle position and V is the particle velocity in iteration t

The velocity is calculated and updated using the following equation:

$$V_{ij}(t+1) = w\left[V_{ij}(t) + r_1c_1(P_{ij}(t) - X_{ij}(t)) + r_2c_2(P_{gj}(t) - X_{ij}(t))\right] \tag{5.4}$$

$$w = \frac{2}{\left|2 - \emptyset - \sqrt{\emptyset^2 - 4\emptyset}\right|} \tag{5.5}$$

$\emptyset = c_1 - c_2$

$\emptyset > 4$

Where,

V_{ij} = the inertia, makes the particle move in the same direction with the same velocity,

w = the inertia coefficient,

P_{ij}= the best individual particle position,

P_{gj} = the best global position,

r_1r_2 = real random numbers between 0 and 1,

c_1, c_2 = cognitive and social parameters (positive constants),

$r_1c_1(P_{ij}(t){-}X_{ij}(t))$ = the cognitive component which allows the particle to return to a previous position of high fitness value,

$r_2c_2(P_{gj}(t) - X_{ij}(t))$ = the social component which allows the particle return to the best region the swarm has found so far and to follow the best neighbours direction.

The first term in the equation is inertia, w inclining the particle to maintain its current velocity and preventing the influence of latter terms early in the process. The second term is a personal memory, which draws the particle back towards its ever best position occupied. The third term is the swarm memory, which draws the particle towards the best position ever occupied by any particle in the swarm. PSO is dependent on the fact that at first, particles tend to move around randomly, exploring multidimensional areas. Then, the particles will tend to surge around the best option found. This allows the search space around the current optimum to be explored in detail. It follows that if $c_1 \gg c_2$, then the particle is attracted to the individual best position and if $c_2 \gg c_1$, the particle is attracted to the global best position.

PSO has four main steps, which include:

- Generate and evaluate each initial particle fitness
- Updating the individual and global best fitness and positions
- Updating the velocity and position of particles
- Terminate when the objective function or the number of iterations is achieved.

Every individual particle retains the best fitness value it has attained during the algorithm run. The particle with the best fitness value, when compared to other particles, is calculated and updated in iterations. PSO proves promising for the future as it is a fast algorithm comparable to several optimisation techniques and far faster than others. Also, it is more accessible to code and requires less storage space than many other optimisation algorithms. It is considered that PSO speed can be improved by fine-tuning the parameters. The trend in research replaces the values of c in the defining equation with other weights to increase the speed of convergence.

PSO flowchart can be seen in Fig 5.4.

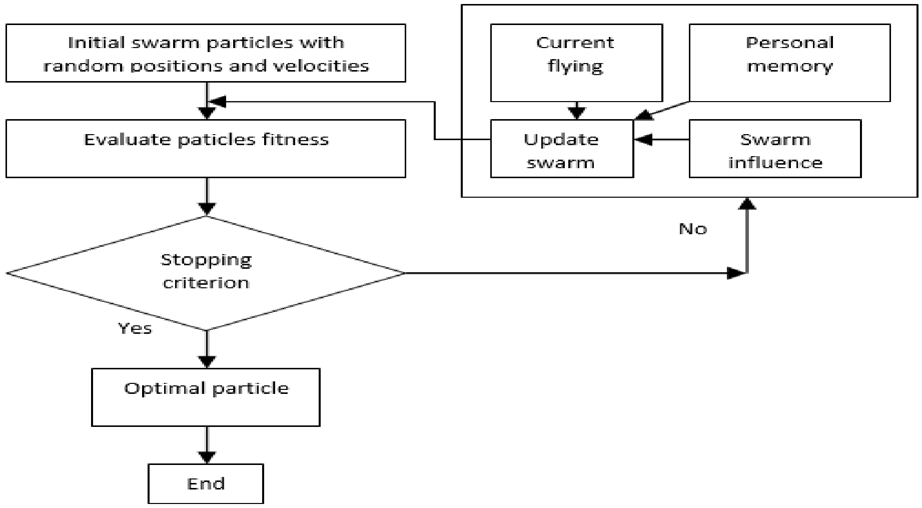

Figure 5.4: PSO Flowchart

PSO has similarities with GAs. The system is initialised with a random solutions population and searches for optimum via updating. Nevertheless, PSO does not have any genetic operators such as crossover and mutation as GAs. PSOs are easy to implement with few adjustable parameters.

Optimisation problems involving many local optima benefit from fast convergence when solved with PSOs. This fast convergence is because standard PSOs exploits neighbourhood information. As highlighted by a few authors in [193–195].

As discussed earlier in Chapter 2, many optimisation strategies have been research to solve either economic, environmental, and energy performance of microgrid systems. Minimising the operational cost of in microgrids is a difficult when it concerns choosing suitable optimisation techniques. Metaheuristic methods are robust, due to their stochastic nature they are able recover from local minima, they do not need gradient information, and are able to tackle objective uncertainties. Metaheuristics methods as describe above have parameters which affect the performance of these strategies in terms of fast convergence and arriving at global optimal solutions. Tuning of these parameters is essential to achieving desired results. As such, GA, PSO, and SA were selected from the different metaheuristic categories, and the parameters tuned to achieve minimum cost of the HGM design studied.

5.3 Component Modelling (MatLab)

The meteorological data and component capacities obtained from the HOMER design of the HMG serve as input parameters in carrying out optimisation simulations in MatLab.

5.3.1 PV System Modelling

The input data for the PV system is the hourly solar radiation to the horizontal surface of the site under consideration. The PV power output is calculated as [100]:

$$P_{PV-out} = P_{STC}\frac{G_C}{G_{STC}}[1 + K_t(T_C - T_{STC})] \tag{5.6}$$

$$T_C = T_{amb} + (0.0256 \times G_C) \tag{5.7}$$

Where

P_{PV-out} = PV hourly output power

P_{STC} = Rated PV power output under STC

G_{STC} = 1000 W/m^2 solar irradiance under STC

G_C = Irradiance at operating point, W/m^2

T_{STC} = 25^0C PV temperature under STC

T_C = cell temperature

T_{amb} =Ambient temperature

K_t = temperature coefficient of power.

STC = standard test conditions with a comparable optical quality of AM1.5 condition.

The PV system energy generated is presented in Figure 5.5 below.

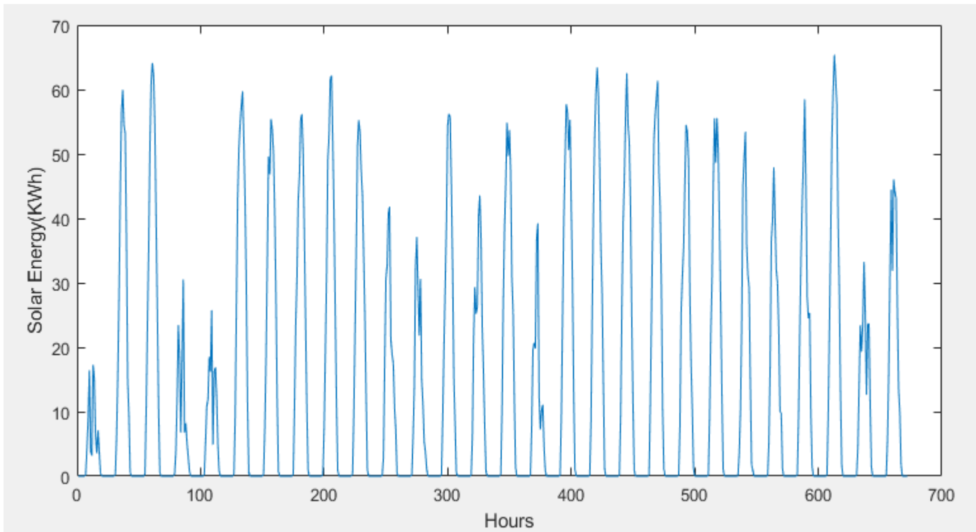

Figure 5.5: PV Power Output.

The Figure 5.5, is a representation of the PV power output (Y-axis) in hours (X-axis). There is power production in the day, with varying outputs depending on the intensity of the solar irradiance, and no production during the dark periods. Also the amount of PV power produced is affected by the seasons experienced in the community.

5.3.2 Wind Turbine Modelling

The input data for the WT system is the hourly wind speed at a reference height for the site under consideration. The power from the wind is calculated as [103]:

$$P_{WT}(v) = \begin{cases} 0, & v < v_{ci}, v > v_{co} \\ \frac{P_{WT-rated}(v-v_{ci})}{v_r-v_{ci}}, & v_{ci} \leq v < v_r \\ P_{WT-rated,} & v_r \leq v > v_{co} \end{cases} \tag{5.8}$$

$$\frac{v}{v_{ref}} = \left(\frac{h_{hub}}{h_{ref}}\right)^{\alpha} \tag{5.9}$$

Where

$v =$ Wind speed at desired hub height,($h_{hub} = 50$)

$v_{ref} =$ Wind speed at reference height, ($h_{ref} = 10$)

$\alpha =$ is the ground friction coefficient

$v_{ci} =$ Cut-in wind speed

$v_{co} =$ Cut-off wind speed

$v_r =$ Rated wind speed

$P_{WT-rated}$= Wind turbine rated power output

The WT system energy generated is presented in Figure 5.6 below.

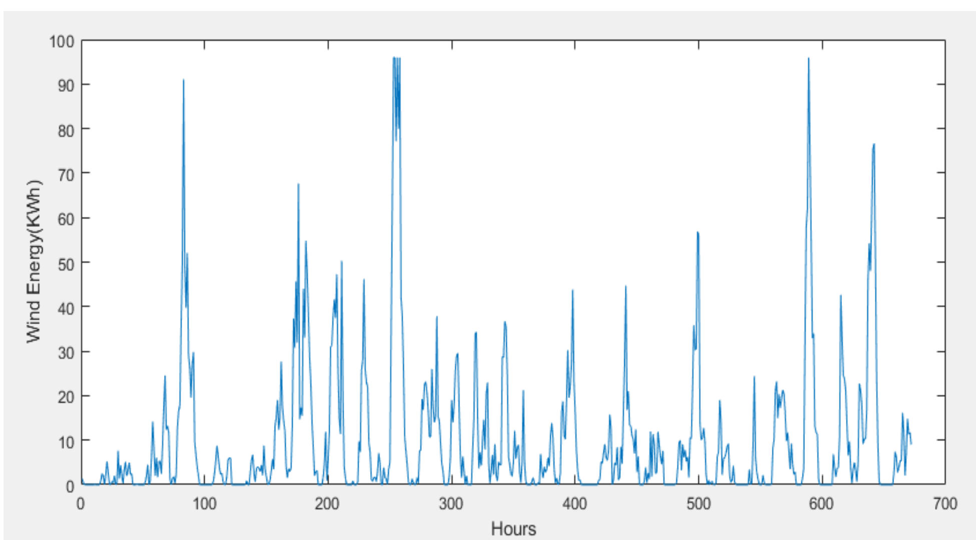

Figure 5.6: WT Power Output.

Figure 5.6, shows the amount of power generated by the wind turbines, as with RERs, these are dependent on the wind speeds per time. Power production is achieved at speeds > 4.0m/s. At wind 2.5m/s - 4m/s water pumping is possible.

5.3.3 Battery Storage System Modelling

The battery storage systems are energy storage electrochemical devices. They store energy from either DC or AC sources. The power stored in the batteries are used when there is insufficient power from the renewable source to meet the load. Furthermore, the power in the battery is recharged when the power produced exceeds the load demand. As such the battery storage management plays a vital role in the overall performance of the HMG. In other to design the battery storage, assumptions taken into account include: at any scheduling time, the state of charge, SoC of the BSS should be within the specified operating range, which can be expressed as [129]:

$$SoC_{min} \leq SoC \leq SoC_{max} \tag{5.10}$$

Where

$SoC_{min/max}$ = The lower and upper limit of state of charge.

The storage capacity to cater for the insufficiencies can be gotten from the equation below.

$$S_{cap} = \frac{Lav \times AD}{DOD \times INV_{eff} \times B_{eff}} \tag{5.11}$$

Where

L_{av} = Daily average community load

AD = Autonomy days, number of days the battery can provide power without charging

DOD = Battery depth of discharge (80%)

INV_{eff}, B_{eff} = Inverter and battery efficiency respectively.

According to SoC and the rated power limit of battery charging and discharging, the upper and lower limits of the battery output during each time period is calculated to determine the regulating range of the battery. Let, $P_{MaxC}(t)$ and $P_{MaxD}(t)$ be the maximum charging and discharging power during period t; $SoC(t)$ represents the status of battery during period t. SoC_{max}, SoC_{min} represents the upper and lower limit of battery power. S_{cap} represents the rated capacity of the battery, and $P_{Battery}$ represents the rated power of the charging and discharging machine:

The purpose of the power regulation of the battery is as follows: when the output power from the renewable energy is high, it is used to charge the battery; when the power output of renewable energy is low, the battery is set to discharge to meet the load demand of microgrid.

$$P_{MaxC}(t) = min(S_{cap} \times (SoC_{max} - SoC(t)), P_{Battery}) \tag{5.12}$$

$$P_{MaxD}(t) = min(S_{cap} \times (SoC(t) - SoC_{min}), P_{Battery}) \tag{5.13}$$

The BSS state of charge is presented in Figure 5.7 below, operating within bounds.

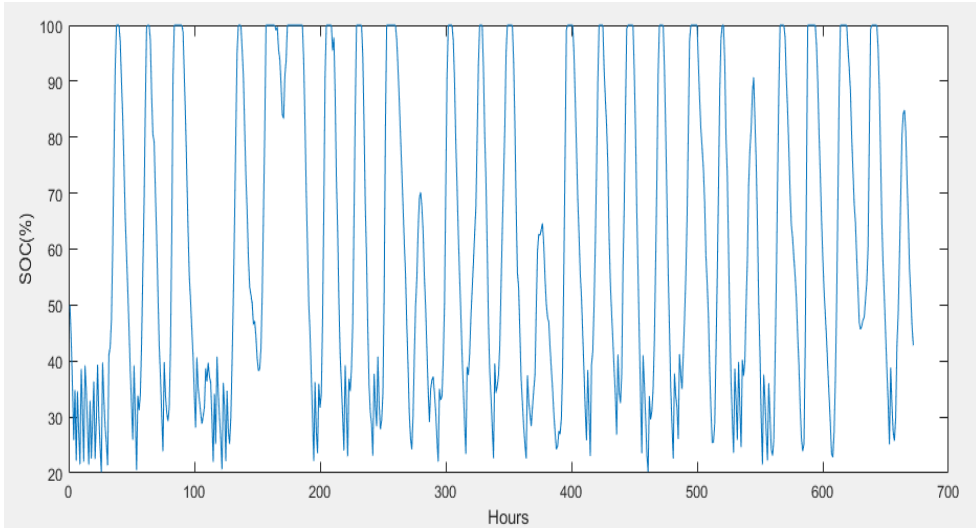

Figure 5.7: Battery State of Charge

The BSS showing the SoC is presented in Figure 5.7. The BSS is designed to discharge power up to 20% of its capacity. Continuous discharge beyond this limits can affect the lifespan of the batteries. Charging of the batteries are achieved when the is excess power production in the system.

5.3.4 Diesel Generator Modelling

Diesel generators are used as a backup power source in the proposed hybrid microgrid power systems. The fuel consumption cost is used to model the actual power output of the generator using a quadratic polynomial. The diesel generator fuel consumption cost (Naira/hr) is given by,

$$GEN = \alpha_{DG} + \beta_{DG}.P_{DG-nom} + \gamma_{DG}.P^2_{DG-out} \tag{5.14}$$

Where

P_{DG-nom} =Diesel generator nominal power, kW

P_{DG-out} =Diesel generator power output

$\alpha_{DG}, \beta_{DG}, \gamma_{DG}$ =Diesel generator coefficient calculated from the manufacturers datasheet.

For instance, the diesel fuel consumption data for a 62kW generic diesel generator is shown in Figure 4.9, with $\alpha_{DG} = 3.375$, $\beta_{DG} = 0.3429$ and $\gamma_{DG} = 0.0005$.

5.4 Problem Formulation

This optimisation process is broad and involves a mixed match of conventional and non-convention power generators to meet a single objective of minimising operation cost. In optimising the operation of power plants, specific considerations are taken into account.

- turning ON/OFF of the power plant using binary variables,
- once turned ON subject to specified operating constraints. The amount of electricity produced is considered a continuous variable.

A combination of the above which describes turning power plant ON/OFF and producing at certain levels is considered in carrying out optimisation processes. Associating these variables to pieces of information about how much it costs to perform those operations forms the central part of the objective function.

Most power plants have a minimum generation at which they operate, so they start at zero and work their way up. Usually, power plants have to be producing several watts of electricity in other to function. So the decision to turn ON is modelled as occurring at a minimum generation level. After that point, they ramp up subject to some constraints.

For research purposes, we consider minimising the cost of operating the microgrid, which could minimise electricity cost and increase system lifespan as the case. It is assumed that the objective function of the program written depicts minimising the total cost of meeting electricity demand. What goes in the objective function depends on the power plant portfolio and the geographical location considered. The location determines what portfolio should be in place and all that is tied to geographical differences in the resource.

In the objective function for trying to minimise the cost of meeting electricity demand, the costs come from decisions made on operating the DG.

- Decisions on generator ON/OFF will need some binary variables involved,
- Decisions on how much power needs to be produced once the generator is turned ON, which involves continuous variables.

Decisions are not made for renewable energy resources as they are stochastic (challenging to predict accurately); their operation and output level is based on the availability of the resources of which cannot be controlled. The RERs are not represented in the objective function to minimize the cost of electricity demand as they have been considered in Chapter 4 in the system design. They are considered in terms of constraints in the sections following.

Therefore, the rest of the electricity that the RERs and battery do not meet is met with fossil fuel plants. Therefore, modelling an optimal way to meet the electricity demand using fossil power plants is contained in the objective function.

In modelling the DG, only the operational cost is considered. The capital cost and money borrowed for investment or finance are not considered as they do not factor in how the plant operates and were considered in the HOMER design. It might affect decisions as to when to retire the plant, but since it is assumed a plant already exists, the focus is minimising the total operational cost.

5.4.1 Operational Cost

In formulating the operational cost, three components are considered, as shown below.

1. Start-up cost: In AC power systems, every plant providing electricity to the grid or a microgrid has to be operating at 50Hz, and so for a power plant to go from offline to online and producing electricity at the right frequency, it takes some time and fuel to ramp up the power plant to the point where it is synchronized to produce electricity at the right frequency. There is a cost associated with this process.

2. Fixed cost can be referred to as the cost that a power plant operator would have to pay regardless of how much generation is produced. As long as a power plant is online, there is a certain amount of cost that is incurred; an example can be the operation and maintenance as a result of the plant being ON. It is certain that when a plant is run for a certain period, something fails and would need fixing at a cost referred to as fixed cost.

3. Variable cost is the cost accrued for the plant operator proportionally with how much electricity is actually produced.

So for the power plant, three different cost components are employed. Remember, for research purposes, we seek to minimise the cost of operation. Therefore, the objective function should represent the cost components above. In other to achieve this, the decision variables are defined as:

START: represented using binary variable $0, 1$, this indicates that the plant is started.

ON: represented using binary variables $0, 1$, if $\text{ON} = 1$ for a given period, this indicates that the plant is online.

GEN: are continuous variables, it can take any value with some bound obviously not zero as most plants have minimum generation level.

Cost coefficients used:

a = start-up cost associated with the plant start, which can be defined in Naira/event or Naira/switching from OFF to ON

b = fixed Naira value that you have to pay every time the generator is ON, regardless of how much electricity is produce. Assumed 5% of the DG initial cost adopted from HOMER.

c = actual amount of electricity multiplied by a variable cost rate for producing the electricity. It is assumed that the variable cost of power plant using marginal cost can be modelled.

$$F_{min} = START * a + ON * b + GEN * c \tag{5.15}$$

5.4.2 Objective Function

It follows that from equations (5.14) and (5.15) the objective function can be written as (5.16)

$$F_{min} = START * a + ON * b + (\alpha_{DG} + \beta_{DG}.P_{DG-nom} + \gamma_{DG}.P_{DG-out}^2) * c \tag{5.16}$$

Where,

$START * a = 0$

$ON * b$ = Maintenance cost (fuel cost * DG running hours)

$GEN * c$ = Fuel consumption cost.

$$F_{min} = ON * b + (\alpha_{DG} + \beta_{DG}.P_{DG-nom} + \gamma_{DG}.P^2_{DG-out}) * c \tag{5.17}$$

5.4.3 Constraints

The objective function is subject to a number of constraints which include:

1. System constraints

- System Power Balance

$$P_{DG}(t) + P_{PV-out}(t) + P_{WT}(t) + P_{BSS}(t) = P_L(t) \tag{5.18}$$

Where $P_{DG}(t), P_{PV-out}(t), P_{WT}(t), P_{BSS}(t), P_L(t)$ are the diesel generator output, PV output, wind power output, battery output and the load demand. P_{BSS} is positive when discharging and negative when charging.

2. Component constraints

- Generator unit

$$P_{min} \leq P_{DG} \leq P_{max} \tag{5.19}$$

Where $P_{max}$is the rated power of the DG. For real DGs, there is a lower limit P_{min}during its operation. For research purpose, it is set to be 95% of its rated power.

- Battery unit

$$P_{MaxC} \leq P_{Battery}(t) \leq P_{MaxD} \tag{5.20}$$

Where P_{MaxD} is the maximum output when the battery is discharging; $P_{MaxC}$is the maximum output when the battery is charging.

- Battery state of charge limit

$$SoC_{min} \leq SoC(t) \leq SoC_{max} \tag{5.21}$$

where SoC_{min} and SoC_{max} are the minimum and maximum value of the SoC of the battery; $SoC(t)$ is the SoC of the battery during period t.

5.5 Simulations

The MatLab optimisation toolbox is used in the simulations of the three algorithms. The steps carried out for each optimisation process is described. Different parameters are experimented on and fine-tuned for each algorithm to produce desired results for the DG performance and six load models are used for experiments. The first two load models represent the developed first-year demand profile without variability (WoV) and with variability (WV). The remaining are the forecasted load (WoV and WV) demand for year 5 and year 10.

5.5.1 Particle Swarm Optimisation Implementation

Initial particles are first generated with initial velocities assigned to them. The objective function is then evaluated at each particle location, and the best function value and the best location determined. Next, new velocities are selected based on the current velocity, the best locations for individual particles and their neighbours. The particle locations, velocities, and neighbours are further updated iteratively. The

Iteration process continues until the algorithm reaches a stopping criterion. Details of the steps and experimental results (Table 5.3) are shown below.

Initialisation

- Load RERs data
- Load characteristics of components
- Load economic parameters
- Set the HMG system constraints
- Randomly select an initial position and velocity of the particles and evaluate particles objective function within bounds to find the best particle providing a minor DG operation and production.
- PSO records best particle current position and initialize neighbours, inertia and stall counter
- Adjustable parameters include SelfAdjustmentWeight and SocialAdjustmentWeight (c_1, c_2).

Iteration Steps The swarm is updated via, for particle i, which at position $x(i)$:

1. Choose a random subset S of N particles other than i.
2. Find the best objective function among the neighbours and the position of the neighbour with the best objective function.
3. Update the velocity (equation 20) for $r_1$and r_2 uniformly distributed random vectors $(0, 1)$.

This update uses a weighted sum of:

- The previous velocity $V_{ij}(t)$
- The difference between the current and the best positions seen by the particle $r_1c_1(P_{ij}(t) - X_{ij}(t))$
- The difference between the current and the best positions in the current neighbourhood $r_2c_2(P_{gj}(t) - X_{ij}(t))$

4. Update the position $x = x + v$.
5. Apply bounds; if any component of x is outside a bound, set it equal to that bound.
6. Evaluate the objective function (equation 33).
7. If $F_{min} < fun(p)$, set $p = x$. Step 7 ensures p has the best position the particle is stored.
8. If $F_{min} < b$, set $b = f$ and $d = x$. Step 8 ensures b and d have the best objective function and location, respectively, in the swarm.
9. If the best function value lowers in step 8, then set flag $=$ true. Otherwise, flag $=$ false. The flag value is used in the next step.
10. Update the neighbourhood. If flag $=$ true:

- Set $c_1c_2 = max(0, c - 1)$.
- Set N to $minNeighborhoodSize$.
- If $c_1c_2 < 2$, set $w = 2 * w$.
- If $c_1c_2 > 5$, set $w = w/2$.
- Make sure w is in the bounds of the InertiaRange option.

If flag = false:

- Set $c_1c_2 = c_1c_2 + 1$.
- Set $N = min(N + minNeighborhoodSize, SwarmSize)$.

Stopping Criterion Check that the number of maximum iterations is reached; otherwise, repeat the iteration process.

5.5.2 Genetic Algorithm Implementation

Firstly, GA generates an initial random population, followed by generating a sequence of new populations. At every step, the GA uses the current generation of individuals for the next population generation. In creating the new population, GA performs the following: compute the fitness value for the current population and score each individual (raw fitness scores). Scales the raw fitness scores to convert them into a more usable range of values. The scaled values are referred to as expectation values. Selects members (parents) based on their expectation. Individuals in the current population having lower fitness are selected as elites and passed to the next population. Children are then produced from the parents either by making random changes to a single parent (referred to as mutation) or combining the vector entries of a pair of parents (referred to as crossover). Replace the current population with the next generation children. The GA terminates when a stopping criterion is met. A detailed step implementation is described as follows:

Initialisation

1. Load RERs data
2. Load characteristics of components

3. Load economic parameters
4. Set the HMG system constraints
5. Initialize a random population of possible solutions.
6. Decode the load demand, battery SoC, DG operation and determine the total power generated by applying the constraints
7. Evaluate the fitness function, F_{min}.

Next Generation

1. Apply the genetic operating parameters to create a new population. GA parameters adjustable to application include

- Selection
- Reproduction (Elitism)
- Crossover
- Mutation

Stopping criterion. If the iteration number exceeds the maximum iteration number, then stop; otherwise, go to next generation 1.

5.5.3 Simulated Annealing Implementation

In the simulated annealing implementation, SA generates a trial solution within bounds randomly and selects the distance of the trial solution from the current solution by probability distribution with a scale-dependent on the current temperature. The SA compares the new and current solutions for the better solution to become the next solution point. If the new is worse; it could still be accepted as the following solution based on a default acceptance function. Next, SA lowers the temperature while storing the best solutions found; else, SA reanneals to values lower than iteration values raising every dimension's temperature. The annealing parameters depend on the values of estimated gradients of the objective function in each dimension. Finally, SA terminates when the average change in the objective function compared to the function tolerance is minimal or any other stopping criterion. Details are described below.

Initialisation

1. Load RERs data
2. Load characteristics of components
3. Load economic parameters
4. Set the HMG system constraints
5. Initialize all variables(load demand, economic and generator characteristics) and set iteration counter
6. Randomly find an initial feasible solution against the constraints
7. Calculate the F_{min}.

Iteration Process

1. Determine the initial temperature that results in the high probability of accepting any solution.
2. If the equilibrium is achieved, go to stopping criterion, otherwise, repeat iteration process 3 and 4 for the same temperature until the equilibrium criterion is satisfied.

3. Find the trial solution, which is a neighbour to an initial solution, with F_{min}.

4. Perform the acceptance test to accept or reject the trial solution.

Stopping Criterion If the stopping criterion is satisfied, stop, else decrease the temperature and go to iteration process 2.

5.6 Parameter Setting

Parameter setting significantly affects the performance of meta-heuristics. Therefore, experiments with a wide range of parameter values are used for trial and error to converge on the values that provide the best DG running hours and production. A list of parameters used for evaluation are presented in Table 5.1 below.

Table 5.1: List of Algorithm Parameters

Particle Swarm	Genetic Algorithms	Simulated Annealing
Swarmsize	Population size	Temperature
InertiaRange	Selection	AnnealingFcn
SelfAdjustmentweight	EliteCount	ReannealInterval
SocialAdjustmentweight	MutationFcn	AcceptanceFcn
MinNeighborFraction	CrossoverFraction	-
-	MaxGeneration	-

5.6.1 Definition of the Parameter Terms

The definitions of terms explored and their effects on their various optimisation strategies are presented. Recall that the PSOs and GAs are population-based. Population size and swarm size represent the number of initially random populations of the algorithms. The significant the number, the greater the chances of achieving a feasible solution as it allows for exploration and exploitation of a more extensive search space and increases the simulation time.Initial swarm span, maximum iteration, and maximum generation increase all algorithm simulations search space and time.

InertiaRange (PSO), which Shi and Eberhart introduced to regulate the influence of the previous velocity histories on the current velocities, consequently mentioned earlier. Excluding it in the simulation limits the explorative abilities of the algorithm, causing solutions to be found at local minima.

SelfAdjustmentweight and SocialAdjustmentweight are parameters that influence how the algorithms explore the behaviours of the individual particles and the swarm behaviours. With SelfAdjustmentweight $>$ SocialAdjustmentweight, the solutions tend towards a local minimum, and With SelfAdjustmentweight $<$ SocialAdjustmentweight, a global solution could be achieved.

MinNeighborFraction forces the swarm particles towards the use of SocialAdjustmentweight target.

The parameters adjustable for parameters for GA having significant effects on the performance and violating system constraints are CrossoverFraction and @selectiongaussian (selection function).

5.7 Results and Discussions

5.7.1 Parameter Settings and Results

The parameters set for the different experiments are detailed in Table 5.2 below. The experiments considered the standard, poor and tuned parameters to investigate the effects of adjustable parameters on the performance of each algorithm.

Table 5.2: Parameter Values Considered

Parameters	Standard	Poor	Fine Tuned
Particle Swarm			
Swarmsize	10*nvars	$>$ 100	200
InitialSwarmSpan	2000	$>$2000	20
Inertia range	[0.01,1.1]	[0,0]	[0,1]
SelfAdjustmentweight	1.49	2	-
SocialAdjustmentweight	1.49	1	-
MinNeighborFraction	0.25	0.4	-
MaximumIterations	200	$>$ 200	20
Genetic Algorithms			
PopulationSize	[]	$>$ 50	50
SelectionFcn	@selectionstochunif	@selectiongaussian	-
EliteCount	0.05*PopulationSize	-	20
CrossoverFraction	0.8	0	0.7
CrossoverFcn	@crossoverscattered	-	-
MaxGeneration	100*nvars	inf	12
Simulated Annealing			
InitialTemperature	100	-	$>$50
Temperature	@temperatureexp	@temperaturefast	@temperatureboltz
AnnealingFcn	@annealingfast	@annealingboltz	@annealingfast
ReannealInterval	100	-	-
AcceptanceFcn	@acceptancesa	-	-
MaxIterations	Inf	-	20

5.7.1.1 Standard MatLab Parameters

The algorithms were experimented using standard MatLab parameters Table 5.2, and results presented in Figure 5.8 below. Figure 5.8, depicts the DG run hours over six consecutive simulations for the standard algorithm parameters. It can be seen from the graph that for all runs and experiments except Yr10 load WoV and Yr1 load WV, PSO and SA produce constantly similar results, with GA reaching similar optimum results on different runs. Yr10 load WoV, had only PSO achieving the lowest DG running hours.

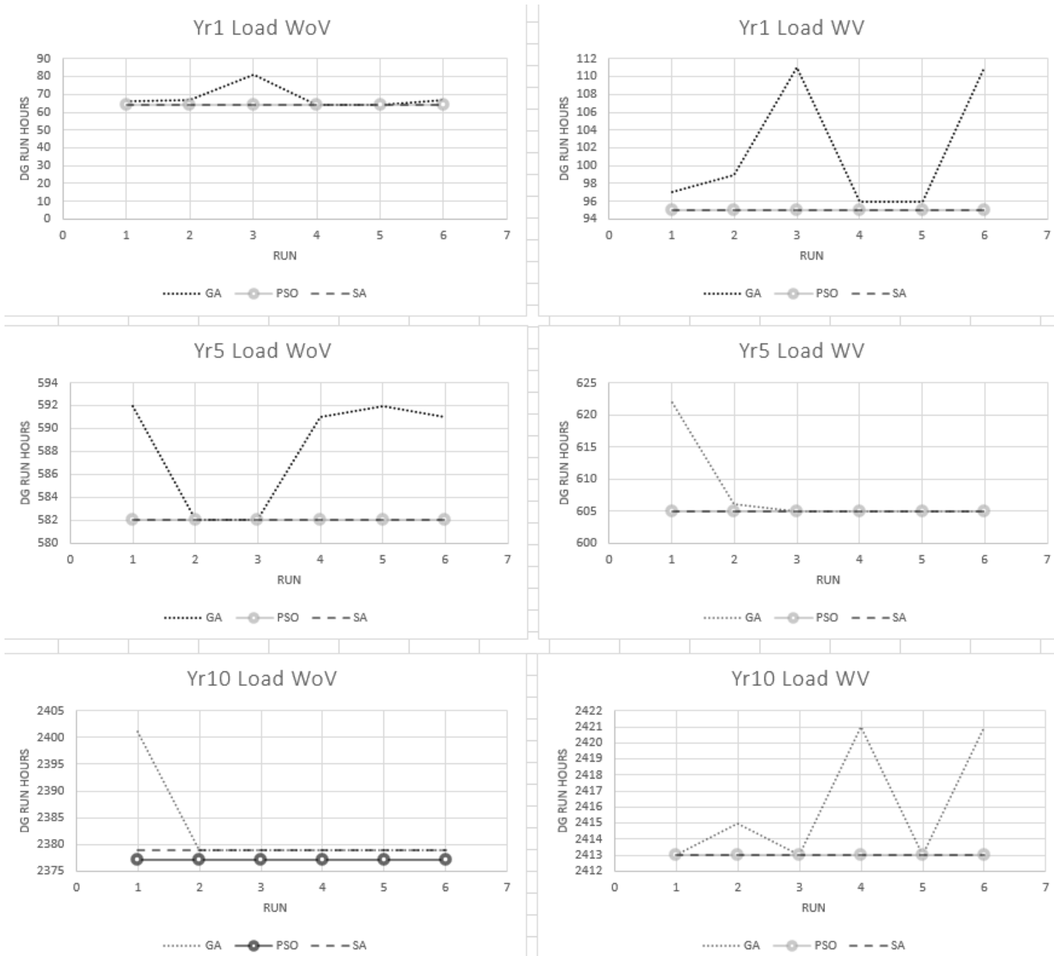

Figure 5.8: Standard MatLab Parameter Results

Figure 5.8, presents six experimental simulations each for 3 different years, and having 2 different load cases. On the Y- axis of each plot is the minimum number of run hours experienced by the DG simulation, and on the X-axis is the the number of simulations carried out. Standard MatLab parameters are MatLab default algorithm parameters for the 3 algorithms employed. For example, Yr1 Load WoV on its first simulation, PSO and SA arrived at the same solution of 65 DG run hours while GA produced a 67 hours for the operation of the DG. While for Yr1 Load WV, PSO and SA produced 65 DG run hours and GA produced 97 DG run hours. The difference in the number of DG run hours arises from the difference in the type of loads considered. On every simulation as can be seen, PSO and SA arrived at the same solution except for Yr10 Load WoV. The difference arises with the simulation time and quality of the solution as will be seen later.

5.7.1.2 Poor Case Parameters

Figure 5.9 shows the effects wrong choice of parameters can have on achieving an optimal or near optimal solution. The parameters were gotten experimentally. SA parameter setting violated system constraints on the battery capacity, charge and discharge limits, causing it to achieve infeasible results. GA and PSO achieved corresponding results at certain points yet their results differ and are not as good as those achieved in the experiments with standard parameters.

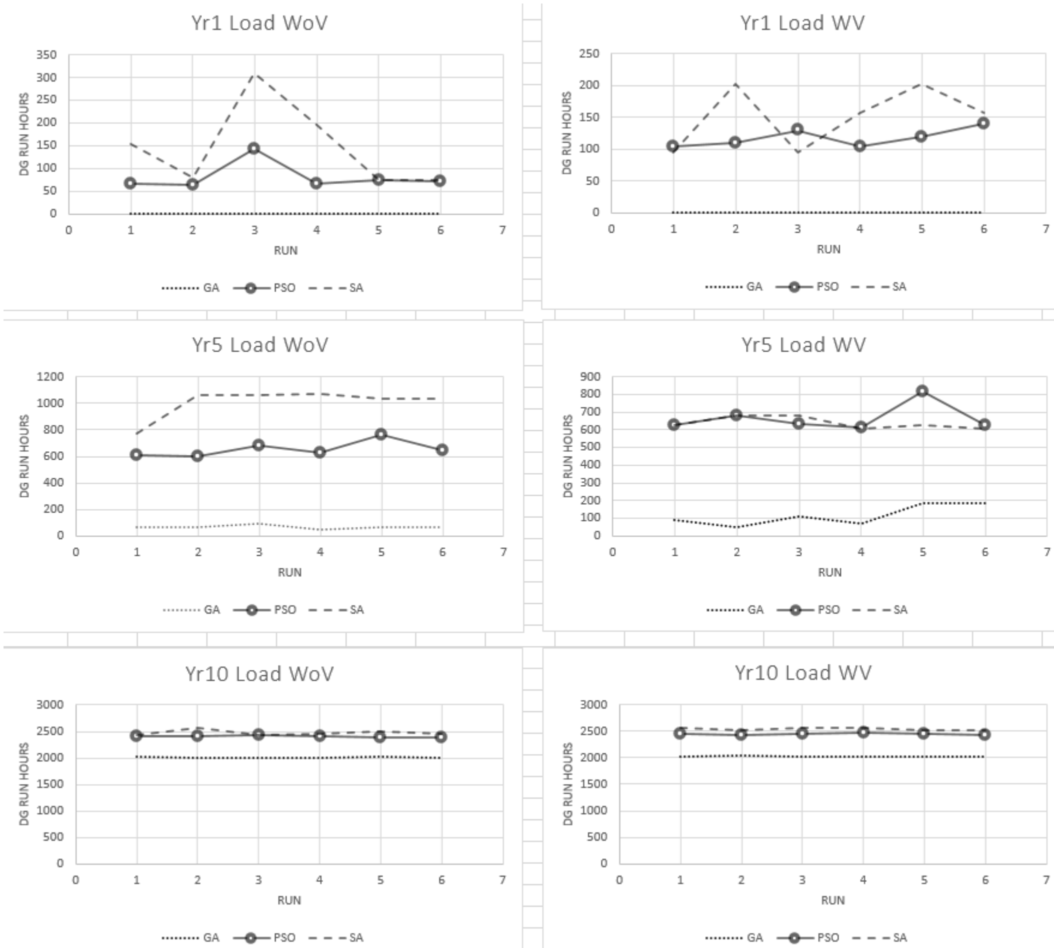

Figure 5.9: Poor MatLab Parameter Results

For instance, Yr5 Load WoV and Yr5 Load WV in Figure 5.9 for the poor case parameters,on the 1st run, SA produced the least DG operating hours >100 hours compared to PSO and GA (600 and 780 respectively). The quality of results produced with these parameters were affected as the HMG constraints were not adhered to especially for the SA simulations. The GA and PSO arrived at solutions having poor quality when compared to the solutions arrived in the standard MatLab parameters in Figure 5.8.

5.7.1.3 Tuned Parameters

The simulation results as obtained for six experimental runs of the algorithms are presented below. This section contains both the numerical and graphical results from the simulations for the experimentally tuned parameters in MatLab. From Table 5.3, Table 5.4 and Table 5.5, for each run, the DG run hours, DG energy production, and simulation time are recorded for the scenarios considered. Finally an average is calculated and presented below.

PSO: From the results of the particle swarm optimisation simulation shown in Table 5.3, the DG running hours and production for six runs of simulation is observed to remain constant on every run with a difference in their individual run time. Six load models are simulated, the Ideal developed load model for year 1 with its corresponding variable load profile, forecasted load models for Year 5 and Year 10 with and without variability in their load models are also experimented.

Table 5.3: PSO Simulation Results

Run	Indices	Yr1 Load WoV	Yr1 Load WV	Yr5 Load WoV	Yr5 Load WV	Yr10 Load WoV	Yr10 Load WV
1	DG running hours, hrs	64	95	582	605	2,377	2,413
	DG energy production, kWh	2,984	4,335.1	24,444	23,538	66,309	63,114
	Simulation time, sec	9.393206	11.657326	11.435814	11.616815	12.067121	11.971537
2	DG running hours, hrs	64	95	582	605	2,377	2,413
	DG energy production, kWh	2,955.9	4,335.1	24,444	23,538	66,309	63,114
	Simulation time, sec	10.700651	11.491941	11.426648	11.806260	11.512777	12.589839
3	DG running hours, hrs	64	95	582	605	2,377	2,413
	DG energy production, kWh	2,984	4,335.1	24,444	23,538	66,309	63,114
	Simulation time, sec	11.496307	11.564373	11.775431	11.761047	11.675598	11.841824
4	DG running hours, hrs	64	95	582	605	2,377	2,413
	DG energy production, kWh	2,984	4,335.1	24,444	23,538	66,309	63,114
	Simulation time, sec	11.913215	11.468620	11.569017	11.599374	11.979193	11.700885
5	DG running hours, hrs	64	95	582	605	2,377	2,413
	DG energy production, kWh	2,984	4,335.1	24,444	23,538	66,309	63,114
	Simulation time, sec	11.363467	11.589729	11.333113	12.029442	11.901710	12.193644
6	DG running hours, hrs	64	95	582	605	2,377	2,413
	DG energy production, kWh	2,984	4,335.1	24,444	23,538	66,309	63,114
	Simulation time, sec	10.589017	11.573892	11.689003	11.943687	11.721070	11.932116
Average	DG running hours, hrs	64	95	582	605	2,377	2,413
	DG energy production, kWh	2,984	4,335.1	24,444	23,538	66,309	63,114
	Simulation time, sec	10.9093105	11.557647	11.538171	11.792770	11.809578	12.038307

The average DG running hours obtained for the all simulated load model are 67, 95, 582, 605, 2,377 and 2,413, all in hours as depicted in Table 5.3, and having simulation times ranging between 10.9 - 12.0 seconds. Results remained constant throughout the simulation with difference occurring in the simulation time and energy produced by the DG. This is as a result of the algorithm working with stored information in its memory.

GA: Table 5.4, presents six runs for the genetic algorithms for corresponding load models discussed under the PSO simulation. Experiments with different values of the CrossoverFraction, in the range [0-1], and obtained the best results with 0.7. Similarly, we found the best results with the EliteCount of 20 for a population of 50. For larger population sizes, simulation run times proved to be extensive. This could also be achieved with a population size of 50 and the number of generations set at 20.

Table 5.4: GA Simulation Results

Run	Indices	Yr1 Load WoV	Yr1 Load WV	Yr5 Load WoV	Yr5 Load WV	Yr10 Load WoV	Yr10 Load WV
1	DG running hours, hrs	67	95	591	605	2,388	2,413
	DG energy production, kWh	3,102	4,333	24,838	23,486	66,517	58,416
	Simulation time, sec	16.776352	20.026988	14.873497	21.068880	16.331345	23.224219
2	DG running hours, hrs	64	98	582	622	2,377	2,413
	DG energy production, kWh	2,955.9	4,496.6	24,443	24,393	66,299	63,084
	Simulation time, sec	14.870741	19.901935	14.986535	21.367525	19.3204	23.413295
3	DG running hours, hrs	68	99	617	606	2,379	2,415
	DG energy production, kWh	3,163.6	4,522.4	25,984	23,487	66,182	63,126
	Simulation time, sec	14.958067	19.829818	14.988210	21.836453	19.173149	23.845271
4	DG running hours, hrs	65	97	599	634	2,406	2,439
	DG energy production, kWh	3,008.1	4,447.3	25,171	24,837	66,819	63,777
	Simulation time, sec	13.868774	20.073414	16.250719	21.722687	19.025808	23.611527
5	DG running hours, hrs	66	96	600	629	2,395	2,431
	DG energy production, kWh	3,050.2	4,380.8	25,243	24,599	66,494	63,397
	Simulation time, sec	13.676512	19.968871	17.945343	21.699121	19.215036	24.265682
6	DG running hours, hrs	72	111	585	607	2,435	2,421
	DG energy production, kWh	3,390.3	5,096.2	24,645	23,534	67,394	63,161
	Simulation time, sec	13.711166	20.197515	14.859788	22.292605	19.622041	23.664084
Average	DG running hours, hrs	67	99.33	595.67	617.17	2,396.67	2,422
	DG energy production, kWh	3,111.68	4,546.05	25,054	24,056	66,617.5	62,493.5
	Simulation time, sec	14.643602	19.999756	15.650682	21.664545	18.781296	23.670679

From Table 5.4, the average DG running hours obtained for all simulated load model are 67, 99.33, 595.67, 617.17, 2,396.67 and 2,422, all in hours as depicted in Table 5.4, and having simulation times ranging between 14.6 - 23.7 seconds. When compared with the PSO in Table 5.3, PSO produced better results on the average. From the results, it can be seen that the solution values change for every run due to GAs stochastic nature.

SA: Table 5.5, presents six runs for the simulated annealing for corresponding load models discussed in previous simulations. Experiments with different TemperatureFcn options and set to temperatureboltz and obtained the best results with MaxIterations of 20. For larger iteration values, simulation run times proved to be extensive. This could also be achieved with iteration values of 20.

Table 5.5: SA Simulation Results

Run	Indices	Yr1 Load WoV	Yr1 Load WV	Yr5 Load WoV	Yr5 Load WV	Yr10 Load WoV	Yr10 Load WV
1	DG running hours, hrs	67	95	582	605	2,377	2,417
	DG energy production, kWh	3,108.9	4,333	24,437	23,528	66,304	63,217
	Simulation time, sec	1.968065	2.008826	1.975905	2.050727	1.990296	2.073074
2	DG running hours, hrs	64	95	585	614	2,379	2,415
	DG energy production, kWh	2,961.2	4,335.8	24,563	23,891	66,287	63,126
	Simulation time, sec	1.906009	1.975468	1.954165	2.084704	1.974019	2.154231
3	DG running hours, hrs	64	132	582	606	2,381	2,413
	DG energy production, kWh	2,955.9	6,187.7	24,443	23,554	66,276	63,084
	Simulation time, sec	1.819288	1.968395	1.916309	1.956200	2.121482	2.113240
4	DG running hours, hrs	67	95	583	606	2,377	2,415
	DG energy production, kWh	3,106.9	4,335.1	24,497	23,545	66,309	63,223
	Simulation time, sec	1.931449	1.966912	2.109935	1.987646	1.993600	1.988008
5	DG running hours, hrs	68	96	596	610	2,380	2,413
	DG energy production, kWh	3,169.8	4,388.7	25,095	23,695	66,245	63,086
	Simulation time, sec	1.968348	1.956972	1.974295	1.956309	2.039441	2.053794
6	DG running hours, hrs	71	105	592	605	2,384	2,417
	DG energy production, kWh	3,294	4,803.2	25,009	23,530	66,425	63,198
	Simulation time, sec	1.956889	2.025967	2.104170	1.968394	2.075128	1.997101
Average	DG running hours, hrs	66.83	103	586.67	607.67	2,379.67	2,415
	DG energy production, kWh	3,099.45	4,730.58	24,674	23,623.83	66,307.67	63,155.67
	Simulation time, sec	1.925008	1.983756	2.005796	2.000663	2.0323276	2.063241

From the results in Table 5.5, it can be seen that for every run, the solution values changes. The average DG running hours obtained for all simulated load model are 66.8, 103, 586.67, 607.67, 2,379.67 and 2,415, all in hours as depicted in Table 5.5, and having simulation times ranging between 1.9 - 2.1 seconds.

It can be inferred from Table 5.3, Table 5.4 and Table 5.5, the algorithms take different times to complete a run, with SA, having the shortest running time and GA, having the longest running times.

The Figure 5.10 presents the results obtained from tuning the algorithm parameters. For all experiments, every algorithm achieved similar and near solutions on certain runs. Here also, the speed of simulation is also improved over a considerable iterations, starting points and initial population/ swarmsize as the case maybe.

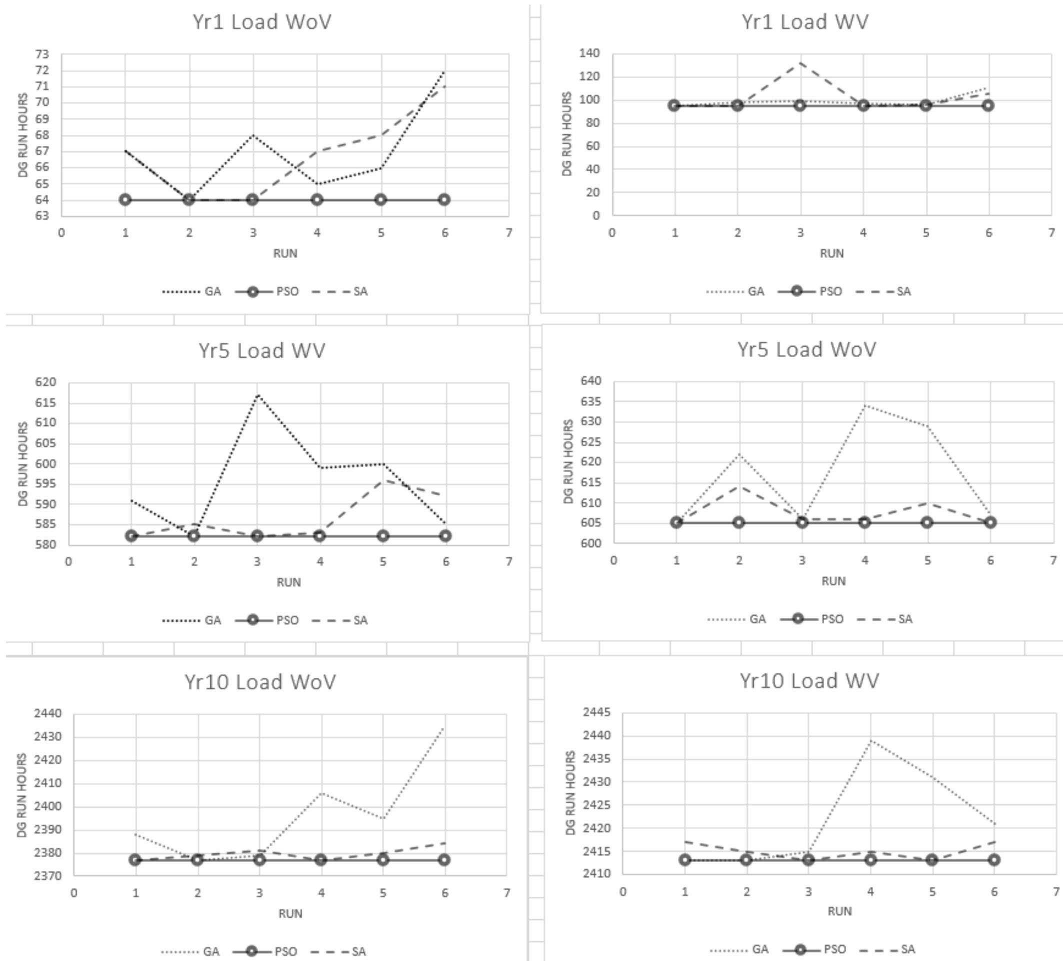

Figure 5.10: Fine Tuning of Parameters

Considering Yr10 Load WoV and Yr10 Load WV from Figure 5.10, two algorithms on some simulations arrived at similar results for the DG run hours. With this simulations, all system constraints were adhered to, simulation time improved, and the desired quality of results achieved. Again, the GA result pattern is as a result of its stochastic nature of operating.

5.7.2 Convergence Results

For the effects of parameter tuning, the convergence of the fitness solution is also considered using Year 5 load WV and results presented.

5.7.2.1 Particle Swarm Optimisation Convergence Comparison

The Figure 5.11 is a representation of the effects of the various parameter settings on the ease of convergence of arriving at the final solution.

From Figure 5.11, it can be inferred that the tuned parameters achieved faster convergence compared to the standard and worse simulation solutions. Also as a result of parameter tuning, the fitness values are attained with lesser iteration numbers, which reduces the simulation time.

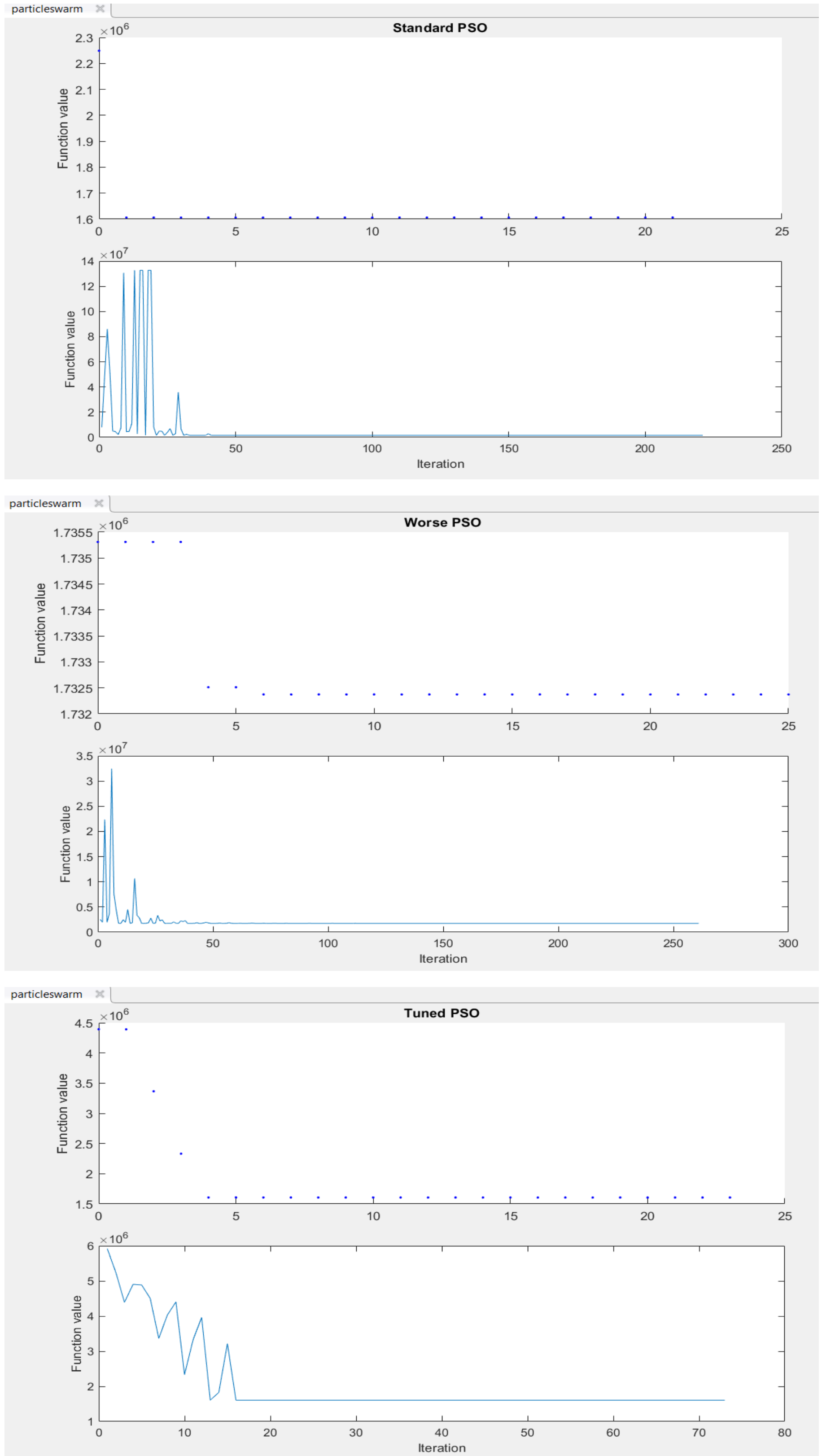

Figure 5.11: Standard, Worse and Tuned Convergence plots for PSO

Function values achieved for the simulations are

- Standard = N1,606,000
- Worse = N1,732,400
- Tuned PSO = N1,606,000

5.7.2.2 Genetic Algorithm Convergence Comparison

The Figure 5.12 below is a representation of the effects of the various parameter settings on the ease of convergence of arriving at the final solution.

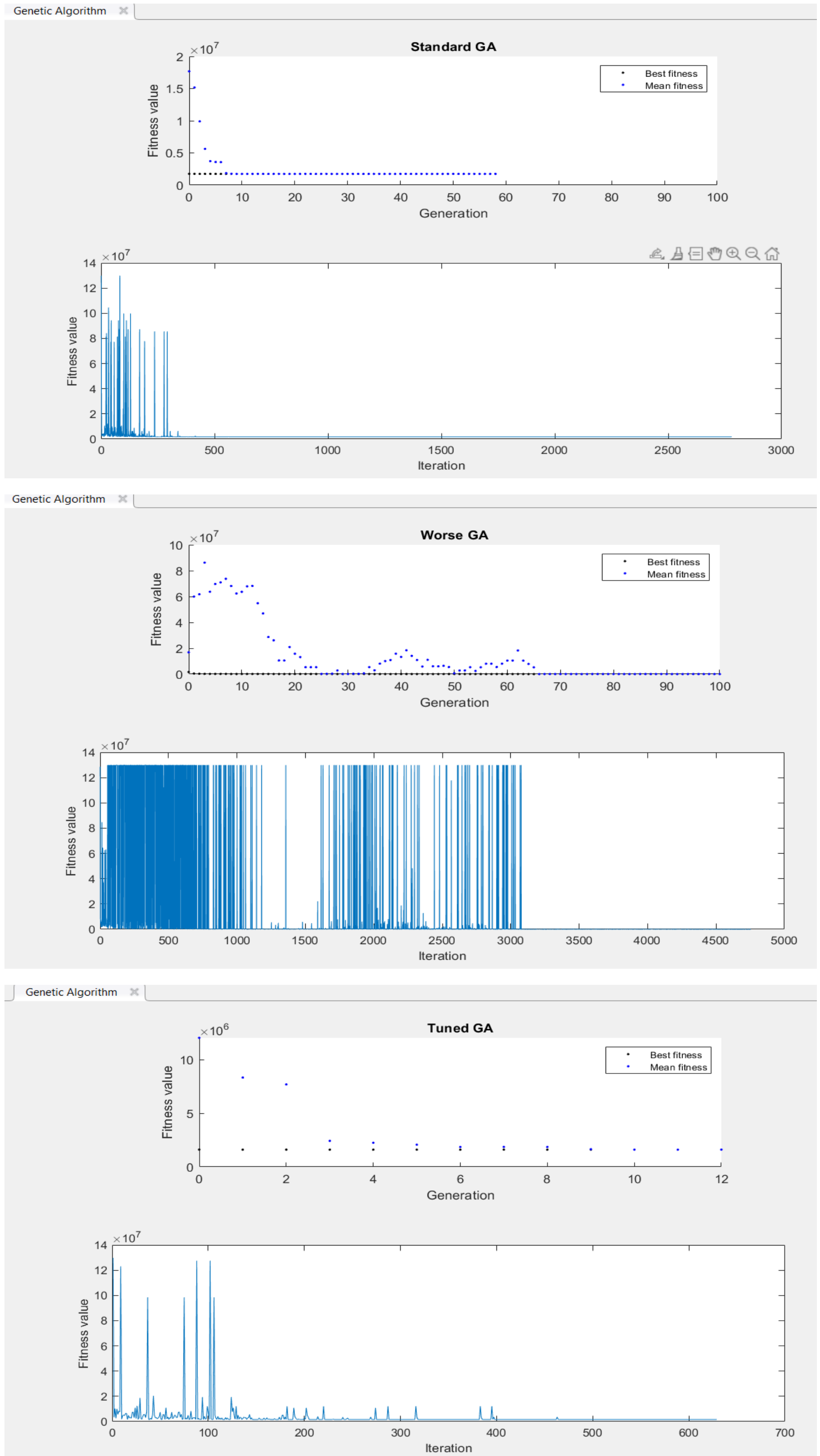

Figure 5.12: Standard, Worse and Tuned Convergence plots for GA

- Standard GA = N1,738,400
- Worse GA = N17,739
- Tuned GA =N1,604,100

Figure 5.12 the results show that better fitness values were achieved using tuned parameters. The case of the worse parameter simulation violated system constraints on the battery.

5.7.2.3 Simulated Annealing Comparison

The Figure 5.13 below is a representation of the effects of the various parameter settings on the ease of convergence of arriving at the final solution.

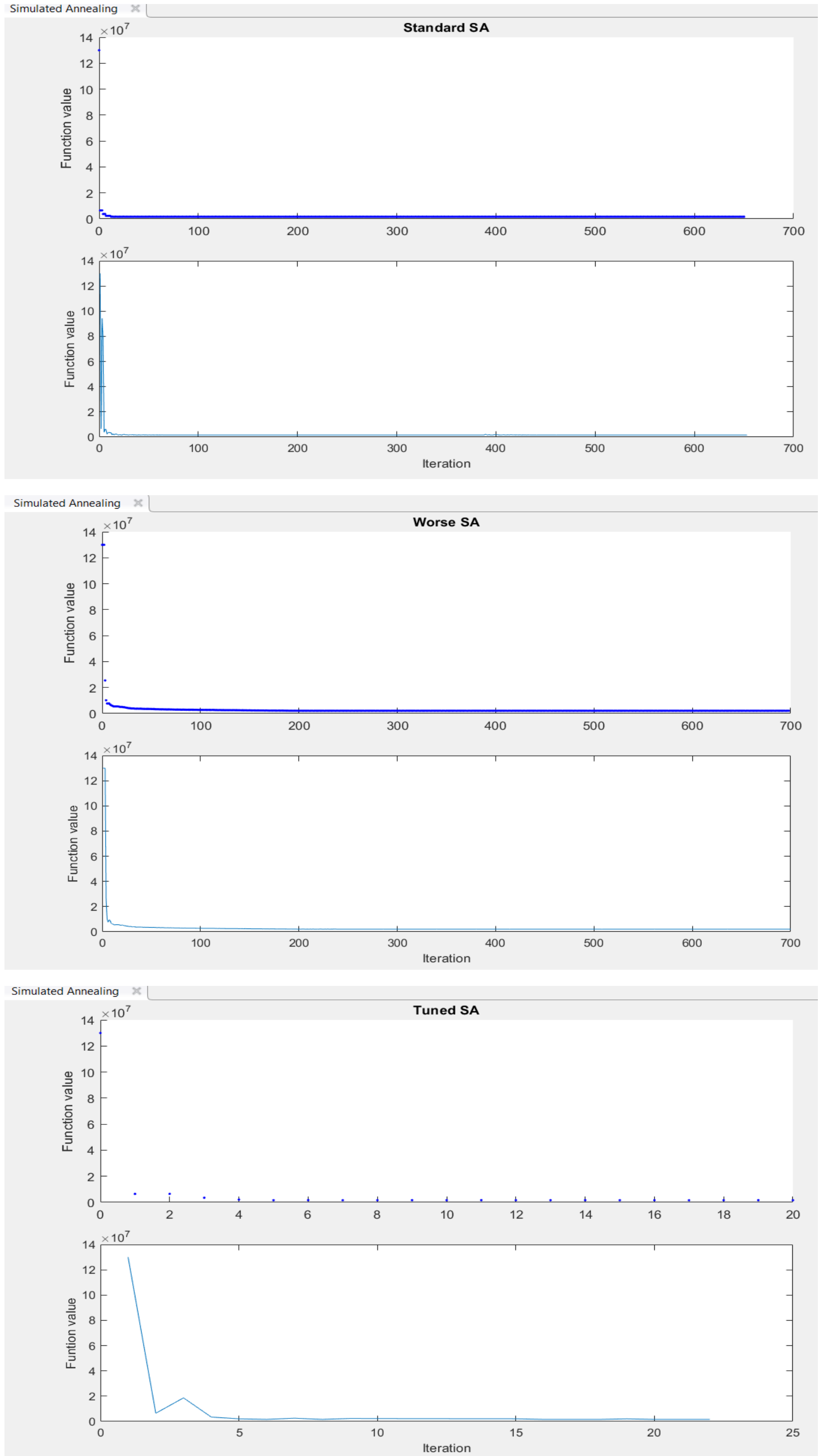

Figure 5.13: Standard, Worse and Tuned Convergence plots for SA

- Standard SA = N1,606,900
- Worse SA = N2,105,200
- Tuned SA = N1,606,900

From Figure 5.13, it is seen that though the standard and tuned simulations achieved similar function values, the convergence differ with the tuned simulation having a more progressive decline over the iteration period.

5.7.2.4 PSO, GA, and SA Convergence Comparison

Figure 5.14 presents a convergence comparison of the three algorithms using the tuned parameter settings.

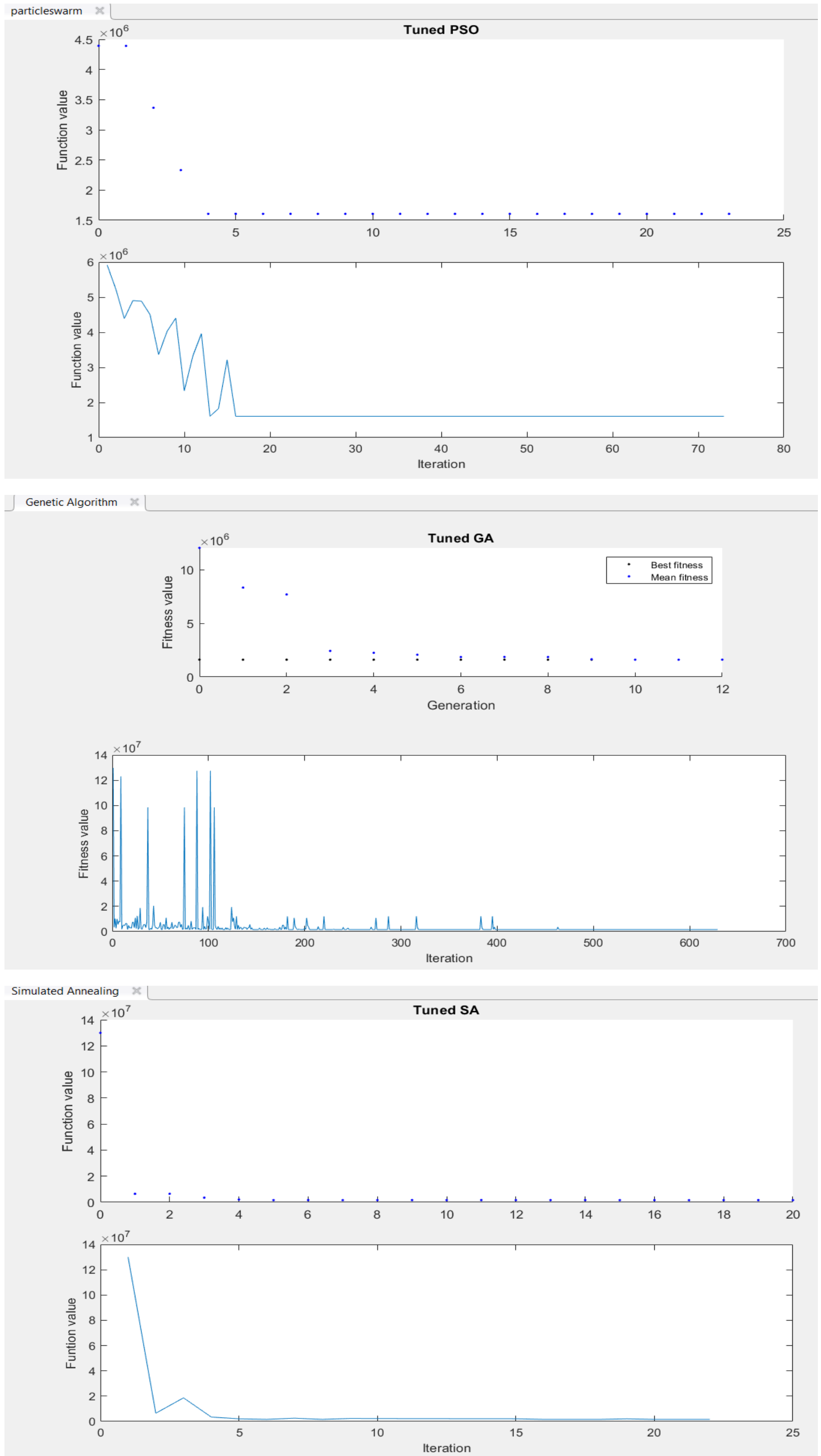

Figure 5.14: Tuned PSO, GA and SA converging Comparison

Figure 5.14, all algorithms start at different fitness values and work their way through to their individual final fitness score of N1,606,000, N1,604,100, N1,606,900 for PSO, GA and SA, respectively. PSO and SA achieved similar fitness values while GA achieved the least fitness score.

5.7.3 Average Result of Tuned Parameter Experiments

Table 5.6, Table 5.7 and Table 5.8, shows the average simulation results of running the optimisation strategies for different variable loads corresponding to the different load models. The system specifications employed were gotten from the HMG design from Homer Pro.

The optimisation simulations carried out aimed at minimising the running operation of the diesel generator while ensuring that the consumer demand is always met. The RERs are efficiently utilised for serving the load demand and charging the battery with the power excess from the RERs and DG. The DG, acting as a back-up comes online when the PV+WT+BSS is unable to meet the load. The optimisation technique parameters are simulated to give optimal results.

Table 5.6: Average Year 1 Simulation Results

Year 1 Load without Variability.

	DG Run Hours	DG Energy Production, kW	Simulation Time, sec
PSO	64	2,984	10.9093105
GA	67	3,111.68	14.643602
SA	66.83	3,099.45	1.925008

Year1 Variable Load.

	DG Run Hours	DG Energy Production, kW	Simulation Time, sec
PSO	95	4,335.1	11.557647
GA	99.33	4,546.05	19.999756
SA	103	4,730.58	1.983756

Results presented in Table 5.6 Year 1 Load without Variability and Year 1 Variable Load shows PSO to have the lowest DG running hours and DG energy production. While SA achieved the shortest simulation times of 17.7% of the PSO simulation time.

Table 5.7: Average Year 5 Simulation Results

Year 5 Load without Variability.

	DG Run Hours	DG Energy Production, kW	Simulation Time, sec
PSO	582	24,444	11.538171
GA	595.67	25,054	15.650682
SA	586.67	24.674	2.005796

Year 5 Variable Load.

	DG Run Hours	DG Energy Production, kW	Simulation Time, sec
PSO	605	23,538	11.792770
GA	617.17	24,056	21.664545
SA	607	23,623.83	2.000663

Results presented in Table 5.7 Year 5 Load without Variability and Year 5 Variable Load, shows PSO to have the lowest DG running hours and DG energy production. At the same time, SA achieved the shortest simulation times of 17.4% of the PSO simulation time.

Table 5.8: Average Year 10 Simulation Results

Year 10 Load without Variability.

	DG Run Hours	DG Energy Production, kW	Simulation Time, sec
PSO	2,377	66,309	11.809578
GA	2,396.67	66,617.5	18.781296
SA	2,379.67	66,307.67	2.0323276

Year 10 Variable Load.

	DG Run Hours	DG Energy Production, kW	Simulation Time, sec
PSO	2,413	63,114	12.038307
GA	2,422	62,493.5	23.670679
SA	2,415	63,155.67	2.063241

Results presented in Table 5.8 Year 10 Load without variability shows PSO to have the lowest DG running hours, SA has the lowest DG energy production and achieved the shortest simulation time. While results for the Year 10 Variable load, it is observed that the PSO had the least DG running hours, GA produced the least DG energy and SA the lowest run time.

5.7.4 Individual Run Comparison

From Table 5.3, Table 5.4 and Table 5.5, it can also be deduced the though the PSO results were constant for DG running hours and energy production, the GA and SA also achieved the lowest results on particular simulation runs. Table 5.4 loads WoV, best results in terms of DG running hours and energy production were achieved on the 2nd run. Furthermore, for loads WV, corresponding best results were achieved on the 1st run.

From Table 5.5 load WoV, best results were achieved on the 2nd, 1st and 1st run, respectively. Furthermore, for the loads WV, the best results were achieved on the 1st, 1st and 3rd run.

From all the three algorithms simulated, the system is observed to meet the load at all times, with the DG generating just enough power to meet the excess load primarily as shown in the Figure 5.15 below.

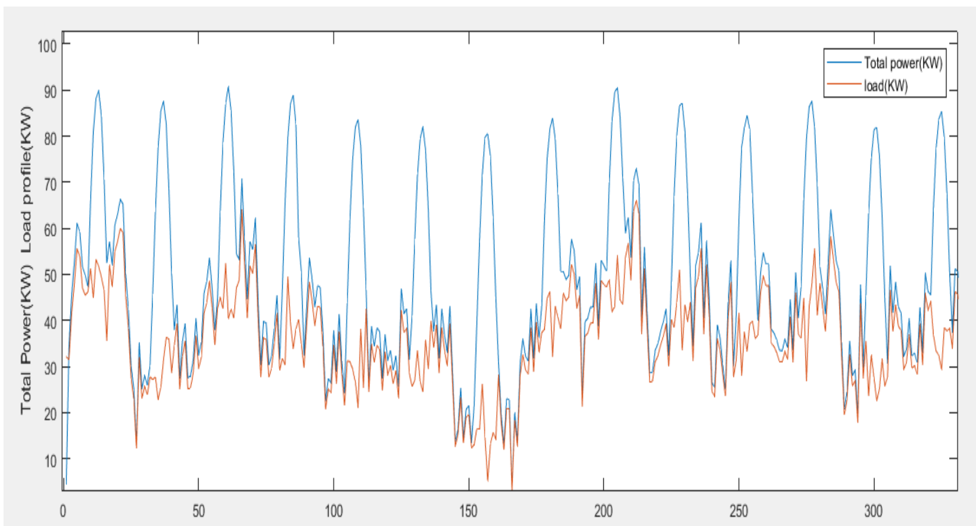

Figure 5.15: Total Generation vs Load WV.

5.8 Conclusions

In this chapter, the three algorithms employed in the optimisation of the HMG operation are described and implemented. The HMG system components are modelled in MatLab. The HMG is then experimented with using adjustable simulation parameters, with parameters fine-tuned to produce desirable results while operating within design constraints and ensuring the load demand is met at all times.

The performances of the methods implemented are assessed in regards to the effects of parameter tuning on algorithms, the convergence of algorithms using tuned parameters, quality of the solutions, simulation runtime, and repeatability.

5.8.1 Quality of Solution

Six simulations from each metaheuristic methods are evaluated. Their corresponding solutions are also presented in Table 5.3, Table 5.4 and Table 5.5. It can be seen that within the set operating parameters, the performances of every algorithm differ. The optimal solutions are achieved at certain runs for all experiments conducted on all the algorithms with the appropriate tuning of parameters that suit problems of this kind.

5.8.2 Simulation Runtime

Each optimisation method was repeated six times, and the average simulation runtime are listed in Table 5.3, Table 5.4, and Table 5.5. GA and PSO have comparable runtime. SA runs faster per iteration because SA generates only one solution per iteration while the other two methods generate 50 solutions in each iteration. However, since SA cannot find optimal solutions with less iteration, its total runtime is longer than the other two methods.

5.8.3 Repeatability

The DG running hours for the experimental runs are used to evaluate the repeatability of each method. From the simulation results, it can be suggested that solutions from

PSO were repeatable than solutions from the GAs and SAs.

The use of traditional optimisation methods for solving DG operation problems in a HMG was limited due to lack of historical data. Introducing meta-heuristic population based algorithms appears promising in handling problems of such kind. In this study, the efficacy of dynamic non-linear inertia weight based particle swarm optimisation was examined through solving HMG problems and compared with genetic and simulated annealing algorithms. The findings of simulations show that PSO achieved similar final results at the end of every run, only changing with simulation time, offering a more promising technique for optimal DG operation in the HMG system network as the number of times the function needed to be evaluated and computation time were less when compared with the genetic algorithm and the simulated annealing algorithms. Randomness in reaching a solution performs a vital role; like GAs and SAs, it is seldom to assume the optimal values of PSO parameters. Nevertheless, introducing the non-linear inertia weight accelerates the exploration of a global solution.

GA took the lengthiest simulation runtime, producing different results at every run, also containing the best solution amongst simulation conducted. As with [196–198], GAs suffer the downsides of weak exploitative abilities and premature convergence in optimising continuous multi-mode functions in particular. Loss of diversity in the solutions population often causes premature convergence to a local optimal solution. Optimization problems having many local optima points suffer from extremely slow convergence when solved with GA because standard GAs do not exploit the neighbourhood information [194, 195, 199]. Furthermore, GAs converge steadily initially and slows down their rate of convergences after a number of iterations. When discrete variables are expressed in binary forms, moving the decision variable to neighbourhood point is rare through the crossover and mutation process. Good solutions are made in multiple copies through the selection process in each generation;

when these solutions undergo crossover and mutation process, more poor solutions generally result.

SA having the least simulation run time on every simulation produced results that were greater than the least results when averaged. This could be attributed to the fact that SAs generate only one trial initial solution per iteration compared to randomly generated initial solutions for PSOs and GAs. Furthermore, SAs require many iterations to find an optimum reason for their high average result quality.

Furthermore, spikes were introduced to the 5th year load demand WV. It is observed that the total power generated failed to meet the load at periods the spikes were introduced owing to the limits of the system design.

Chapter 6

General Conclusions and Future Work

This chapter presents the general conclusions of the objectives, goals of this research, and the contributions achieved. The thesis limitations are outlined and also possible areas for further research is presented.

6.1 General Conclusions

This study aimed to design an adaptive hybrid microgrid solution to meet the needs of electricity demand in remote rural communities that have no access to any form of centralised grid systems. With rural electrification by developing countries continually seeking ways to improve their rate of electrification while adopting the global trend of high renewable penetration to the main power grid or independently of the grid, and the need for efficient operations and management to reduces energy waste, system cost and global warming effects on the environment, the primary objectives of undertaking this research were:

- The need to understand the background of the limitations to rural electrification,

- Identify possible solutions affordable to the developing countries based on available renewable resources and technological applications
- The need to design reliable, efficient, cost-effective systems with significant renewable resource penetration and have the system adaptable to changes over the years.

Chapter 1 introduced the issues with rural electrification and the energy situation for the country of study. It also presented the efforts of the GoN in providing policies to enhance the use of alternative energy sources to help the lapses experienced by the centralised grid that is inefficient to cater for its continually increasing population. The current microgrid projects were presented alongside the potentials of harnessing renewable energy, including the research motivation described suggesting decentralised renewable energy-based systems as possible solutions to rural electrification.

Chapter 2 presented an overview of microgrids concept, its inception, and research around the world. It described the available technologies in existence, the benefits, their designs, and optimal planning and operations optimisation practices. It also presented the applications of different optimisation strategies to different aspects of interest and applications. The microgrid configuration and development are discussed, and tools for implementation presented. It concluded with a proposal for the microgrid configuration and the selected metaheuristic optimisation strategies implemented in the following chapters.

Chapter 3 presented a background of the rural location considered for the research and developed a load model from data collected whilst making some assumptions that considered possible changes likely to occur in the application being implemented. A developed socio-economic forecast method was utilised to predict the community's electricity demand for ten years, utilising assumed load factors, system losses, and miscellaneous loads. The chapter ended with a load model to depict the load growth over the ten years and introduced the concept of load variability to enable a robust HMG design.

The hybrid microgrid is designed in Chapter 4. This chapter utilises weather data specific to the application for system development. Generic components and their costs are utilised for the microgrid design. Two load types (loads without variability and loads with variability) for the fifth year is implemented for the design. Three system configurations (diesel only, renewable resource only and hybrid microgrid) considered. The results are discussed; the HMG offered a more cost-effective and reliable system than the other configurations and a reduced environmental effect compared to the diesel generator only configuration. The results from was then utilised in Chapter 5.

Chapter 5 presented the description and implementation of the three optimisation strategies (particle swarm optimisation, genetic algorithms and simulated annealing) to the HMG system designed in chapter 4. The various components of the HMG were modelled in MatLab, the optimisation cost function developed, and constraints set on the system. The objective of this chapter was to minimise the DG running hours in the system, compare among the metaheuristic strategies their performance, and evaluate the effects of the algorithm parameter settings on the different strategies at achieving optimal results. The experiments were carried out on Year 1, Year 5 and Year 10 loads (with and without variability). The results showed that each algorithm presented effects of the parameter settings on their mode and rate of convergence, simulation time and quality of results attained. The tuned parameters improved the algorithms the convergence of solutions, simulation time, and reduced the DG running hours at different experimental run by the three algorithms. A 65.2% reduction was achieved from PSO application. Finally, spikes were introduced to the load to establish uncertain events that could cause the system to fail to meet the load. The spikes were introduced at different hours through the year to represent weather variation and holiday periods when possible changes beyond the design limits could cause the system to fail as an introduction to applying machine learning to learn from past events and accurately predict the expected electricity demand.

The conclusions of thesis are

- Electrification of remote rural communities in Nigeria is achievable using enabling technologies such as HMG that allows the mix of RERs and conventional systems.

- Load estimation and forecasting plays a pivot role in designing a cost effective and reliable system. Using of low energy appliances helps in saving energy.

- Constant power supply gives room to growth and development. This in turn causes individuals to seek better ways of survival, seeking comfort, easy business operations affecting load forecasting.

- The self replenishing nature of RERs allows for high penetration and adoption of its technologies in achieving clean power generation, stable and reliable power, and reducing dependence on fossil fuels. For example the adoption of BSS allows for continuous power supply during peak loads and night times.

- Further cost minimisation of the HMG operations of 65.2% could be realised from employing metaheuristic techniques in its operation. Algorithm parameters influence the quality of results achieved, repeatability, and simulation time. Therefore tuning these parameters produces desired cost saving objectives and environmental preservation from reduced fossil fuel burning in DGs.

6.2 Further Work

Limitation encountered in the course of this study and suggested for future attention include: data availability, studied community under safety alert and global pandemic at the time of study.

1. Load estimation methodology.

An area for future research is in the area of load estimation. The approach proposed can be expanded to accommodate more extensive questionnaires in the electrical survey, emphasising other considerations not considered. Future work can also be carried out to develop physical building properties and gender effect indicators to compare consumption characteristics. As well as, using data gathered from employing smart meters for more accurate estimations.

2. Studies on other microgrid components.

This study can be expanded to include consideration of other cost components in the costing of the microgrid (cables, installations, controls, communications, and other electronics). This further study would involve a specific detailed cost assessment of these components and the effect on the overall cost of the system.

3. Studies on microgrid clusters.

This research can be further developed by looking at the possibilities of microgrid interconnection between communities. To reduce excess energy losses and allow the microgrids to compensate each other.

4. Incorporation of independent house electricity usage.

Further research can also involve investigating each independent demand profile for the different building types, which would involve the demand-side management based on a combination of direct load control and real-time pricing/time of day. This should put into consideration the nature of the communities and customers being served as the success of demand-side management highly depends on the percentage of controlled loads. Customer education and awareness is essential for its success.

5. Machine learning application.

Regarding the adaptability and sustainability of the system, future work includes further development and implementation of real-time neural network applications to evaluate the effects and correlation of influencing factors such as festivals, weather, and electricity price on the communities electricity consumption behaviour.

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Appendix A

Load Data Questionnaire

Questionnaire for individual households

A. Respondent characteristics

House Number	Occupant	Male/Female	Age	Level of Education	Occupation	Monthly income

B. Household characteristics

1. What is your current source of electricity?

2. What electrical appliances do you have now?

Appliance	Number	Time of use, Day/Night	Total hours/day of use

3. What new appliances will you have in the near future?

Appliance	Number	Time of use, Day/Night	Total hours/day of use

C. Demand increase

4. Do you have visitors during the holiday?
   Yes/No
5. How many visitors?

Visitor	Male/Female	Age	Time in the year	Duration

D. Willingness to pay for electricity

6. Are you willing to pay for electricity supplied?
   Yes/No
7. How much are you willing to pay?

Figure A.1: Residential Load Use Questionnaire

Questionnaire for Organisational building

A. Building characteristics

1. What is the name of organisation?

2. What is your current source of electricity?

3. What electrical appliances do you have now?

Appliance	Number	Time of use, Day/Night	Total hours/day of use

4. What new appliances will you have in the near future?

Appliance	Number	Time of use, Day/Night	Total hours/day of use

B. Willingness to pay for electricity

5. Are you willing to pay for electricity supply?
   Yes/No
6. How much are you willing to pay for electricity supplied?

Questionnaire for commercial building

A. Building characteristics

1. What is the purpose of the building?

2. What is your current source of electricity?

3. What electrical appliances do you have now?

Appliance	Number	Time of use, Day/Night	Total hours/day of use

4. What new appliances will you have in the near future?

Appliance	Number	Time of use, Day/Night	Total hours/day of use

B. Willingness to pay for electricity

5. Are you willing to pay for electricity supply?
   Yes/No
6. How much are you willing to pay for electricity supplied?

Figure A.2: Organisation and Commercial Load Use Questionnaire