Optimization of hybrid renewable energy generation using a nature-inspired algorithm with advanced IoT analytics

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ABSTRACT

A stable and cost-effective power supply in an autonomous hybrid energy system requires an efficient design process for renewable energy technologies. Accordingly, the best design of a standalone hybrid renewable energy system (HRES) should consider several factors such as renewable energy data, load profile, technical and economic analysis of the renewable technologies, ideal location for the power system, etc. Different data from renewable energy sources are modelled into an optimization problem which incorporates the crucial point, in HRES, of the correct sizing of the various power components, which directly affect the cost and power security/reliability of the system. This thesis proposes an innovative meta-heuristic optimization algorithm called Social Spider-Prey (SSP) that mimics the foraging behaviour of social spiders and prey(s) on the social web. By examining the foraging behavioural traits of social spiders and prey(s), a global optimization algorithm was developed to solve a hybrid renewable energy optimization problem of correct sizing, minimal cost, and highest reliability. In SSP, artificial spiders are considered search agents. On the one hand, every spider can freely roam the social web, a hyperdimensional search space, to implement an exploratory search scheme. On the other hand, nearby spiders relative to a captured prey search the neighbourhood, which is implemented as an exploitative search mechanism. These two search strategies are harmonized in SSP to solve the multi-source renewable power generation optimization problem effectively. Four different power generation scenarios were analysed to determine optimal power generation using experimental real-time environment data collected with sensors and secondary data retrieved from a benchmark dataset, National Renewable Energy Laboratory (NREL). The optimization algorithms inspired by nature, namely Social Spider-Prey (SSP), Particle Swarm Optimization (PSO), Teaching-Learning Based Optimization (TLBO) algorithm and Social Spider Algorithm (SSA), were used in a comparative study to search for a near-optimal result for the hybrid system configuration that satisfies the optimization problem. The results show the economic and reliable implications of different system configurations that meet the specified combined criteria, as indicated in the HRES optimization problem, to make the best investment decision. The SSP guaranteed optimal annualized system costs and met the reliability constraints for all the case scenarios: wind/biomass/battery (ZAR 3,431,512.26 and LPSP of 0.011), PV/wind/ biomass (ZAR 2,549,792.71 and LPSP of 0, 0011), PV/biomass/battery (ZAR1, 638,628.82 and LPSP of 0.00021) and PV/wind/biomass/battery (ZAR1, 412,142.80 and LPSP of 0.0141). Based on this result, the study proposes the SSP as an optimization approach for the solar PV/wind/biomass/battery hybrid system, as it ensures 99.98% power reliability. In addition, a Kruskal-Wallis test was performed to determine the significant differences among the comparison algorithms.

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DECLARATION

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I hereby declare that this research project is the result of my own work, except for quotations and summaries that have been duly acknowledged.

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DEDICATION

To Him who is able to do more than we ask, and who also constantly keeps us from giving up to perfecting ourselves into the kind of people we should be, praise Almighty Father forever. This work is dedicated to my parents Mr. Anthony and Mrs. Rosina Frimpong who did not get the opportunity to pursue formal education to the levels they desired, my wife Diana and my children Michelle, Kendrick, Brayden and unborn, my brothers Daniel, Dominic, and my sisters Juliet, Elizabeth, Agnes and Comfort. I appreciate your unwavering support and encouragement throughout this journey. He has made everything beautiful in his time. Eccl 3:11

Finally, I dedicate this work to each individual who contributes to making this world a better place to live.

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ABBREVIATIONS

ACO	Ant Colony Optimization
AFSO	Artificial Fish Swarm Optimization
AI	Artificial Intelligence
ALO	Ant Lion Optimizer
ANN	Artificial Neural Networks
ASC	Annualized System Cost
cEHO	Converged Elephant Herd Optimization
COD	Chemical Oxygen Demand
COE	Cost of Energy
CRI	Check- Reduce-Improve
CSA	Crow Search Algorithm
DA	Dragonfly Algorithm
DG	Diesel Generator
EO	Equilibrium Optimizer
GA	Genetic Algorithms
GHG	Greenhouse Gas
GOA	Grasshopper Optimization Algorithm
GWO	Grey Wolf Optimizer
HRES	Hybrid Renewable Energy System
IAEO	Improved Artificial Ecosystem Optimization
IDE	Integrated Development Environment
IEA	International Energy Agency
IoT	Internet of Things
I_{SC}	Short Circuit Current
LCOE	Levelized Cost Of Energy
LPSP	Loss Of Power Probability
MCS	Monte Carlo Simulation
MFOA	Moth-Flame Optimization Algorithm
MOPSO	Multi-Objective Particle Swarm Optimization
MPP	Maximum Power Point
NIA	Nature-Inspired Algorithms
NPC	Net Present Cost
NREL	National Renewable Energy Laboratory
NSGA	Non-Domination Based Genetic Algorithm
OSSO	Opposition Based Social Spider Optimization
PSO	Particle Swarm Optimization
PV	Photovoltaic
REN21	Renewable Energy Policy Network For The 21st Century
RES	Renewable Energy Source
SDG	Sustainable Development Goals
SI	Swarm Intelligence

SOC	State of Charge
SSA_1	Salp Swarm Algorithm
SSA	Social Spider Algorithm
SSO	Social Spider Optimization
SSP	Social Spider and Prey
STC	Standard Temperature Conditions
TLBO	Teaching Learning-Based Optimization
UN	United Nations
V_{OC}	Open Circuit Voltage
WT	Wind Turbine

NOMENCLATURE

P_{RWT}	Wind turbine rated power
v_{cin}	Cut in speed
v_{cout}	Cut out speed
v_R	Rated wind speed
CC_{WT}	Capital cost per kW of wind turbine
RC_{WT}	Replacement cost pre kW of wind turbine
MC_{WT}	O & M cost per kW of wind turbine
H_{WT}	Hub height of wind turbine
η_{WT}	Overall efficiency of wind turbine
WT_{life}	Wind turbine Lifetime
P_{RSP}	Rated power of solar PV
η_{SP}	Derating factor/efficiency of solar PV
CC_{PV}	Capital cost per kW of solar PV
RC_{PV}	Replacement cost per kW of solar PV
MC_{PV}	O & M cost per kW of solar PV
PV_{life}	Soar PV Lifetime
C_{batt}	Nominal capacity of battery
V_{batt}	Nominal voltage of battery
I_{max}	Maximum charging current of battery
SOC_{max}	Maximum state of charge of battery
SOC_{min}	Minimum state of charge of battery
η_{batt}	Battery efficiency
CC_{Batt}	Capital cost per unit battery
RC_{Batt}	Replacement cost per unit of battery
MC_{Batt}	O & M cost per unit of battery
$Batt_{life}$	Battery Lifetime
CV_{bm}	Calorific value of biomass
η_{bmg}	Conversion efficiency of biomass
CC_{BMG}	Capital cost per kW of biomass
RC_{BMG}	Replacement cost per kW of biomass
MC_{BMG}	O & M cost per kW of biomass
BMG_{life}	Biomass gasifier Lifetime
P_{invR}	Inverter rated power
η_{inv}	Efficiency of inverter
CC_{inv}	Capital cost per kW of inverter
RC_{inv}	Replacement cost per kW of inverter
MC_{inv}	O & M cost per kW of inverter
Inv_{life}	Inverter Lifetime
i	Interest rate
N	project lifetime
inf	Inflation rate

CHAPTER 1: GENERAL INTRODUCTION

1.1 Introduction

Electricity is an indispensable utility for maintaining a quality lifestyle and driving socioeconomic development in modern societies (World Bank, 2019). In most urban cities, essential household activities such as cooking, lighting, heating, cooling etc. depend on electrical power. Similarly, manufacturing as well as most service industries or institutions rely heavily on electricity for the provision of goods and services. Furthermore, with the advent of the fourth industrial revolution, more and more devices require a connection between the cyber-physical world, biological entities, and the environment which entails energy consumption. The advancement in the technological field alongside socioeconomic developments including population growth, urbanization, industrialization to name a few are leading to the growing trends of ever-increasing demand for electricity consumption (Ratshomo et al., 2019). The need for electricity in every human society cannot be overemphasized considering the role it plays in effective healthcare delivery, quality formal education, profitable commercial activities, etc., which is the reason electricity is considered a key catalyst for economic transformations (World Bank, 2019).

Notwithstanding the tremendous benefits of electricity and the high demand in most societies, many developing countries, particularly in Africa and Asia, lack the infrastructure and/or systems to provide enough electricity to meet the needs of electricity consumers (REN21 2020). In most cases, a high proportion of the rural dwellers on these continents do not have access to electricity, let alone possessing a reliable electricity supply. Several factors account for the low level of electrification in second world economies, particularly in rural communities; These include insufficient power generation capacity, power infrastructure and economics. When the grid infrastructure is distant apart from a community the cost of expanding the grid to every corner of a nation could be unreasonable. Consequently, a gap remains between energy demand and supply on the energy market. The unbalanced situation destabilizes the energy sector, forcing the sector to adopt sometimes ad hoc measures such as load shedding, intermittent blackouts and/or total blackouts to cope with power shortages (Iqbal et al. 2019; Pfenninger, Hawkes & Keirstead 2014). These interventions are not only uncomfortable to many energy users but also, it hampers the socioeconomic development and eventually, compromising the quality of living that humans want.

To promote economic growth in all sectors of society and areas in disadvantaged communities (rural settlements in developing and underdeveloped countries), a form of electrification that does not require national grid infrastructure would be an ideal option (Come Zebra, van der Windt, Nhumaio & Faaij 2021). This off-grid system must be both economically sustainable and maintainable to efficiently provide maximum and reliable power to the service area (Guezgouz, Jurasz & Bekkouche 2019). Thus, for that purpose, a hybrid renewable energy system is the most plausible option available to mitigate the energy demand deficit in a more sustainable and economical way (Mayer, Szilágyi & Gróf 2020; Tazvinga, Dzobo & Mapako 2020; Owusu & Asumadu-Sarkodie 2016).

This thesis endeavours to propose an advanced IoT analytics and metaheuristic optimization technique to provide a sustainable but economical and reliable power supply from a hybrid renewable energy system. In this chapter, the study presents a brief background of the global energy problem, with a focus on the need for expansion of the rural electrification project in Africa, where this study is being conducted. Then, in the preceding sections, the objectives, research questions, problem statement, rationale and significance, and scope of the study are discussed. Finally, the structure of the work is presented. It is worth noting that the terms ‘energy’, ‘electricity’ and ‘power’ have been used interchangeably throughout the work to refer to electrical energy.

1.2 Background of the study

With ever-increasing energy demand, the power sector is lagging in terms of infrastructure and rudimentary facilities to double energy production to meet user demand. There is therefore a market for the distribution of imbalanced energy. Accordingly, the World Energy Outlook 2019 report estimates that around one billion people in the world do not have access to electricity. The global outcry over this number has spawned various policy interventions being enacted by international and multinational organizations on energy for sustainable development. The goals for sustainable development (Sustainable Development Goals, SDG) of the United Nations (UN), adopted in 2013, attach importance to remedying the lack of global energy supply by 2030. This policy document outlines three core frameworks for realizing the policy mandate, namely affordable, reliable, sustainable and modern energy for all. Therefore, SDG7 emphasizes universal access to modern energy services, which have the potential to double the global rate of improvement in energy efficiency. To counteract the energy shortage, SDG7 also recommends a substantial share of renewable energies in the global energy mix. Renewable energy sources such as solar, wind, biomass, hydroelectric power, etc. are preferred over conventional energy sources such as coal or natural gas due to the greater spread of variable renewable resources around the world (Qazi et al. 2019). Moreover, renewable energy systems bring long term financial gain and are environmentally friendly (Sweerts, Longa & van der Zwaan 2019; Panwar, Kaushik & Kothari 2011). In addition, the flexibility of scaling renewable energy technologies makes them a preferred choice over the national grid system for electrification projects in rural, isolated, or dispersed settlements. Additionally, renewable energy sources are inexhaustible, giving them another comparative advantage over fossil fuels, which are being rapidly depleted(Surroop & Raghoo 2018).

Another major problem arises from the high use of fossil fuels as the primary source of energy production in the face of climate change and environmental degradation. The scientific evidence shows that much more needs to be done to stop the devastating environmental impacts of fossil fuel residues, which amount to global warming and greenhouse effects, as fossil fuels provide much of the energy in the market today (REN21 2020). The adverse effect of fossil fuel by-products such as hydrocarbons is a threat to both humans and other living organisms. Hydrocarbons are carcinogenic and neurotoxic organic pollutants because their continuous release into the ecosystem is harmful to human health. On the one hand, fossil fuel exploration is a threat to energy security in all geopolitical jurisdictions, as it creates unnecessary tensions between oil-based countries. On the other hand, rising crude oil prices negatively impact low-income countries as they eventually disrupt their energy supply chain (Ouedraogo 2019; Aliyu, Modu & Tan 2018). Renewable energy resources can complement the conventional supply or in some instances or serve as an alternative option to achieving sustainable power supply. The usage of renewable energy resources contributes to resolving the energy crisis as well as reducing the environmental pollution. Table 1.1 shows the various forms of renewable energy resources and outlines their advantages and disadvantages in power generation.

Table 1.1 Advantages and disadvantages of renewable resources in power generation

Resource	Disadvantage	Advantage
Hydro	Geographically determined, as bodies of water are the primary component. Seasonal factors, particularly precipitation, impact the usage of energy generation.	Hydropower, the main renewable energy source, is comparatively inexpensive compared to fossil fuels.
Wind	Intermittent energy source The energy source wind is seasonally and demographically variable	Wind is a free resource and does not pollute the environment
Solar	unavailable at night and on days with clouds	Available anywhere almost all year round; solar irradiance is a free resource and environmentally friendly.
Geothermal	Geothermal energy is restricted to tectonic extraction locations	It offers a reliable power source or backups during hot springs.
Biomass	Although the raw materials may be free, there are logistical expenses associated with transporting them to the production facilities. The seasonal availability of some raw materials may conflict with human needs.	Different biomass technologies focus on a range of feedstocks. These solutions can be used to meet a variety of power needs, from large industrial plants to small rural applications. Biofuels are environmentally safe

1.2.1 Global Energy Scenario and the African situation

As the world population and economy continue to grow, it is imperative that energy growth be adjusted. The global populace is approximately 7.54 billion today (2022) and estimated 783 million people will not have access to electricity (REN21, 2020). According to the IEA report 2021, the world population is estimated at 9.7 billion people by 2050 and of these, 750 million individuals, none will have electric power, and approximately 95% of this individuals in the sub-Sahara, Africa are expected to lack access to electricity according to projections. Figure 1.1 shows the world population growth rate by zone and total GDP.

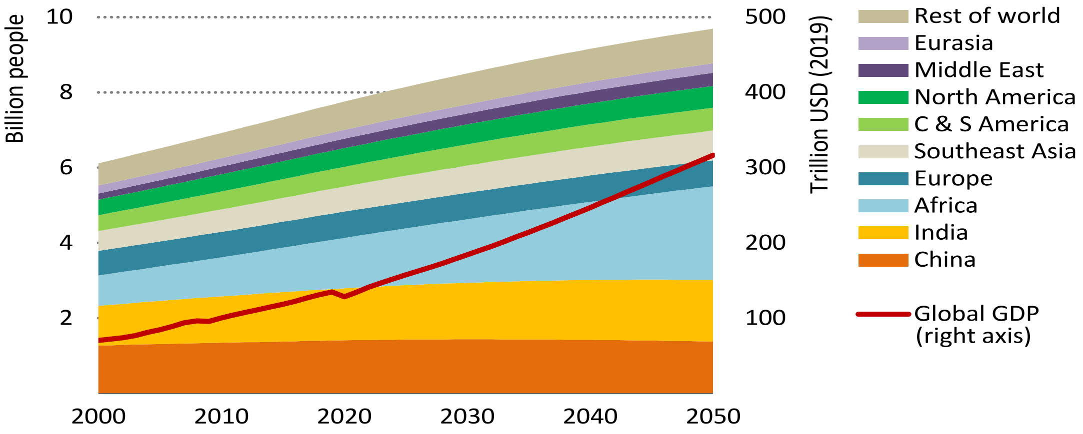


Figure 1.1: The world's population expands to 9.7 billion people by 2050

Sources: International Energy Agency (2021), Net Zero by 2050, IEA, Paris

Accordingly, more and more energy interventions are being introduced each year to alleviate the energy supply deficit in many societies. Installations and investments in capacity continue to grow globally and distributed renewable energy systems are delivering power and clean cooking services to more homes in developing and emerging countries (Kalananda & Komanapalli, 2021). The IEA's 2021 Net Zero Emissions Report provides an overview of the global transition to an efficient energy society. Renewable energy technologies are receiving more attention in finding solutions to the energy challenges facing the world today. In the year 2020, total power capacity increased by almost 10% (2,839 GW) including hydro; non-hydro power accounts for 6.6% of the increase, of which 256 GW came from renewable sources: solar PV added 139 GW, while wind added 93 GW (REN21, 2020).

There is still more to be done to make energy accessible for all by following UN SDG7. Projected numbers to achieve at least 90 percent coverage for people without access to electricity will require greater penetration of sustainable energy sources. Figure 1.2 shows a projection of the global energy production trend and the expected contribution of the different energy resources. Here, solar and wind power are getting a powerful boost, increasing the share of renewable energy in total generation from 29% in 2020 to 90% in 2050. This renewable power generation performance is linked to the technological maturity of the renewable energy system and incentives (discount) for purchasing renewable energy equipment (Khare, Khare, Nema & Baredar 2021; Foster et al. 2017).

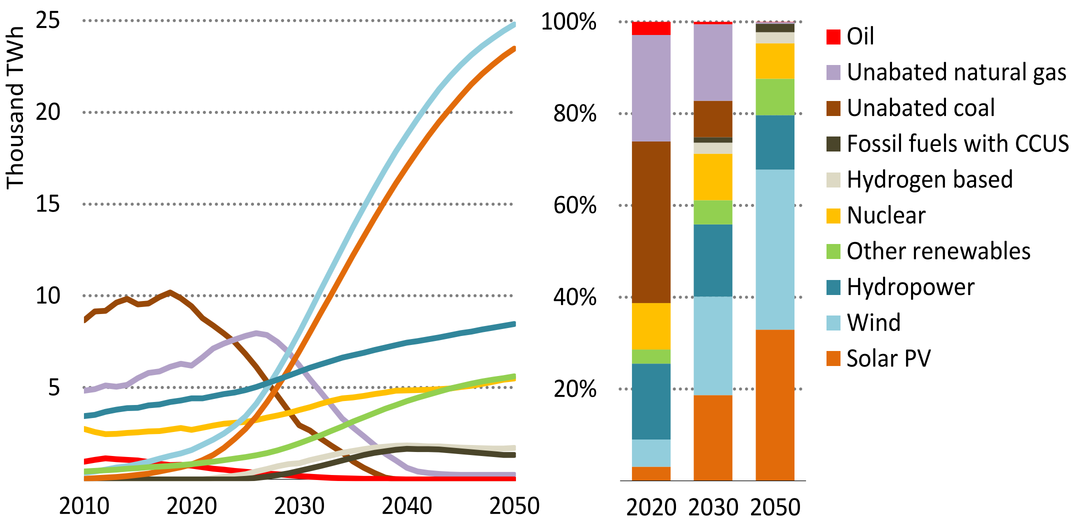


Figure 1.2: Global electricity generation by source from 2010 – 2050
(Source: International Energy Agency (2021), Net Zero by 2050, IEA, Paris)

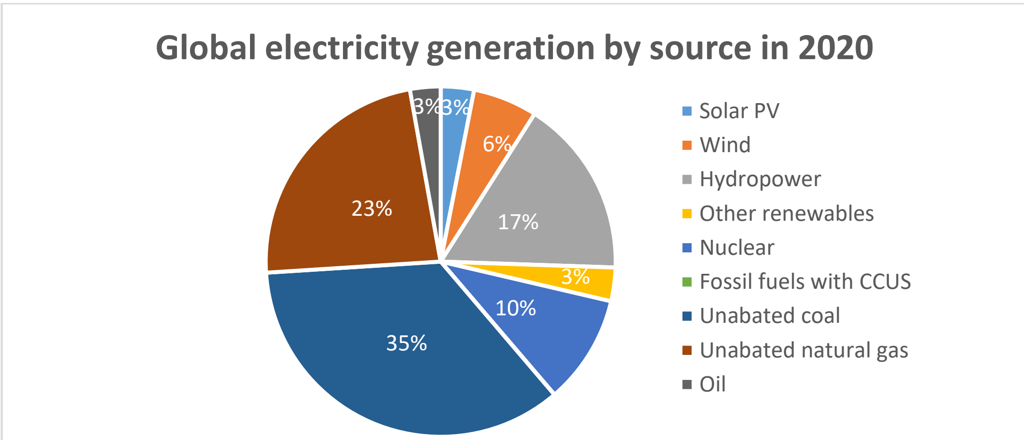


Figure 1.3 Global electricity generation by source in 2020
Source: International Energy Agency (2021), Net Zero by 2050, IEA, Paris

As shown in Figure 1.3, as the proportion of renewable energy used to generate electricity continued to rise globally, so did support for sustainable power and understanding of its various advantages, including the decrease of carbon dioxide (CO2) emissions. However, despite Sub-Saharan Africa's abundant renewable energy resources, the area is struggling to fulfil consumer electricity demands (Ratshomo et al. 2019b). Among the fundamental factors challenging the energy sector in Africa is a lack of infrastructure, economy, among other constraints. Several countries in this region have sparse and remote rural communities with large populations. Providing access to electricity in these communities through national grid expansion is resource-intensive and economically unsustainable. Considering that a great distance should be covered before the network reaches those communities that are naturally less densely populated in one place, the cost of the infrastructure makes this infeasible. Since the grid operates under maximum capacity in most cases(Ambrosius, Egerer, Grimm & Weijde 2020; Ali, Padmanaban, Twala & Marwala 2017), it cannot afford to power additional consumers.

Therefore, given the rapid advances in renewable energy technologies alongside the promising potential in sub-Saharan Africa, it would be particularly beneficial for the continent to seek an implementation strategy that would give a boost to the uptake of renewable energy in isolated or disadvantaged communities of energy infrastructure. When considering a rural settlement electrification project, emphasis should be placed on designing a reliable power supply system that can meet the power demand of the connected load. This level of reliability is not achievable with a renewable energy system based solely on renewable sources such as solar photovoltaic, wind turbine or biomass gasifier etc. The limitations of each renewable energy source shown in Table 1.1 can be overcome by combining two or more renewable technologies into a hybrid Renewable Energy System (HRES) to provide grid-level or better energy security. By adding an energy storage system, e.g., a battery, excess power generated by the HRES could be stored and used when the power generating units are unable to meet the power demand of the load(Kharrich et al. 2021; Singh, Singh & Kaushik 2016a; Fathima & Palanisamy 2015).

1.3 Problem statement

Renewable energy technologies are developing faster and several of these technologies are on the market today (Freire-Gormaly & Bilton, 2015; Vivas et al., 2018). This development has not only led to a progressive acceptance of renewable energy in the world, but also to a steady decrease in the initial costs (Kahwash, Maheri & Mahkamov 2021). The widespread use of renewable energy is beneficial to both humans and other living organisms. However, due to the dependence of most renewable resources on climatic weather conditions (Ayodele & Ogunjuyigbe 2016) or other variability as shown in Table 1.1, operating a single-source renewable energy system may not be ideal in most cases. For example, solar energy is only available during the day when the sun is available; The wind pattern does not typically correlate with peak loads, so it may be discarded if not sufficiently available for a useful purpose. Also, in the case of biogas or biofuel production, the availability of resources and the associated logistics can affect the efficiency of their use as a reliable source of energy. Therefore, it is important to combine different renewable energy sources in a Hybrid Renewable Energy System (HRES) to complement each other for a reliable power supply.

In rural electrification projects HRES has a high propensity to avert the energy supply deficit and associated socio-economic problems that the energy situation imposes on many societies. The three well known energy issues discussed in the scientific literature include energy supply reliability, economics, and environmental concerns (Faccio, Gamberi, Bortolini & Nedaei 2018), commonly referred to as the 'energy trilemma' (Šprajc, Bjegović & Vasić 2019). However, with a better design and proper system configuration an optimally sized HRES would considerably address the challenging issues related to renewable power system. This will pave the way to contain the uncertainties of renewable based power systems and curtail the variability of climatic weather conditions to provide a reliable power supply.

The problem this research tries to solve is one of optimization. The production of reliable hybrid renewable energy is modelled as an optimization problem. Thereafter, an investigation will be undertaken to conduct a feasibility assessment for the optimal sizing of HRES. The optimization goal is to produce a reliable power supply to a given load by utilizing locally available renewable sources namely solar, wind and biomass while minimizing the cost of the system. With an HRES like the one proposed for this study the energy demand/load is met by the solar PV panel and the wind turbine. There is also a battery storage system which toggles between taking the excess power, from the power generation units (solar PV module or wind turbine) and injecting into the system when supply is in deficit of load demand. The biomass gasifier is optimally sized to power the load when both solar PV, wind turbine, and battery storage system are unable to cover the load. Therefore, the biomass gasifier is modelled as an alternative energy storage or power retention source that could be accessible when sun, wind, or their combination as well as the battery system is not satisfying the load requirement. In this way, the hybrid system becomes more resilient to the stochastic nature of the energy sources, making the hybrid system less dependent on an intermittent renewable energy source (Singh, Singh & Kaushik 2016a).

The motivation for selecting solar PV, wind turbine and biomass gasifier as the renewable technologies.

Firstly, both solar PV system and wind turbine are matured renewable energy technologies whose adoption for electrification projects on a larger or small scale have recorded huge successes over the years. It is observed from the literature (Quarton et al. 2019) that the initial investment cost of these systems is on the decline. Moreover, solar and wind energy resource are easily accessible everywhere despite the seemingly variations from one place to the other. In Africa, where this study is mainly targeting, the climatic weather conditions are highly favourable for such system configuration. For example, (Mugodo, Magama & Dhavu 2017) purport that South Africa, Kenya, Ghana, and Nigeria are rich in these resources to produce enough electricity to augment what already exists. Therefore, coupling there two relatively advanced renewable energy systems as a primary power source would be suitable for the electrification projects particularly, in the rural settlement where this study will be of more benefits.

To control the stochastic pattern of both wind and solar energy generation, battery storage system and biomass gasifier are both considered under different scenarios. Biomass is another potential renewable source of energy in Africa (Mugodo et al. 2017). Therefore, it is considered as a power retention source for the proposed hybrid system. There are three basic approaches for generating useful energy from biomass.

The first option is to turn biomass into fuel (biofuel). At present, this is largely dependent on turning plant sugars (often used in food) into alcohol to serve as fuel. Some research into turning waste products, such as cellulose, into fuel but nothing fully viable yet. Given that producing this type of energy would deplete the food supply, it is often infeasible. In addition, the growing of food requires energy (tractors and fuel) so it may be an energy negative alternative (Sharma, Meena, Sharma & Goyal 2014a; Faaij 2006). The second option involves burning the biomass into a combustible fuel. Here, some of the biomass may not burn easily and will lead to producing more CO_2 and other pollutants which detract from the environmental benefit the study wants to contribute (Faaij 2006). The final option involves capturing methane for fuel/power: this option reduces the negative environmental effects of harmful gas like methane by converting it into useful energy (Saur & Milbrandt 2014; Sharma et al. 2014a). Therefor option 3 is the choice for this thesis for the following reasons:

- escaped methane from decomposing biomass, which is the norm in most garbage dumps, is much more harmful than CO2 to global warming. Hence, converting this harmful gas into useful energy has environmental benefits.
- burning methane, that would have escaped into the atmosphere is more environmentally friendly than using fossil fuels or diesel generator.

In summary, this study presents an optimization problem that requires a global solution to satisfy certain specified constraints of the power generation units. The approach for solving this problem is detailed in chapter three where the method used to collect data, and the algorithmic structure for the search technique are discussed in detail. This thesis showcases a novel metaheuristic algorithm referred to as social spider-prey (SSP) optimizer as a search technique to look for a global best solution from multiple renewable production units. SSP is a nature-inspired search technique that mimics the foraging behaviour of the social spider and the prey on a social web. The ability of a social spider to detect vibration of prey and to distinct this vibration from that of another spider characterizes the design methodology of SSP algorithm to find an optimal solution for a micro grid (hybrid) system.

1.4 Field of research

The field of study is Information Technology, and the subject area is an application of a nature-inspired algorithm in optimal hybrid renewable energy production.

1.5 General objective

This study aims to model and design an algorithmic framework that estimates near-optimal power generation from a hybrid renewable energy system. In this way, the study attempts to design and develop a tool that takes renewable resource data such as solar irradiance, wind speed, ambient temperature, biomass volume, biomass calorific value as well as electrical load demand data and technical specifications of the power generation systems as input to the proposed system. After that, a simulation of the optimization process is triggered to find the best solution to the hybrid power system in terms of evaluated cost of the system and power reliability goal. The output solution can support good decision making for sustainable energy development.

To achieve this study goal, it is imperative to model the hybrid renewable energy generation problem into a multi-goal optimization problem. The optimization goal as well as the system constraints would ensure that the solution is achievable with the application of the appropriate optimization technique. Therefore, this study formulates an objective function that aims to minimize the cost of energy production for a given year for the lifetime of the hybrid system. These costs are referred to as annualized system costs (ASC). With the proposed standalone hybrid system, maintaining maximum reliability is critical to providing sustainable power which is why the Loss of Power Supply Probability index (LPSP) must be kept as low as possible. Hence, the optimization mechanism employed enjoins the optimal solution to meet a stated LPSP value which ought not to exceed 1%. The optimization technique employed in this study is the Social Spider and Prey (SSP) algorithm that is manipulated to search for an optimal solution that meets the load demand with the available renewable resources, and the techno-economic constraints of the energy systems.

1.5.1 Specific objectives

The specific objectives of the study are:

1. Deploy IoT devices (sensors) to collect real-time environmental data, and after extrapolating this data for an entire year along with the use of supplementary historical data, to determine the optimal configuration of hybrid renewable energy system based on the availability of the renewable resources on site.
2. Modelling and mathematical formulation of selected aspects of social spider and prey behaviour, which are then transformed into a global optimization algorithm to determine optimal hybrid power generation.
3. Develop a hybrid renewable energy generation scenario into an optimization problem and determine the near-optimal power generation from the PV-wind-based hybrid system using the newly developed metaheuristic algorithm.

4. Carrying out a comparative evaluation on the performance of the social spider prey algorithm against selected comparable optimization techniques using the benchmark dataset.

1.6 Research questions

It is very important to focus the study on the issues raised to achieve the study goals. A helpful tool that leads the research direction perfectly to the goal is a set of four research questions asked by the researcher. The research questions guide the study to achieve its objectives.

The research questions are:

1. Can real-time sensor data collected from the environment over a period of time and supplemented with historical environmental data be extrapolated to present a time series of climatic weather data showing a whole year's variation for effective optimization of a hybrid renewable energy system?
2. After modelling the social characteristics of spider-prey interaction in the social web, would the representation adequately represent a global optimization algorithm that can solve the optimal power generation from the proposed hybrid renewable energy system?
3. Could the stochastic but dynamic climatic weather conditions that solar and wind energy rely on be modelled into an optimization problem and further explored to determine a near-optimal hybrid renewable energy system using a meta-heuristic algorithm?
4. Can the evaluation of the model and the algorithmic structure be empirically validated against corresponding meta-heuristic algorithms using a benchmark dataset?

1.7 Justification of the study

Generating electricity in full capacity to meet power consumers' demand remains a worldwide challenge. The energy sector should therefore look out for sustainable approaches to augment electricity production in the face of continuous rise in electricity demand. To address this challenge both the scientific and engineering communities have given considerable attention to renewable power systems. The renewable power system utilizes natural resources such as wind, solar, biomass etc. These resources are inexhaustible, unlike fossil fuel which may take forever to be replenished. Therefore, this study envisages the shortage of electricity supply on the energy market as problematic given that renewable energy resources and technologies are readily available to generate sustainable electricity. Particularly, in rural communities across the Sub-Saharan Africa region it is reported that most rural dwellers lack access to electricity supply. However, renewable energy sources such as solar, wind, biomass, etc. can fill this gap by supplying useful energy in the form of electricity. Hence, solving the HRES generation optimization problem could potentially mitigate the energy challenges confronting many societies and improve the quality of life.

1.8 Significance of the study

Renewable energy sources such as wind and solar have a stochastic distribution pattern where the climatic weather condition is a major determinant. To manage the stochastic phenomenon this study employs the foraging behavioural of the social spider hunting tactics on the social web; it models some selected behavioural characteristics of the social spider and prey into an algorithmic framework, and then uses the algorithm to solve the optimization problem defined for HRES power production. By mapping the behavioural characteristics exhibited on the social web namely vibration intensity (measure the strength, how good is the power source), frequency (availability of the source) and amplitude (reliability of the source) an informed HRES production decision is made. Thus, the algorithmic tool developed in this study can find a near optimal renewable power generation solution for the proposed hybrid system.

The usage of the appropriate dataset for the optimization process is crucial in obtaining better results. Meteorological data such as solar radiance, ambient temperature, and wind speed among others serve as input to the optimization process. Since a PV-wind based hybrid system is dependent on-site resources, a reliable system configuration should consider the availability of surrounding renewable resources. Therefore, low-cost environmental sensors are deployed in an experimental setup to collect and send real-time data to the edge where pre-processing of the data is carried out to remove redundant data, thus preparing the data for the optimization. This is done to provide real-time but also on-site energy data to the HRES to accurately estimate the system size.

The availability of reliable information on renewable energy sources with special mention of solar and wind energy is necessary, they are important resources for global sustainable development. However, ground-based radiometric stations are scarce, especially in large, sparsely populated regions and developing countries, making it difficult to validate solar radiation detection methods (Prieto & García 2022). Therefore, providing radiation data from multiple climatic variables can be measured with inexpensive equipment and calibrated using data from secondary station networks. However, model accuracy decreases when estimates have to be made at a distance from calibration locations (Prieto & García 2022). In data-sparse locations, it is critical that models that account for the influence of geographic and topographical features help reduce this disadvantage. Using IoT and advanced analytics to analyze real-time sensor data to determine the optimal configuration of a PV-wind based hybrid system, this study aimed to overcome the difficult problem of reliable data availability. Moreover, relying only on solar and wind energy may not supply reliable power to the load as such biomass resources which are less weather dependent are utilized to fill in the power reliability gap. When the climatic weather conditions are unfavourable, a battery storage facility could also be utilized to stabilize power supply. Therefore, this study also considers battery storage system in providing reliable power supply to the attached load.

The optimization technique used in this study is the SSP algorithm. The design and development of the SSP algorithm define a suitable feasibility framework for optimization problems in hybrid renewable energy systems. The SSP operating strategy makes it a robust optimization tool that makes it useful to be applied in a new field that advances knowledge of metaheuristic algorithms used to solve a technical problem. The optimization goal along with the limitations imposed by the technical, economic and reliability constraints is to ensure that the proposed system is optimally designed to meet the load requirement in a more reliable and economical way.

1.9 Scope and limitation

In this study, a hybrid system comprising of wind turbines, solar PVs, biogas gasifier and battery storage system have been considered to supply reliable power to an attached load.

The biogas gasifier is modelled as a power retention system, while the solar PV and wind turbine are implemented as the primary energy sources to meet the load demand. Both solar PV and wind turbines are considered mature technologies as they have been used in many applications (Come Zebra et al. 2021; Khan, Pal & Saeed 2018) including stand-alone and grid-tied systems thus, the reliability of these technologies is guaranteed. In addition, battery storage system provides additional security to the system as it takes excess energy out of the system and returns it to the system when the primary energy sources cannot meet the load demand. Therefore, the aim of this study is to optimize the PV-wind-biomass-battery hybrid system in a cost-effective way by sizing the system components optimally, while maintaining high system reliability.

Although several studies (Aliyu et al. 2018) suggest energy storage systems like batteries to improve hybrid renewable energy system's reliability, this study investigates an additional renewable alternative (biomass resources) as a supplementary power system in situations when solar, wind, their combination, or battery storage system are unable to meet the load demand. The inclusion of biomass energy in the power mix is to ensure that the proposed hybrid system minimises power loss probability to the barest level. This could also minimize the number of battery units on the system which would have to be replaced periodically within the system lifetime. The reduction in battery units can accrue economic benefits to the system by minimizing the replacement and maintenance cost of battery storage system.

The approach adapted in this study can provide reliable power supply in a standalone mode making it attractive for deployment in rural electrification projects. Despite the differences in configuration modes for HRES, this study only considered a standalone hybrid PV-wind-biomass-battery system. The flexibility of integrating renewable energy systems into already existing energy infrastructure in either a grid-connected or standalone mode makes its adoption quite simpler without major modification. But for this study, only the stand-alone system configuration is considered. It should be noted that, this study does not consider different energy storage systems as in the case studied by (Kumar & Prasad 2020), or varying specifications of the selected system components which could also be considered when designing a system such as the one proposed in this thesis. The specification of each system component was kept constant for the purpose of analysis with different optimization techniques.

It is acknowledged that the configuration of a reliable hybrid renewable energy system involves several factors other than technical and economic issues which are the focus of this study. For instance, when installing an HRES for a rural community, some social-political considerations (Eriksson & Gray 2017) including adoption and acceptance of the system are keen, in addition, the billing rate (tariff) per utility ought to be agreed upon, also the rapid expansion of the community because of electricity accessibility must be given considerable attention as such development will affect the reliable power supply. Despite these important considerations for the configuration of HRES only the techno-economic aspects of the hybrid system are investigated.

1.10 Outline of the thesis

Chapter 1 gives a general introduction to the study. The background of the study, the general and the specific objectives, the research questions, the problem statement, and the justification as well as the significance of the study are discussed. Finally, the chapter closes with an outline of the thesis.

Chapter 2 reviews relevant literature on the subject matter of hybrid renewable energy system optimization. There is a section that outlines the various renewable energy resources vis-à-vis their merit and demerits in the application of hybrid system implementation. For effective implantation of a hybrid system there is the need to employ tools and techniques to examine its adoption on case-by-case level. Hence, various techniques, including meta-heuristic algorithms are used to solve standalone HRES optimization problems. The approaches and techniques in optimizing HRES have thoroughly been reviewed. Further discussion focuses on the concept of stream data pre-processing, which is an integral feature for the study framework for collecting and communicating renewable energy data to solve the optimization problem. In addition, the inspiration for the novel algorithmic framework is discussed. The chapter ends by proposing a framework to support the thesis.

For Chapter 3, the methodological framework of the work is discussed. The chapter deals with the philosophical worldview that forms the basis for the thesis in the scientific field and the methodology used in the optimization process, as well as the result verification mechanism. The phases of the methodological framework developed for the study are explained. In addition, the discussion of the instrumentation of the technique used for the study to collect renewable energy data and to perform experiments for the simulations of the optimization process is also presented. Finally, the chapter provides an overview of the comparison algorithms and how they were set up for the comparison study along with the software packages used in the research study.

Chapter 4 describes the modelling and testing of the SSP algorithm on selected benchmark functions and most importantly, the application of SSP to the HRES optimization problem. Both sensor-collected data and secondary data are used in the optimization process to estimate the hybrid system components. The test results obtained from the simulation are presented in graphs and tables. The results presented include the solution of the comparative algorithms. Finally, a summary of what the chapter entails is provided at the end.

In chapter 5, the results from the previous chapter are discussed in detail. The optimal solution to the posed HRES optimization problem is explained by detailing the contribution of each system component to the economic value of the hybrid system. The chapter includes a case-by-case analysis using different renewable system configurations to evaluate the economic benefits of the optimal solution achieved. In addition, the chapter presents statistical validation of the obtained results to verify the significance of the designed algorithm to solve the optimization problem.

Chapter 6 draws conclusions from the various results discussed in Chapter 5 and the rest of the work. The limitations in terms of scope of this research, as well as the information gleaned from the study, are used to provide recommendations for future work.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The statistical indices place Africa in a lower sustainable development category because a significant number of African countries are unable to meet their energy needs for consumers, despite the high potential of renewable resources across the continent (Ibrahim et al. 2021; Yüksel 2010). Most African nations are dependent on fossil fuels and cannot meet their energy needs even on this basis (Ibrahim et al. 2021). Renewable energy offers both a solution to fill the demand gap and a way to replace fossil fuels.

The challenge however in using renewable energy system is that renewable exhibit the behaviours of uncertainties which make them unpredictable as they are either climatic weather dependent (solar and wind energy) or influenced by seasonal variations (hydro and geothermal) (Ayodele & Ogunjuyigbe 2016). This phenomenon ensue that individual renewable energy sources lack the potential to supply reliable power all year round. By combining two or more renewable energy technologies for electricity generation the system's security improves. Accordingly, optimizing hybrid renewable energy systems (HRES) has become a topical subject among the scientific and engineering communities (Kalananda & Komanapalli 2021a; Khezri & Mahmoudi 2020; Hassas, Pourhossein & Azad 2017; Ghofrani & Hosseini 2016).

Hybridizing multiple resources (renewable and/or non-renewable) to produce reliable energy to match a specific load requires thorough feasibility analysis in the early stages of the system design. This analysis is intended to ensure the correct dimensioning and location of the hybrid system to reliably generate electricity that meet the attached load requirement. The aspect of technical and economic analysis of a hybrid system is given importance in the initial phase to properly design and effectively manage the system. Should the system be undersized, it will not be reliable and cannot meet the load requirements. On the other hand, oversizing the hybrid system would be economically unattractive. The optimization of HRES is therefore aimed at the economic management of hybrid renewable energy systems as well as the satisfaction of end-user needs (Suresh, Muralidhar & Kiranmayi 2020).

Therefore, in this chapter an overview of literature on the optimization of hybrid renewable energy systems is given. First, the different renewable energy sources used in electricity generation are discussed by highlighting the advantages and disadvantages of each resource. This is important to recognize the wide range of renewable energy data to work with when optimizing HRES. The importance of hybridizing renewable energy systems to provide reliable and economical energy to users remains paramount in this study. To this end, three renewable energy sources, namely solar, wind and biomass, are purposely chosen to narrow the study focus. The selection of these resources is based on their availability and energy potential in the African context (Sweerts et al. 2019) in which this research is being conducted. In addition, the selection criteria for these resources also considered the maturity of the selected renewable energy technologies (Kahwash et al. 2021; Ahmad et al. 2018). Energy models, which serve as a tool to estimate the amount of energy each renewable system could produce, are then studied for each renewable resource. Finally, the approaches used to optimize the proposed HRES are discussed in line with the benefits of choosing a nature-inspired search method for this study. The chapter concludes by proposing a framework for optimizing hybrid renewable energy systems with the application of IoT and advanced analytics to collect and communicate renewable energy data.

2.2 Renewable Energy Resources

The International Renewable Energy Agency (IRENA, 2018) report claims that renewable energy sources such as solar, wind, biomass, hydroelectric power, geothermal, and tidal wave have been used to power the world. Consequently, renewable energies are good candidates to complement, if not replace, the energy economy based on finite fossil fuels. The desire for a renewable energy system to generate electricity has many advantages. In remote areas in particular, renewable electricity can replace conventional power plants such as diesel generators (DG) in a cost-effective manner. In addition, the fossil fuels needed for conventional generation could become more expensive or no longer available in the most remote areas. The disadvantages of traditional energy sources are not inherited by renewable energy technologies, where they do not require fuel and do not affect the environment, therefore an efficient deployment strategy and intelligent management of renewable energy systems have both economic and environmental benefits (Aljohani, Ebrahim & Mohammed 2020; Nguyen et al. 2020).

The various renewable energy resources namely, hydropower, geothermal, tide/wave, solar energy, wind energy, and biomass alongside their advantages and disadvantages for power generation would be discussed in the next subsections.

2.2.1 Hydropower

Hydroelectric power is one of the most established and significant renewable energy sources. Its energy is obtained from falling water flowing from a higher to a lower altitude as it passes through a water turbine or a converting device. Thus, the fundamental source of energy for hydropower technologies is gravity and the height of the water falling into the turbine. The various sizes of hydroelectric projects include dams, run-of-rivers and in-stream. Hydropower projects use a fluctuating resource (Owusu & Asumadu-Sarkodie 2016). Reservoir operations often reflect its multiple usage, such as flood prevention, agriculture irrigation project, drinking, and transportation etc.

Hydroelectricity does not create greenhouse gas emissions, but the construction of dams of a river can pose serious environmental problems about quality of water and nature conservation particularly of aquatic habitat (Kajela & Manshahia 2017). Hydropower causes almost no fine dust pollution and can store energy for many hours. The turbines are designed for any water flow rate (Owusu & Asumadu-Sarkodie, 2016). However, it has both positives and downsides. It improves a country's socio-economic development by providing low-cost electricity; but also given the social impact, it drives many people out of their homes to build it (Bagher, Vahid, Mohsen & Parvin 2015), although they may be compensated, it is not sufficient. Utilization of hydroelectric places, such as reservoirs, which are usually man-made, results in the flooding of the previous natural region(Li, Chen, Fan & Cheng 2018; Yüksel 2010).

In addition, with pipes, and the often-observed turbines, water is carried across great distances from lakes and rivers. By constructing dams, dikes, and weirs, hydropower facilities affect the ecology of river bodies, primarily by altering their hydrological qualities and breaking the biological coherence of material flow and fish migration (Li et al. 2018; Bagher et al. 2015). Large vegetation or crops are flooded during the construction of a dam, methane gas can be created as plants begin to decay in the water, either immediately or after the water has been treated (Sibtain, Li, Bashir & Azam 2021; Owusu & Asumadu-Sarkodie 2016; Igweonu & Joshua 2012).

2.2.2 Geothermal

The heat energy that naturally emanates from the earth's core is the source of the energy produced by geothermal power plants. There is a relation between the planet as well as the physical processes that occur there, and the production of heat in the interior. The geothermal power plant uses the high temperature in the interior of the earth to produce steam, which then powers turbines to generate energy (Barbier 2002). Even though heat is abundant in the earth's crust, it is extremely high at its deepest regions. The heat in the depths of the earth is irregularly distributed, seldom concentrated, and frequently at too great a depth to be physically extracted (Wilberforce et al. 2019; Barbier 2002). However, there are drillable places to harness geothermal energy as detailed in (Barbier 2002).

Heat is extracted from geothermal reservoirs using a variety of processes. Storage tanks which are usually enough heated and permeable are referred to as hydrothermal reservoirs, whereas storage tanks that are naturally adequately hot but have been boosted by hydraulic stimulation are referred to as enhanced geothermal systems (ESG). Once raised to the surface, liquids of variable temperatures can be used to generate electricity and for other thermal energy-requiring usage (Owusu & Asumadu-Sarkodie 2016).

In a sense, geothermal energy is non-renewable since the earth's core will eventually cool. This period is so distant in the future (perhaps thousands or millions of years) that we regard it to be regenerative. When the seasons change, geothermal systems employ compressors to push heat into or out of the earth. Seasonal cycles replenish the energy that enters and leaves the planet. Compressors can be powered by either conventional or renewable energy sources (Owusu & Asumadu-Sarkodie 2016; Barbier 2002).

2.2.3 Ocean energy (tide and wave)

Ocean energy is considered renewable since it is dependent on a range of ocean wave characteristics, such as water temperature, currents, and salinity. The moon, sun, and other components of the solar system are responsible for, among other things, the formation of tides/waves and solar radiation. Wind generates surface waves by moving over the water's surface (ocean). The higher the wind speed, the longer the duration of the wind, the greater the distance the wind goes, the greater the wave height, and the bigger the energy created by the waves. Ocean energy is comprised of waves, tidal currents, ocean heat, tidal barriers, and salt gradient energy. Up to seven percent of the world's power is generated by marine renewable energy (Esteban and Leary 2012). Comparatively, tide current and offshore wind systems contribute approximately 0.75 percent of global energy consumption (Esteban and Leary 2012). This suggests that tide power has a bigger potential than offshore wind or wave power. Nevertheless, limited areas are suited for harvesting energy from the oceans. The technology for harvesting tidal current energy is still in its infancy; nonetheless, it has immense potential to become a crucial component of the future energy mix for sites in the United Kingdom, Canada, and France (Guillou et al. 2018; Coles et al. 2017), Spain, Norway (Gonzlez-Caballn et al. 2016); China (Gao et al. 2015), Philippines (Buhali et al. 2012) etc.

The ocean tides have a tremendous energy potential and might be an excellent source of electrical energy. The year 2008 saw the beginning of the first generation of commercial ocean energy technology, with the installation of the first units at UK-SeaGen and Portugal-Pelamis (Owusu & Asumadu-Sarkodie 2016). Along with other technologies, tidal barriers have been studied to determine how to successfully harness ocean energy. Tidal energy is not currently a widespread commercial energy source, but it has the potential to be utilized as a renewable energy source for commercial purposes. In addition, tidal energy is less polluting than other renewable sources and may provide vast amounts of electricity. The tidal flow velocity can result in high power output if the turbine is positioned in an optimal location (Rourke et al. 2010).

There are many obstacles to the broad application of tidal energy and related technology. For example, the turbine throughput is modest, the cost of establishing a power plant is high, and society awareness is extremely low, even though there are four primary ways to gather energy from the ocean: wind, tides, waves, and the temperature of the water in deep sea water (Esteban & Leary, 2012).

2.2.4 Solar energy

The energy derived from the sun is generally referred as solar energy. There are two main ways of producing electrical energy from the solar source (Owusu & Asumadu-Sarkodie 2016). They are solar photovoltaic (PV) and concentrated solar power (CSP), also known as solar thermal energy. In a CSP process, the solar system or plant utilizes special mirrors to converge solar irradiation to produce heat energy for driving traditional steam turbine or engine which eventually generate electricity. This system is not very efficient as much energy is lost in the process for heating the equipment, hence very large plants produce relatively small amount of energy. Building CSP system is economically inefficient as the material sourcing requires excessive mining for a tracking system, on the other hand, PV is the most widespread type of solar energy and is generated when electrical energy is generated by converting solar radiation into a flow of electrons to obtain direct current using semiconductors that exhibit the photovoltaic effect (Naraharisetti, Devarapalli & Bathina 2020). This phenomenon requires a system consisting of solar panels with integrated semiconducting solar cells that are used to convert solar energy into direct current. Whenever the sun's rays hit a solar cell, electrons move, and electricity is generated. When no sunlight shines on the panel, however, no electricity is generated. The electrical output of the PV module is proportional to the area of the solar module. In estimating the energy yield of a PV system, the module area or the number of solar modules is a decisive optimization parameter(Marsa, Houcine, Zaafouri & Chaari 2021; Mahdi, Baygi & Farzaneh 2020).

In general, solar PV modules can be connected in various ways to meet the output voltage or current demand of the load. Nevertheless, a typical PV cell is only a few centimetres in size, so many cells are combined to form a PV module. Multiple PV modules are connected to form an array commonly referred to as a solar panel, and solar panels are often used in extremely large systems to meet power needs. While solar cells are commonly used in electronic devices such as calculators and some satellite devices, technological advances have enabled solar panels to power an entire building, institution, or community (Das & Mahanta 2019).

There has been significant increase of PV system application in recent times owing to the maturity and improvement in the technology. Solar PV system has been around over the past four decades and the continuous enhancement of PV system efficiency has improved its performance in power generation (Khare, Nema & Baredar 2016). Currently, many PV systems are being integrated into the national power system either through the grid or distributed power system (Ren, Feng & Yang 2020; DOE 2019; Ouedraogo 2019). The ease of implementing PV system, improved efficiency as compared with CSP, and policy framework (Mauger & Barnard 2018) of solar system adoption makes it very attractive option in most application.

2.2.4.1 *Advantages and disadvantages of Solar Power system*

Solar energy is among the principal renewable energy resources with a very high potential in the African energy sector (Sarazola, Arsalane, Contejean, Goodson & Walton 2018; Surroop & Raghoo 2018; Huld, Müller & Gambardella 2012). Among the several advantages of solar systems or technologies adoption are wide scale availability of solar resource, economic value, and the environmental benefits.

First, solar energy is environmentally clean with less or no pollution to the ecosystem. The technology in use for Solar cells to generate electricity makes absolutely no noise nor does it produce greenhouse gas emission (Ibrahim et al. 2021). On the contrary, the huge oil extraction and extraction machines are incredibly noisy and spew toxic pollutants into the environment. In addition, solar resources are free and widely available in every region of the planet, but the distribution of tidal waves, hydroelectric power, and biomass depends on location. Once the installation costs are paid, solar power systems are inexpensive and free for life. Solar cells require minimal maintenance to stay operational. There are no moving elements in a solar cell, making it difficult to inflict significant damage. Due to the amount of free energy a solar panel can provide, there can be a significant return on investment in the long term (Zahraee, Khalaji Assadi & Saidur 2016).

However, there are downsides to generating power utilizing solar energy. The fundamental disadvantage of solar power generation is the intermittent nature of solar resources, necessitating the need of a backup energy storage system. For example, in a standalone hybrid power system, component sizing may involve greater storage capacity to increase power system reliability(Mahdi et al. 2020; Mohammed, Amirat & Benbouzid 2019). The inclusion of batteries or storage system eventually increases the cost of the system.

Meanwhile, solar power system needs batteries for storage purposes because solar energy could be used to charge batteries so that power would be available at night when solar panels aren’t generating electricity. The batteries can often be large, heavy, take up space and need to be replaced from time to time, increasing the cost of running the system (Kajela & Manshahia 2017). Another challenge with solar power system involves the initial capital requirement to setup solar based power generation plant. The cost of solar system components can be expensive to install resulting in a time-lag of many years for savings on energy bills to match initial investments, return on investment (Siddaiah &

Saini 2016; Pfenninger et al. 2014). However, recent studies show a tremendous price decrement in solar systems applications (Ganguly, Kalam & Zayegh 2018). Finally, solar power generation is entirely dependent on a country's solar radiation; this could be limited by a country's local climate. Therefore, it is ideal to hybridize solar power system with other renewable technologies like biomass power plant or wind power system to generate reliable power supply (Dawoud 2021; Geleta & Manshahia 2021).

2.2.5 Wind energy

Wind energy is generated by air moving due to a pressure difference created by the irradiation of the earth with solar energy. Consequently, wind energy is a subset of solar energy, but unlike solar energy, which is the result of solar radiation, wind is created by the uneven heating of the earth's surface at different times. Wind movements occur on numerous scales, from local breezes caused by minute-long warming of land surfaces to global winds caused by the Earth's solar heating. Wind power is the conversion of wind energy into a more usable form. Wind possesses energy due to its speed, and wind turbines are used to generate electricity (Khare et al. 2016). Wind energy is a possible choice among various nonconventional energy sources for rural sustainable energy development (Khan et al. 2018; Kajela & Manshahia 2017).

Wind-generated electricity is composed of the following factors: (Kajela & Manshahia 2017; Bhandari, Lee, Lee, Cho & Ahn 2015):

1) A wind turbine that transforms wind energy into mechanical energy (through rotation).
2) Gear system that regulates the wind speed for transmission through a rotor.
3) A generator that transforms rotary energy to electrical energy.
4) Controllers to sense wind direction and speed, generator power and temperature, and initiate appropriate control signals to take control action.
5) The Yaw motor gear in the wind turbine is a mechanism used to turn the turbines against the wind. The area of wind flow swept by the wind turbine is greater when the blades are pointing into the wind, so there is Yaw error if the rotor is not perpendicular to the wind.

2.2.5.1 Advantages and disadvantages of wind power

There are several reasons that contribute to the global proliferation of wind energy. With an average cost ranging from two cents to six cents per kilowatt-hour wind energy is now considered among the least expensive forms of useable energy accessible today (Kajela & Manshahia, 2017). Wind energy minimizes the price fluctuations associated with fuel costs and the ecological effects of utilizing conventional energy sources like fossil fuels or coal and gas. Wind energy is eco-friendly since it has no ecological consequences and does not pollute the air like power plants that rely on fossil fuels such as coal or natural gas, which emit particulate matter, nitrogen oxides, and sulphur dioxide that are detrimental to human health and the economy (Maradin 2021). Wind generators do not lead to acid rain, pollution, or emissions of carbon dioxide. In addition, wind energy is unlimited and, when coupled with other renewable energy sources, may create sustainable power.

Another advantage of wind turbines is that they may be constructed on existing farms and ranches. This has a tremendous positive impact on the rural economy. Farmers and ranchers may continue to cultivate the land because wind turbines occupy just a small portion of it. Landowners receive additional revenue because of lease payments made by wind turbine owners to farmers or ranchers for use of the property (Kajela & Manshahia, 2017). In addition, it benefits society as a source of jobs, as a domestic source of energy that engages the local community, and as a contributor to the growth of the world economy. Hybridized with other renewable energy systems, it is also capable of powering energy deserts when conventional energy is not possible (Maradin 2021; Lakatos, Hevessy & Kovács 2011).

On the other hand, wind power systems must still compete on a cost basis with conventional generating sources because of their comparatively high initial cost (Elkadeem et al. 2020). Nevertheless, wind energy system investments might be advantageous in the long run. Notable is the fact that good wind locations are frequently located in rural regions, far from cities where power is most required. Typically, transmission lines must be constructed to transport the energy from the wind farm to the city. Transmission line construction may considerably increase the price of increasing wind power. It is crucial, then, to situate renewable energy systems closer to the load, particularly in regions where other sources, such as conventional resources or the national grid, need expensive power feed-in equipment.

Wind turbines may also generate noise and visual pollution. Although wind turbines have a relatively low environmental impact compared to traditional power plants such as coal-fired power plants or diesel generators, there are still issues regarding the noise generated by the turbine blades and the aesthetic impact on the landscape. Small birds have been killed by turbine blades after colliding with them in flight. Recent technical advances in the manufacturing of wind turbines have eliminated or substantially reduced most of these issues. Wind farm noise emissions may be lowered further by wind turbine design and strategic placement (Wang & Wang, 2015).

2.2.6 Biomass Energy

Biomass energy production includes the process of producing fuel from plant and animal waste, either locally or with simple technology (Kajela & Manshahia 2017; Bhandari et al. 2015). Biomass technology mainly uses organic matter in which the energy of sunlight is stored in chemical bonds. When the bonds between carbon, hydrogen and oxygen molecules are broken, the stored energy is released. Biomass energy can be consumed in urban and rural communities (Aliyu et al. 2018). There are primary, secondary, and tertiary sources of biomass energy. Primary biomass energy is derived directly from plants and is produced directly through photosynthesis. Examples are wheat straw, tree bark, corn stalks and so on. Secondary biomass energy is the results of physical, chemical, or biological processing of the primary resources. Examples of secondary biomass resources are sawdust in mills, liquor from the pulping process, animal manure, etc. Tertiary biomass resources are all other biomass derived from post-consumer residues, including fats and oils (vegetable oils, fats, animal fats) (Owusu & Asumadu-Sarkodie 2016).

Due to the variety of biomass resources, there are various conversion technologies that can convert biomass resources into usable energy, i.e., electricity, heat, or fuel. In general, the conversion processes include incineration, gasification, and fermentation (Sharma et al., 2014). In the combustion process, biomass resources are burned in a boiler to generate high-pressure steam that drives a turbine that may be linked to an electrical generator. Gasification transforms biomass resources into fuel gas or syngas that may be burned. Digestion is suitable for wet biomass resources ranging from feedstocks such as municipal solid waste, organic industrial waste, manure, sludge, etc. Aerobic digestion transforms biomass, especially waste products like municipal solid waste and market garbage. A bioconversion process in which active bacteria break down organic materials in the absence of oxygen and create methane and carbon dioxide is ecologically favorable, and cost-effective. The wastewater and fermenter residues, which are rich in nitrogen and phosphorus, can be returned to the soil as organic manure or fertiliser (Kajela & Manshahia 2017).

The importance of biomass will further increase its acceptance as national energy policies and strategies follow the trend towards renewable energy sources (Sharma et al. 2014a). The energy source biomass has gained particular interest in recent years due to the ongoing reduction in conventional fossil fuels, which has led to an increasing use of renewable energy sources. Biomass technologies and uptake are widespread across Europe and bioenergy applications are becoming increasingly popular in developing countries (Malico, Nepomuceno Pereira, Gonçalves & Sousa 2019; Mugodo et al. 2017). The use of homogeneous wet organic waste for bioenergy production is widespread, although heterogeneous wet waste such as municipal waste can also produce energy. For example, biogas with a high methane content (about 60% or more) is the by-product of anaerobic digestion (Heydari & Askarzadeh 2016), which breaks down organic matter in the absence of oxygen. An anaerobic digester can convert energy stored in organic matter contained in manure, industrial wastewater, or sludge into biogas (Sharma et al. 2014).

Biogas could be used to cook, light lamps, or generate electricity. Power generation from biomass ranges from a few kilowatts of energy (kWe) to several megawatts of energy (Mwe). Many considerations, including biomass feedstock type, volume/amount of biomass and their peculiar characteristics, end-use requirements, environmental legislation, economics, geography, and project-specific factors, impact the choice of conversion method. The conversion process is determined by the kind of energy required and the availability of raw materials. The implementation and operation of biomass conversion technologies impact the greenhouse gas (GHG) emissions that may come from their use(Singh, Singh & Kaushik 2016; Sharma et al. 2014).

The potential for power generation from biomass is significant in South Africa, for example, where some of the paper packaging and sugar mills burn bagasse with biomass to generate steam and generate about 210 GWh of electricity annually (Aliyu et al. 2018). Biomass, considered renewable and carbon-free, has its own ecological disadvantages. The biggest challenges for energy production from biomass include food security, biodiversity, water scarcity, high investment costs, strong competition with fossil fuels, and availability of raw materials (Aliyu et al. 2018). Therefore, it is important to think about effective monitoring of biomass resources and their availability for sustainable power generation. Table 2.1 summarizes the different forms of renewable energy sources and their use to generate electricity. Table 2.1 summarizes the various forms of renewable energy sources and their use in power generation.

Table 2.1: Renewable energy sources and their use

Source	**Option for energy conversion and utilization**
Hydropower	Electricity generation from hydropower
Geothermal	Power generation, hydrothermal, city or domestic heating
Ocean/wave	Barrage, tidal stream, several designs
Solar	Power generation, thermal power, solar dryers, water heaters
wind	Electricity generation, windmills, water pumping
biomass	Power generation, heat generation, gasification, digestion

Source: (Owusu & Asumadu-Sarkodie 2016)

Despite the benefits of using renewable resources in power generation, sole sourcing a power system with any renewable resource compromises the system's security. For instance, if a power system exclusively relies on solar energy, then in the absence of the sun at night or during cloudy days the system cannot generate the needed power. Similarly, using wind alone to power an energy generating system will amount to a system failure when the wind is not blowing above a minimum threshold or is blowing excessively beyond the wind turbine rated cut-off speed. In any of the aforementioned situations, a backup power source is necessary to keep the energy-generating system operational and supply the energy demand. The alternative energy source could be provided by battery bank, a conventional diesel engine, a power retention system such as a biogas gasifier/bio generator, or the grid if the system is connected to it.

An ideal solution presented in most of the literature is the hybridization of two or more renewable energy technologies that can complement each other to provide electricity reliably (Nehrir et al., 2011; Shivarama Krishna & Sathish Kumar, 2015). In several cases, hybrid systems based on solar and wind were more suitable (Alsharif, 2018; V. Khare et al., 2016), among others because of their environmental and economic and technological advantages. Additionally, both solar and wind technologies have evolved over several decades, in contrast to tidal/wave, which is still in its infancy, and hybrid solar and wind power systems may not require a huge area of land for their construction, unlike hydropower systems, which will require construction of dams and reservoirs. Also, solar PV modules could be mounted on building roofs.

In the next section, the study focus is on the investigation of HRES to generate a reliable but economic power supply. The importance of hybridizing power systems is discussed using a few examples. Finally, in this section we will look at how the model and turn an HRES design problem into an optimization problem with the appropriate mathematical models used to estimate the amount of energy produced from the different components of the HRES.

2.3 Hybrid renewable energy systems

An HRES integrates two or more renewable energy sources, or at least one renewable energy source and another non-renewable energy source, to satisfy the energy requirements of the load related to the power system. Such a power system can operate independently in a stand-alone mode or be connected to the grid infrastructure. With advances in renewable technology and the power system electronics used to modulate power from the renewable power source to the load, the use of HRES is becoming increasingly attractive, particularly for rural and urban electrification projects. Effective utilization of the operating characteristics of power generation technologies to achieve greater efficiencies than would be possible by installing an unit power source for a given region is another reason for the recent high adoption rate of HRES. When dealing with hybrid power generation systems, several factors must be considered. The most important features include reliability of the power supply, economic factors, and environmental concerns, which some authors describe as the energy trilemma (Šprajc et al. 2019; Hannan et al. 2018). There are many good reasons to choose hybrid power generation systems over single source power systems as the former are more reliable and cost effective. In addition, the authors Kajela & Manshahia (2017) attribute the widespread adoption of the HRES system to increasing awareness of climate change, rising fuel prices, fuel transportation costs, etc., and similar factors are repeated (Kalananda & Komanapalli 2021).

The economic benefits of renewable hybrid systems are enormous and promising for sustainable power generation in developing countries (Schwerhoff & Sy, 2017; Tazvinga et al., 2020). However, the two popular renewable energy sources, namely sun and wind, are climate dependent. These resources have a random distribution curve inherent in their nature. Solar energy potential varies during the day, and it is not available at all at night. Wind resources, on the other hand, are sporadic, they may not be available when electricity is needed most, as a fair distribution of wind speeds is observed at night (Celik, 2003; Lakatos et al., 2011). Therefore, to generate sustainable renewable energy, combining wind and solar energy technologies together with energy storage systems (ESS) such as batteries can improve system reliability (Mohamad & Teh 2018). In some instances, biomass resources could provide even more security and economic value to the power system (Porcu et al. 2019; Heydari & Askarzadeh 2016).

Renewable energy sourced from solar, wind and biomass has proven useful and satisfactory over the years to mitigate the energy crisis in some countries (Das & Mahanta, 2019a; Singh, Singh, Kaushik, et al., 2016). These resources are universal and have positive environmental impacts (Mayer et al., 2020), once installed they require very little or no fuel costs (Sharma et al., 2014). Recently, the adoption of renewable energy technologies is spreading rapidly to meet society's ever-increasing energy demands (Kajela & Manshahia, 2017), but these resources are unreliable due to the stochastic nature of their occurrence. HRES powered by a combination of wind turbine, solar PV system and biomass generator can overcome the weakness of a stand-alone source.

In addition, the introduction of renewable-based power system used for rural electrification systems in areas where grid expansion is not feasible can be optimized for economic benefits. When extending grid power to outskate, dispersed or rural communities, due to long distances, cable costs, costs of digging ditches or costs of acquiring electricity poles, and other logistics the expenditure for electrification project could be unreasonably high. A HRES located near to the site might save operating expenses by decreasing fuel usage, enhancing system efficiency, and decreasing noise and pollution (Askarzadeh 2017). When a hybrid PV-wind system is outfitted with biomass generators to meet peak load demand during the brief periods when there is insufficient energy to fulfil load demand, the system's dependability can be significantly enhanced. (Nawaz, Rahim, Shakoor & Anwar 2019; Singh, Singh, Kaushik & Chandra 2016). Such a hybrid system configuration could efficiently manage the use of a diesel generator, battery bank, or other energy conservation systems.

Even if an energy storage system (ESS) such as batteries is attached to the hybrid system, the battery life will be prolonged if the batteries are kept near to 100 percent of their capacity or returned to this level after a partial or deep drain.(Liu, Chen, Yang & Shan 2021; Chakir, Tabaa, Moutaouakkil, Medromi & Alami 2019). The usage of PV modules alone may not always provide protection against severe discharge for batteries. During periods of little or no sunlight, the load consumes more energy than can be replaced by PVs(Kajela & Manshahia 2017; Shivarama Krishna & Sathish Kumar 2015). Wind turbines are a more dynamic energy source that complements solar power plants. By adding a biomass power system, such as a gasifier or reactor, to function as a power conservation unit, a PV-wind hybrid system could protect batteries from deep depletion, thus extending their lifespan and increasing system reliability(Kajela & Manshahia 2017).

2.3.1 Importance of Hybrid Energy

The application and adoption of hybrid systems has increased in recent year as they appear to be the best answer for clean and decentralized power generation(Kajela & Manshahia 2017). By using hybrid wind/PV/biomass systems, the system can reliably improve power supply. There are several good reasons for choosing an HRES. Since the energy sources can adjust for each other's power variations, the system's daily production is reliable and stable. Even if the amount of sunshine changes, the total system will create energy day and night because wind power is not restricted by its availability. Obviously, output will be greater during the day, but it does not cease at night. Should both wind and solar PV fail, a biomass power plant could serve as electricity storage to expand the power supply. Second, a PV-wind hybrid system helps mitigate seasonal changes, since wind turbines are more useful during the winter and solar PV systems are more resourceful during the summer. Together, the two systems are more productive annually; seasonal changes in production are evened out. In addition, the biomass system stands by to cover the supply deficit in case the hybrid system cannot meet the load demand(Singh, Singh, Kaushik, et al. 2016).

It is highly recommended to integrate the battery storage system with a PV-wind based hybrid system to achieve grid-level reliability or better (Hadidian Moghaddam et al. 2019; Moghaddam, Bigdeli, Moradlou & Siano 2019). Should a battery bank be needed in off-grid mode, the size of the energy storage could be reduced to the bare minimum to reduce replacement costs. Because one of the main sources could work during the day and the other could work at night. This phenomenon could cause batteries to also undergo a less aggressive charge/discharge cycle, increasing their lifespan (Kajela & Manshahia 2017).

Another important feature of an HRES if biomass gasifier is available is that it could be utilized to store electricity and be made smaller because there is less uncertainty about the combined wind and solar energy supply (Das & Mahanta 2019). A smaller biomass size means lower operating and maintenance costs for the system due to the minimal amount of biofuel to run the biomass engine. Finally, there are associated economic, environmental, social, and geopolitical benefits (Mayer et al. 2020; Guezgouz et al. 2019) associated to implementing a hybrid energy system as an alternative to the traditional fossil-based option in rural settlements. By using hybrid wind/PV/biomass systems, the system can reliably improve power supply. In general, implementing a wind PV biomass HRES offers the following advantages compared to a single source based system These include greater power supply dependability; reduced energy storage capacity, particularly when different sources exhibit complementary behaviors; improved efficiency and longer battery life; and economically minimal levelized life cycle power generation costs when the optimal design technique is implemented. Table 2.2 outlines the general advantages and disadvantages of HRESs gathered from previous studies.

Table 2.2: Advantages and disadvantages of HRES as discussed in previous research

Advantages	**Disadvantages**
Use of the natural and renewable sources which **are** free and eco-friendly	Initial expenses for these systems are more than for conventional generators of comparable capacity.
Low level of O&M costs compared to diesel generator	These systems have greater upfront costs than conventional generators of comparable size.
There is no pollution or waste generated by natural sources.	Relatively high cost owing to high initial capital, regular maintenance cost, and battery replacement cost
Minimizing the intermittency as one sub-system complements the other	Peak loads cannot be effectively handled without energy storage.
Lower atmosphere pollution	The difficulty of the design method
Fuel savings because of free renewable resources	Monthly fee charge for maintenance

Therefore, to achieve better performance from an HRES at a reasonable cost, it is crucial to optimally design the system components and accurately size the power generation units (Faccio et al. 2018; Siddaiah & Saini 2016). In the next section, we will discuss the processes for designing and implementing HRES to create the best system that can withstand the stochastics of the climatic weather pattern. Here we highlight the modeling of hybrid renewable energy system components as an empirical approach to the design process. Once the components are mathematically modeled, they are translated into an optimization problem that is plausible to solve using optimization techniques.

2.3.2 Implementation of Hybrid Renewable Energy System

In order for an HRES to function optimally, the physical and technical limits of the system must be observed (Mayer et al. 2020). Physical issues include the geographic location for placement of the power generation system (Kajela & Manshahia 2017). The location of the standalone HRES has a direct impact on the power generation capacity. A hybrid PV/wind system relies on on-site climatic weather data to generate electricity. The technical constraints, on the other hand, include the technological characteristics of the power generation system along with their thresholds and specifications for any given condition (Kajela & Manshahia 2017). It is worth noting that the exact assessment of the components of a hybrid system results in the desired dimensioning of the system(Murugaperumal & Ajay D Vimal Raj 2019). If a system is under sized, it compromises system security and makes it unreliable. However, an oversized system can be reliable, but adds enormous and unnecessary cost to the system, making it economically unattractive (Murugaperumal & Ajay D Vimal Raj 2019; Nawaz et al. 2019; Singh, Singh, Kaushik, et al. 2016). To derive a satisfactory result from a hybrid renewable energy system, it is crucial that a feasibility study is conducted to assess the optimal configuration of the HRES.

2.3.2.1 Feasibility Study

The evaluation of the practicability of hybrid renewable energy systems is one of the most often debated problems in this field. Typically, an HRES feasibility study is done for the desired site. This analysis comprises a review of the proposed site's climatic parameters, the availability of renewable energy sources, and an evaluation of the prospective load demand Figure 2.1 and Figure 2.2 depict the global distribution of wind energy and solar energy potential (Ganguly et al. 2018).

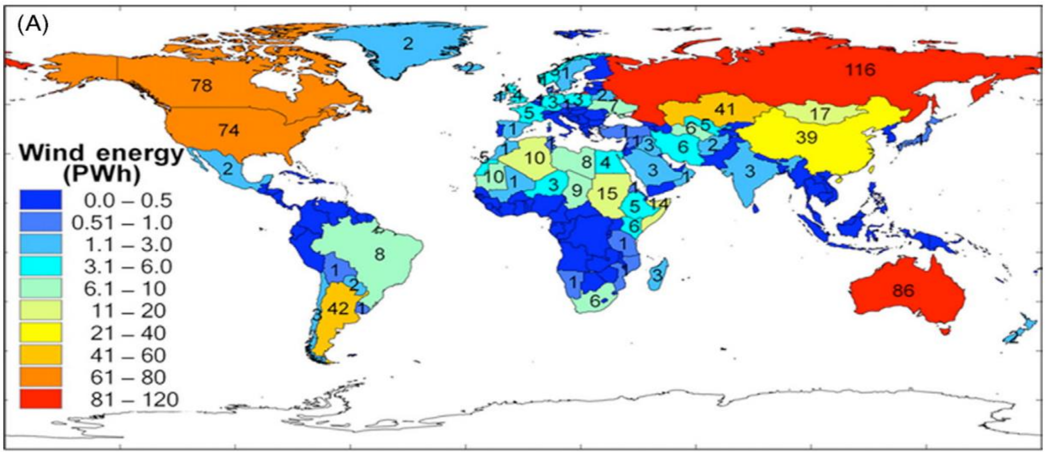


Figure 2.1: Annual wind energy potential country by country, restricted to installations with capacity factors >20% with siting limited. (A) Onshore

Source: (X. Lu et al., 2009)

Prior to installing and operating an HRES, this study is conducted to determine the potential for developing an HRES for a site (Nawaz et al. 2019). The primary features of solar and wind energy in any region rely on the local climate and weather conditions. Changing climatic factors, such as solar radiation, air velocity, and air temperature, exist to varied degrees at different locations. To make more efficient use of solar and wind energy, it is necessary to perform an assessment of solar radiation and wind conditions, as well as an appropriate location to site the system.

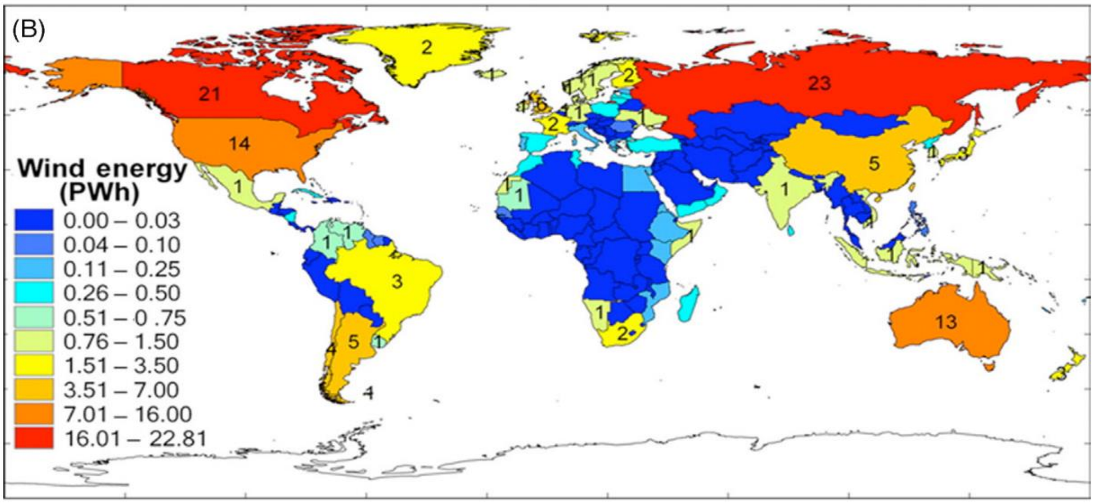


Figure 2.2: Annual wind energy potential country by country, restricted to installations with capacity factors >20% with siting limited (B) Offshore.

Source: (X. Lu et al., 2009)

The feasibility of building a solar wind based HRES mainly depends on the solar irradiance and wind energy potential of the target site. Figure 2.3 shows the global solar energy potential of the regions around the world. Therefore, suitable weather data is required for the design of a hybrid renewable energy system. The evaluation of the appropriate RES technology for the target site should be carried out with precise data and information related to the long-term availability of all possible RES (e.g., radiation and other RES measurements). The two common means of obtaining relevant climate data for application in renewable energy system projects are time-series meteorology or statistical meteorology approaches. It is equally important that the operation of a renewable energy system is evaluated against a reasonable time frame by considering current electrical energy demand and future developments of the HRES to meet changes in electrical energy demand (Ganguly et al., 2018).

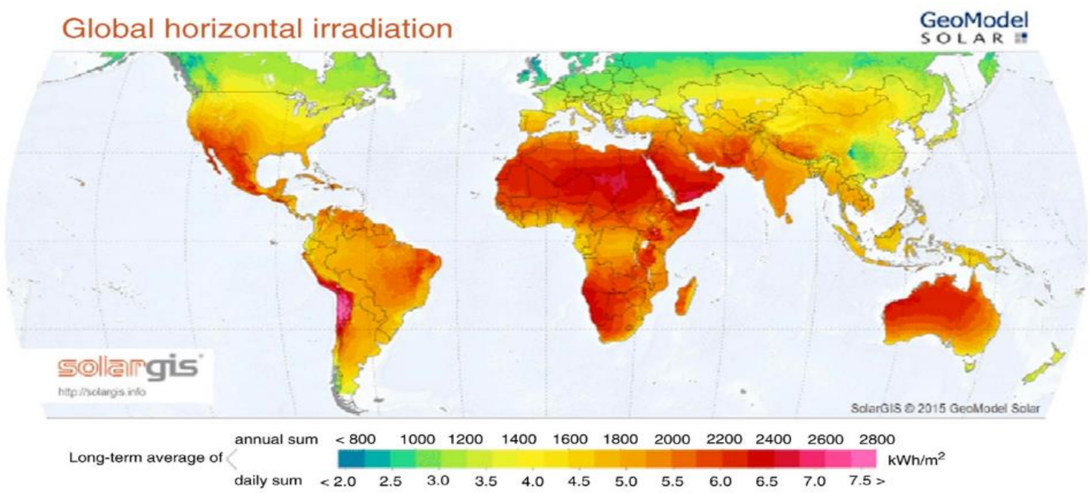


Figure 2.4: Global solar energy potential of the various regions around the world.
Source: (Ganguly et al. 2018)

2.3.2.2 Time-series meteorological data

Long-term system performance is one of the most important design factors for self-sufficient hybrid solar-wind energy systems. Several researchers employed meteorological time series data (Guezgouz et al. 2019; Ganguly et al. 2018) for the feasibility evaluation and design of the HRES. For high performance of these systems, meteorological data including weather data with hourly solar radiation, wind speed, and ambient temperature are necessary. (Ashraf et al. 2020; Moghaddam et al. 2019). The local weather station is one of the sources from which one can easily get information about the global weather. These worldwide local weather trends can be used to evaluate the performance of an HRES. The meteorological baseline from site to site is often required to find the best potential solution. Most research has been conducted to determine the viability of installing solar and wind energy resources in different areas or countries by studying solar and wind energy resources (Abdelaziz Mohamed & Eltamaly, 2018; Y. Li et al., 2017; Prieto et al., 2009).

2.3.2.3 Statistical meteorological data

Hourly records of climate variables over long periods of time are often unavailable for most locations. When measured meteorological data for a location are missing, there are two main approaches to obtaining them. The first way to get the required weather data is to combine it with the monthly averages of the available local meteorological data. Statistical properties of solar irradiance and wind speed can be exploited for this purpose. Second, by making the appropriate corrections, neighbouring weather data can be extrapolated to provide the weather information. Working with synthesized weather data is useful when the amount of weather data for an area is limited, as it reduces the computational load for simulation studies. Most research has focused on the technique utilized to generate solar radiation, wind speed, and temperature data. Prieto & and García (2022) conducted a study on several existing solar irradiance models based on monthly measured temperatures. Additionally, the authors presented a modified temperature-based global solar radiation estimating model for places that lack experimental data (Prieto and García 2022). In Irwan et al. (2013), using the Hargreaves model, the authors estimated the solar irradiance for Kelantan, East Malaysia, in 2011. This estimate is based on the latitude of Kelantan and the daily minimum and maximum temperatures. The observed and projected figures for 2011 solar radiation were compared. The preceding findings indicate that the Hargreaves model may be utilized to predict solar irradiation. Prieto, Garcia, and Garcia suggested a correlation model based on air temperature data to predict monthly mean values of insolation in unmeasured nations. The suggested model was shown to be suitable for the meteorological station data gathered in Asturias, Spain by entities with official status. The methodology was also applied to four other Spanish stations to verify the procedure in locations of different latitudes and climatology (Prieto et al., 2009).

The feasibility assessment of PV/wind-based hybrid renewable system gives the right sizing of the system component which considers the energy storage capacity or auxiliary power storage unit like biomass gasifier. Other controlled energy sources, such as biomass (biogas generator) or energy storage devices, are more suitable for managing the variable nature of solar and wind power supplies (Chakir et al. 2019; Bakhtiari & Naghizadeh 2018), since solar and wind resources cannot be used continuously due to the load the variability and inconsistency of environmental conditions. However, these power derating components introduced to reliably stabilize the power supply add to the complexity of the system design. There is therefore a need for optimization tools/techniques that can efficiently deal with the complex system components. This approach must provide a feasible optimal solution to the problem at hand. Figure 2.5: A scope diagram for the various aspect of HRES optimization is a domain diagram showing the various aspects of HRES.

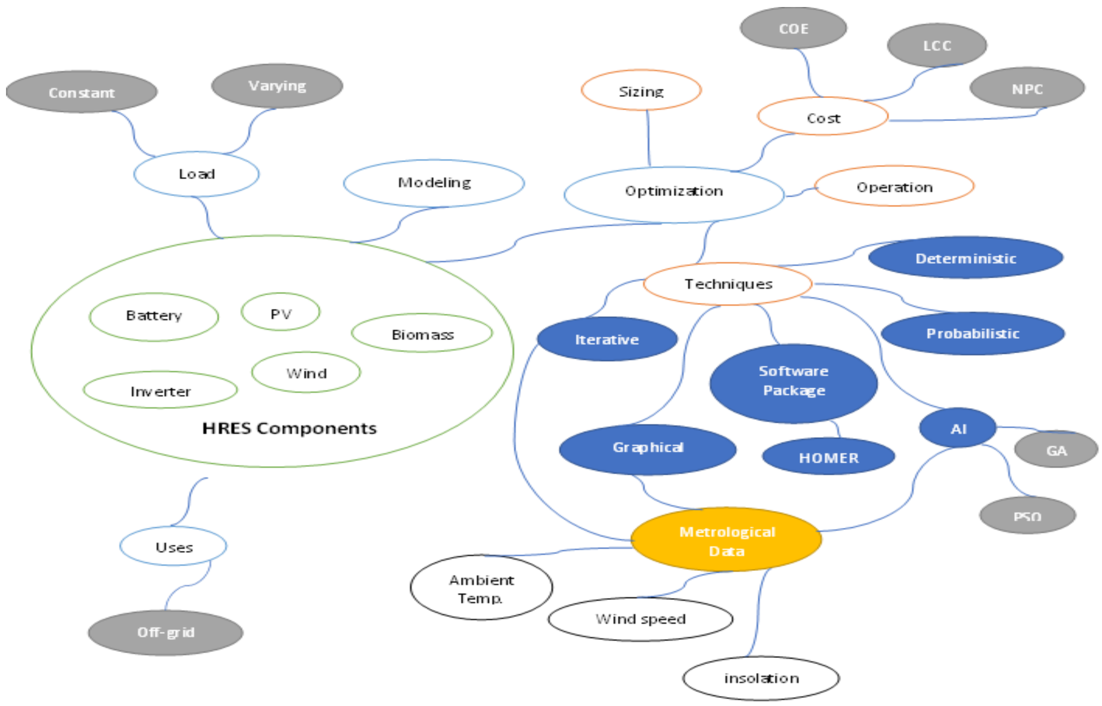


Figure 2.5: A scope diagram for the various aspect of HRES optimization

Solar and wind-based renewable resources are not consistent throughout the year due to the stochastic nature of climate conditions. Meanwhile, the system could be connected to a constant load or a variable load (Singh, Singh, Kaushik, et al. 2016). In order for a hybrid system to provide sustainable energy, measures must be taken to maintain energy balance at most times of the year. Therefore, optimizing HRES will lead to the most efficient sizes for the hybrid system components to attain the design objectives. Optimizing a hybrid renewable energy system is a precursor to reliable energy supply, economic, and environmental benefits (Kajela & Manshahia 2017; Sinha & Chandel 2014). The component sizing is the crucial aspect of most HRES optimization problem (Bukar et al., 2019; Frimpong, Millham, & Agbehadji, 2021; Nabipour-Afrouzi et al., 2018).

2.3.3 Hybrid wind /PV/biomass Renewable Energy System components

There are several methods to setup an HRES system comprised of PV Systems, wind turbine, and biomass sources to create reliable and cost-effective electricity. This system will consist of solar panels, wind turbines, biomass generators, optional energy storage devices (batteries), converters and inverters, and microcontrollers. These components work as follows:

Solar photovoltaic: This is the basic device to capture solar radiation and convert solar energy into direct current. Photovoltaic, then, is the process by which solar radiation is absorbed by solar cells to induce electricity production (Wilberforce et al. 2019; Rashad, El-Samahy, Daowd & Amin 2013). Solar PV/cell is made of semi-conductive material that can emit electrons (charged particles) when it receives solar radiation from the sun (Khare, Nema & Baredar 2016). It includes turning solar energy into electrical energy via the photoelectric effect, a standard principle. The solar cell array or panel is comprised of a suitable number of solar cell modules linked in series or parallel dependent on the desired current and voltage. When developing a solar PV based hybrid system, it is necessary to estimate the number of solar panels or the total area of the solar panels in order to calculate the amount of energy that the solar system can supply (Kajela & Manshahia 2017).

Wind turbines: This is the equipment required to convert wind energy to electricity. The quantity of energy a wind turbine generates is dependent on the wind speed acting on the turbine. A wind turbine's electrical generator turns kinetic energy into electricity. The generator rotates a wind wheel, which powers a wind generator or wind turbine to generate energy (Pfenninger et al. 2014). A rated wind turbine utilizes the wind speed at a specific instant as an input parameter to estimate the wind turbine's output power (Bhandari et al. 2015).

Biomass (biogas gasifier): biomass resources come in different forms and states, including solid, liquid and gas(Kumar, Sinha, Taylor & Alqurashi 2015). Due to the wide variety of biomass, it can be a cumbersome fuel(Kumar & Patel 2008). However, the conversion of biomass to gas makes it versatile to meet a broader range of energy needs including electricity(Bloch-michalik & Gaworski 2020; Kumar et al. 2015). A commercially proven technology for converting wet organic waste and wastewater into biogas is anaerobic digestion. The process produces about 60% methane and about 40% carbon dioxide (Scholz, Melin & Wessling 2013). With proper treatment, the gas produced by anaerobic digestion may be utilized in secondary conversion devices such as an internal combustion engine to create energy (Ekstrand et al. 2013). Almost any biomass including animal and human waste/excreta (Andriani, Wresta, Saepudin & Prawara 2015), biogas may be produced from sewage sludge, agricultural products, industrial processing by-products, and landfill materials, etc. For biogas, the electrical energy is estimated by calculating the calorific value per biogas volume (m^3) produced. Such an estimate informs the configuration size or capacity of the biogas generator for the hybrid system(Heydari & Askarzadeh 2016).

Batteries/energy storage system: batteries are storage devices that store electricity when the renewable systems produce a surplus of electricity that exceeds demand; and they release stored potential in the form of electricity when there is a supply shortage. Therefore, energy storage systems are among the few ways to bring stability into the system by ensuring that load demands are always met. When developing a hybrid power system, the feasibility analysis of the battery system must include size and arrangement type, parallel or series (Momoh & Reddy 2014). By linking batteries in series or parallel, the desired voltage or current storage capacity may be enhanced. The sizing of batteries in an HRES is determined by several variables, including the system's load and the size of its renewable power producing units (El, Yousef & Fergany 2020).

Inverters: These are devices that convert between AC and DC based on the system setup or the power requirements of the connected load. For example, the stored energy in a battery is obtained from the main supply via the inverter, which transforms direct current to alternating current. There is protection against circuit breaker, opposite voltage, and overheating on the inverter. To increase an inverter's lifespan, capacitors or energy storage systems can be incorporated into a HRES (Faccio et al., 2018). If the bidirectional inverter is linked to alternating current (AC), an inverter must be positioned between the PV array output and the inverter. However, the output power influences the efficiency of the inverter.

2.3.4 Model of the Hybrid System Components

Modelling of the individual components of HRES is an important phase in designing and implementing a reliable but cost-effective hybrid system. Modelling the system’s components makes it suitable for further computations and analysis to justify the choice of system combination to meet desire objective(s) (Sanajaoba Singh & Fernandez 2018; Kalappan & Ponnudsamy 2013; Milan, Bojesen & Nielsen 2012). The various components of a hybrid system must be represented mathematically before their combination can be evaluated to meet a specific design objective (Suresh et al. 2020; Milan et al. 2012). A generic modelling technique for PV, wind turbine, biomass, and battery bank is provided in the next section.

2.3.4.1 Modelling of PV system

By analysing the maximum output power behaviour of the PV modules, modelling a PV system ensures that the system is built to provide maximum power. The design approach for a PV system model is generally based on a clear voltage-current curve as shown in Figure 2.6. This curve depicts the characteristics relevant to the power generation of a PV system, specifically the short circuit current point (I_{sc}), the maximum power point (MPP), and the open circuit voltage point (V_{oc}) (Bouali, Schulte & Mami 2019). At the first point I_{sc} the voltage across the circuit is zero, therefore the current inside the circuit is the same as the short-circuit current. At the MPP the current has a value I_{mp} and voltage V_{mp}, and this is the point where the PV module could produce maximum power (Bouali et al. 2019). Eventually the current through the circuit will be zero and the voltage will be at open circuit voltage. The characteristic behavior of these parameters is specific to the arrangement of the PV modules specified in the manufacturer's data sheet (see example in Appendix A)

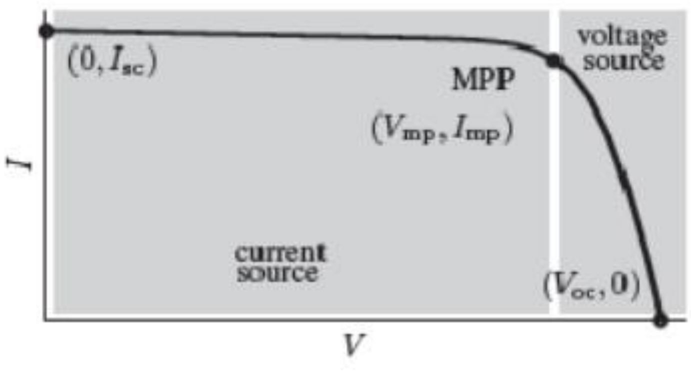


Figure 2.6: Voltage-Current Curve of PV module

Representing the operating conditions of a PV module with mathematical equations is essential and primary task in estimating the amount of power the system could generate. The mathematical equations establish relationships among the parameters for calculating the power output of PV panel. The output power generated by a PV array is dependent on a defined temperature at a given time and standard temperature conditions (STC) solar irradiation. Using the solar radiation available on the solar panel's slanted surface, the ambient temperature T_c and the manufacturers output of the PV generator, the following equations are deduced for calculating the PV power $Pv_{(t)}$ generated at a given time t (Sánchez et al. 2021; Singh, Singh, Kaushik, et al. 2016)

$$Pv_{(t)} = \eta NAG_{(t)} \tag{2.1}$$

where η denotes the PV generation efficiency, A (m^2) is the area of a single PV module used in the setup, N is the number of PV modules constituting the PV arrary, and $G_{(t)}$ (W/m^2) is the incident solar irradiation on the tilted module plane. Certain assumptions are made to cater for energy losses within the system. For example, connection and wiring losses are assumed to be zero. The efficiency η of the PV generator considering all losses is further related to the ambient temperature T_c (Kharrich, Mohammed & Akherraz 2020) as:

$$n = \eta_r \, [1 - \beta(T_c - T_{cref})] \tag{2.2}$$

where η_r denotes the reference module efficiency, T_{cref} is the reference cell temperature in ℃, β is the temperature co-efficient of PV panel. The efficiency of the power tracking device is equal to 1 if a perfect MPPT is used. T_c is the temperature (℃) of the PV cell. T_c can be calculated by the following equation (Diaf, Diaf, Belhamel, Haddadi & Louche 2007).

$$T_c = T_{air} + (\frac{NOCT - 20}{800})R_t \tag{2.3}$$

T_{air} is the air temperature given by the temperature profile, $NOCT$ is the operating temperature of the solar cell in ℃ and R_t is the solar radiation in an instant of time (t) given in (W/m^2). The estimated values of $NOCT$ = 28℃ , and T_{cref} =25℃ (Khan & Javaid 2020).

2.3.4.2 Modelling of Wind Turbine system

The wind turbine power output depends on two main input parameters namely, wind speed at s given hub height, and the characteristics of wind speed (Bhandari et al. 2015). The wind turbine has a distinctive power curve that explains the relation between wind speed (m/s) and the power it can generate (see Figure 2.7: Wind speed power characteristics). An accurate estimation of the wind speed at hub height is calculated using power-law equation (Thapar, Agnihotri & Sethi 2011) as given in (2.4).

$$\frac{V_z}{V_h} = \left[\frac{Z}{Z_h}\right]^x \tag{2.4}$$

where V_z and V_h are wind speeds at hub height and reference height Z and Z_h respectively, and x is the power law exponent which is a function of both the atmospheric stability in the zone and a typical value for low roughness of the site; x is evaluated to be valid for the surface area characteristics (Bhandari et al. 2015). In an open land for example, x is estimated to be 1/7 (Diaf et al. 2007). Once the wind speed has been properly modeled and sufficient but accurate wind data is available, the power produced by the wind turbine at any given point in time $Pw_{(t)}$ can be estimated. Energy is generated between the cut-in wind speed V_{ci}, and the cut-out wind speed, represented as V_{co}.

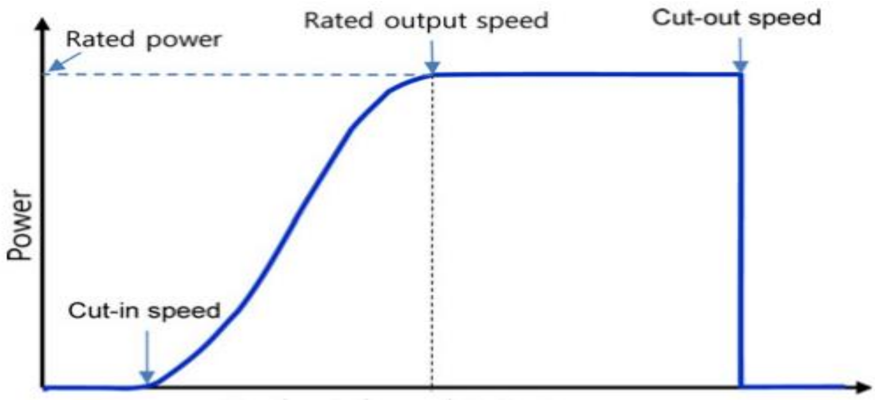


Figure 2.7: Wind speed power characteristics

The output power $Pw_{(t)}$ of wind turbine generator is calculated using Equation (2.5) (Bhandari et al. 2015; Thapar et al. 2011) :

$$Pw_{(t)} = \frac{1}{2} C_p \rho A V_{(t)}^3 \tag{2.5}$$

where C_p denotes the power coefficient for the wind turbine characteristic, ρ is the air density (kg/m3), A is the swept area of the wind turbine rotor (m^2), V is the velocity of the wind.

The wind turbine is characterized by the speed-power curve which is represented as a spline curve (Bhandari et al. 2015). The curve depicts Cut-In speed (V_{ci}), Cut-Out speed

(V_{co}) and rated/nominal wind speed (V_r) of the wind turbine. The V_{ci} is the minimum wind speed threshold with which the wind turbine starts to rotate and generate power; the V_{co} is the maximum wind speed threshold beyond which the wind turbine rotates very fast and stands the risk of damaging the rotor, so a breaking mechanism is enforced to halt the system when V_{co} is exceeded. The V_r is the wind speed between V_{ci} and V_{co} where the power output reaches the maximum. Most wind turbines do not have a uniform gradient line between cut-in wind speed and the rated wind speed. Hence the power characteristic curve as a function of the wind speed is given by Equation (2.6) (Bhandari et al. 2015; Thapar et al. 2011):

$$Pw_{(t)} = \begin{cases} 0, & if\ v(t) < V_{ci} \\ \frac{P_r}{(V_r^3 - V_{ci}^3)} v_{(t)} - \frac{V_{ci}^3}{(V_r^3 - V_{ci}^3)} P_r, & if\ V_{ci} \leq v(t) < V_r \\ P_r, & if V_r \leq v(t) < V_{co} \\ 0, & if\ \ v(t) > V_{co} \end{cases} \quad (2.6)$$

where, P_r is the rated electrical power generated by the system.

Calculations of wind turbine performance must account for the implications of wind turbine installation height. Available power P_W, from the wind turbine can be calculated by (Bhandari et al. 2015):

$$P_W = Pw_{(t)} A_{wind} \eta \quad (2.7)$$

A_{wind} denotes the swept area the wind turbine/blades displace, and η is the wind turbine generator and converter efficiency.

2.3.4.3 Modelling of biomass engine

The estimation of biogas production is highly dependent on characterization and nature of biomass (solid or liquid waste) used in the process. Solid wastes are characterized by type of waste, quantity of waste per feedstock, percentage of total solids, percentage of volatile solids, and biogas yield per ton of feedstock (Bajwa, Peterson, Sharma, Shojaeiarani & Bajwa 2018; Kajela & Manshahia 2017). Similarly, liquid wastes are also characterized by type of waste, waste generated per litre of wastewater, chemical oxygen demand (COD) degradability, and biogas potential per ton of feedstock (Ekstrand et al. 2013). For the calculation of solid waste biogas potential, the following Equation (2.8) is applicable

(Obileke, Mamphweli, Meyer, Makaka & Nwokolo 2021; Ekstrand et al. 2013). The combustible dry matter in solid waste is proportional to the amount of biogas that could be generated, hence for an one-year period, the total amount of volatile solid TVS $_{substrate}$ generated (Kumar & Prasad 2020)is given by:

$$TVS_{substrate}\left(\frac{ton}{year}\right) = SG\left(\frac{ton}{year}\right) \times TS\% \times VS\% \tag{2.8}$$

where SG is the solids generated within the year; this quantity could be determined from the feedstock to be used, TS is the total amount of solids which is the percentage of solids in the biomass, and VS is volatile solid which is the percentage of the combustible solids in TS. The total VS is function of the biogas yield (m^3 biogas/kg VS) for each substrate.

Therefore, for solid waste annual biogas production is given by (Bajwa et al. 2018; Heydari & Askarzadeh 2016c):

$$Biogas\left(\frac{m^3}{year}\right) = TVS_{substrate}\left(\frac{ton}{year}\right) \times Biogas\ yield\ \left(\frac{m^3}{ton}\right) \tag{2.9}$$

In liquid waste, COD is the key estimation factor of biogas generation, and it measures the chemical digestible materials in wastewater. The concentration of COD varies from one feedstock to the other (Heydari & Askarzadeh 2016). Of the total COD found in liquid waste about 70-90% of their values are utilized to generated biogas from anaerobic digestion particularly for agriculture and agro-processing wastes with various technologies (Joale, Ricardo & Medina 2020). The treated COD $COD_{treated}$ for biogas generation using wastewater is given by(Araoye et al. 2021):

$$COD_{treated}\left(\frac{kg}{year}\right) = TWWD\left(\frac{L}{year}\right) \times COD_{conc}\left(\frac{kg}{L}\right) \times 80\% \tag{2.10}$$

where TWWD is the total wastewater discharged for the year and COD_{conc} is the COD concentration for the feedstock. The total amount of biogas generated from the liquid waste per year is the product total amount of COD generated and the COD biogas yield as(Araoye et al. 2021; Singh, Singh, Kaushik, et al. 2016):

$$Annual\ biogas\left(\frac{m^3}{year}\right) = COD_{treated}\left(\frac{kg}{year}\right) \times Biogas\ yield\left(\frac{m^3}{kg}\right) \tag{2.11}$$

The electrical energy derived from biomass could be estimated by:

$$Biomass_{Energy} = Annual\ biogas\ \left(\frac{m^3}{year}\right) \times \frac{6}{1 \times 10^6}\left(\frac{GWh}{m^3}\right) \tag{2.12}$$

The calorific factor of 6 kWh per m^3 of biogas production is provided in South African context (Mugodo et al. 2017). Meanwhile, the efficiency of electrical energy production from biomass varies between 30 and 36 percent (Sharma, Meena, Sharma & Goyal 2014). Therefore, the electrical energy production from biomass is given by(Hidayati, Utomo, Suroso & Maktub 2019; Science, Fatehi & Bai 2014):

$$Total\ biomass\ energy\left(\frac{GWh}{year}\right) = Biomass_{Energy}\left(\frac{GWh}{year}\right) \times 30\% \tag{2.13}$$

Although the net or resultant electrical energy produced from biomass appears to be on the low side given the efficiency of the resource and processes, the overall benefits of electrical energy produced from biomass for sanitation and the environment in general make them closed an extremely attractive resource. In addition, the hybridization of two or more renewable resources complements each other in situations where the energy demand cannot be met by a single power source. Optimization is a safest way to get the best result from multiple subsystems (renewable technologies) working together to meet users' energy needs (Khan et al. 2018; Al-falahi, Jayasinghe & Enshaei 2017).

2.3.5 Hybrid Renewable Energy System Optimization

The optimization of HRES is an essential subject matter for an economical, clean, comfortable and reliable energy supply. Because the optimal design should meet multiple objectives, the application of a multi-objective optimization approach is preferred to a single-objective solution (Khezri & Mahmoudi 2020). A compromise between different optimization goals can be reached by multi-objective optimization. Usually, a multi-objective optimization issue may be reduced to a single optimization problem by combining all objectives into a single function or by recognizing certain objectives as constraints on the primary objective function (Lian, Zhang, Ma, Yang & Chaima 2019; Borhanazad, Mekhilef, Gounder Ganapathy, Modiri-Delshad & Mirtaheri 2014). The HRES optimization problem is modeled to achieve optimal capacity of components by minimizing/maximizing objective functions considering system constraints (Al-falahi et al. 2017). The most common objective functions, system design constraints, and decision variables in HRES optimization are discussed in subsequent subsections.

2.3.5.1 *Optimization objectives for HRES*

Capital expenses for renewable energy systems are often expensive, despite their low operating and maintenance (O&M) costs and reduced fuel prices. Therefore, an economic study is necessary to identify the ideal cost-benefit ratio and to get the lowest feasible HRES unit pricing. Numerous academics have created the following economy-based sub-models: levelized cost of electricity (LCOE), net present cost (NPC), Total Life Cycle Cost (LCC), annualized cost of the system (ACS), Total System Cost (TCS), and average generation cost (AGC) (Siddaiah & Saini, 2016).

Typically, scientists and engineers study HRES to build commercially feasible hybrid system solutions that supply power reliably to the associated load. The sizing of an HRES system entails locating the most cost-effective combination of all renewable technologies (components) sizes and storage capacity that will fulfil the predicted demand load with the lowest acceptable degree of security. Researchers have embraced most design factors based on economics, reliability, load, etc. for optimally developing HRES (Khan 2020; Lian et al. 2019; Al-falahi et al. 2017). Therefore, an HRES optimization objective focuses primarily on the optimal configuration size for system components that minimizes cost and maximizes power supply reliability.

Appropriate sizing of the HRES components guarantees that the load is always powered reliably and that system components are not excessive, incurring additional capital and maintenance expenses. A HRES that is undersized may appear inexpensive, but it will not reliably fulfill the load requirement. In order to establish a balance between cost and dependability, the majority of HRES setups are created with contradictory objectives, such as decreasing cost while maximizing power reliability. It is necessary to do a technical evaluation for a standalone HRES to fulfil load requirements and reliability standards. Power supply probability (PSP), loss of power supply probability (LPSP), and loss of load probability (LOLP or LLP) are typical reliability criteria utilized in HRES optimization to assure steady power supply to the associated load (Khezri & Mahmoudi 2020). Table 2.3 provides instances of current HRES optimizations, along with their purposes and algorithms/techniques.

Table 2.3: Examples of recent HRES optimization and their objectives

Reference	Components	Optimization Algorithm	Objective	Optimization result
(Husain & Shrivastava 2020)	PV, Wind Energy, DG and Battery,	MOPSO, NSGAII, and NSGA III	multi-objective: minimize LPSP, COE, and maximize Renewable factor	With a minimum COE of 0.0588 $/kWh and a maximum COE of 0.14611 $/kWh, NSGA II outperforms the competition.
(Mohseni, Brent & Burmester 2020a)	PV, WT, micro-hydro turbines, fuel cell, electrolyser, hydrogen storage tank, compressors, power converters, supercapacitors (SCs), and biopower plant	MFOA, DA, SSA_1, ALO, GWO, GOA	optimal sizing of HRES components	MFOA discovered a considerable reduction in NPC, outperforming GA and PSO in terms of solution quality by 2.1% and 3.2%, respectively.
(Geleta & Manshahia 2021)	PV, WT, and battery	Hybrid GWO and GA (HGWOGA)	minimize annual cost	HGWOGA, GA, and GWO determined that the best solution is $5,572.01
(Ebrahimi, Attar & Farhang-Moghaddam 2021)	WT, PV, DG, and batteries,	NSGA-II	multi-objective model to size HRES	renewable energy efficiency of 80% is achievable for the chosen climate
(Sultan et al. 2021)	PV, WT, FC, water electrolyser and Hydrogen gas tank	IAEO	minimizing the Cost of Energy (COE), the LPSP dependability index, and extra energy.	PV (17 %), WT (20 %), electrolyze (23 %), hydrogen tank (32 %), FC (2 %), and inverter were discovered to be the energy components contributing the most to the system's NPC (6 %)
(Ghaffari & Askarzadeh 2020)	PV, DG and FC	Modified CSA	optimal sizing	CSA adaptive-AP found the optimal solution
(Mokhtara, Negrou, Settou, Settou & Samy 2021)	PV, WT, DG, and storage batteries	PSO and ε-constraint algorithm	minimizing the cost of energy (COE) while enhancing system stability and radio frequency (RF)	different optimal configurations were found for various sites
(Ashraf et al. 2020)	PV, DG, and battery	cEHO	Minimize the chance of load loss, CO2 emissions, and yearly system cost.	Initial investment of $48,680 can offer reliable supplemental energy for load demand, resulting in a 97.9 percent reduction in CO2 emissions of 1,735 kg per year compared to PSO and HOMER.
(Kharrich et al. 2021)	PV, WT, DG, and battery	EO	minimize the net present cost (NPC),	EO yields the best NPC, LCOE, and LPSP at 74327 dollars, 0.0917 dollars per kilowatt-hour, and 0.04 correspondingly.

2.3.5.2 Cost and reliability criteria for HRES optimization

The average lifespan of a hybrid system is 20 years, and the battery bank is routinely updated every 5 years (Bhandari et al. 2015). The cost of energy also relies on the cost of capital, the cost of operation and maintenance, the depreciation period and the amount of energy generated in a year, the potential decline in equipment costs as production volumes grow, etc. The cost function of a hybrid system is calculated by adding the present value of all the initial or capital investments, the replacement costs of the system components, the annual operation and maintenance costs, the cost of diesel generator and the salvage values of the equipment, as well as any other system-related costs. In terms of cost optimization, the objective function of a hybrid energy system is to minimize either energy cost or levelized cost of energy (LCOE)(Ghofrani & Hosseini 2016) or net present cost (NPC). The LCOE is the ratio of the total cost of the hybrid system to the amount of energy supplied by the system per annum whiles the NPC includes the capital cost of the system components as well as replacement and maintenance cost of the system for its entire life span (Yong & Shaowu 2020; Ghofrani & Hosseini 2016).

Table 2.4: Examples of cost function in hybrid energy system optimization

Reference	**Objective function**	**findings**
(Guezgouz et al. 2019)	$$Min\ COE(\$/kWh) = \frac{TAC(\$)}{\sum_1^{8760} P_{load}} \qquad TAC = \left(\sum NPC\right) \times \frac{i(1+i)^N}{(1+i)^N - 1}$$ The objective is to minimize the cost of energy($/kWh) by dividing the total annualized cost (TAC) by the sum of the load P_{load}, N is the project lifetime whereas i is the real discount rate	This research demonstrates that in Algeria, the cost of generating power from renewable sources is still higher than the cost of electricity from the national grid.
(Abu-Hamdeh & Alnefaie 2019)	$$Min\ LCC = C + O\&M + R$$ where C represents capital cost of all system components, R represents the present value of replacement costs, and O&M represents the present value of all future operating and maintenance expenses (OM), which can be calculated by multiplying the annualized cost of OM by a present worth factor (PWF). $$PWF = \frac{(1+i)^N - 1}{i(1+i)^N}$$ where I represents the annual interest rate, N is the project lifetime,	LCC is a dynamic economic strategy used to determine the optimal and most cost-effective option among several alternatives. It considers the original cost of a system in addition to operating, maintenance, and replacement expenses.
(Amrollahi & Bathaee 2017)	The objective of the optimization problem is to minimize the total net present cost of the micro-grid over its life time $$Min\ TUC = \sum_{k=1}^{K} NPC_k \times N_k$$ where NPC_k is the net present cost of the kth component and N_k is the number/capacity of kth component $$TUC_k = IC_k + RC_k + OM_k + RV_k$$ where IC_k denotes the initial cost of procuring and installing component k, RC_k represents the replacement cost of kth component, OM_k *is the* operation and maintenance cost, and RV_k is the residual value of kth component that is calculated by the capital recovery factor (CRF). $CRF(i,N) = \frac{i(1+i)^N}{(1+i)^N - 1}$ N is the project lifetime whereas i is the real discount rate	The optimization of component sizing and the corresponding cost reduction are implemented by reducing or eliminating the discrepancy between generation and consumption profiles.

The reliability of supply objective function is commonly used in stand-alone HES. Since the customers in the grid-connected HES are supplied via the main grid, the security of supply as an objective function is not important for such systems. Maximizing security of supply means reducing supply disruptions in the system. An HRES can be designed to have a desirable supply to load balance based on certain probabilities estimations. LPSP likelihood is a typical metric for measuring the reliability of hybrid systems. This is the likelihood that the associated load may experience inadequate power supply. To calculate LPSP for an HRES, it might be monitored as the primary constraint for the optimization goal. Different techniques, such as loss of load expected and loss of energy anticipated, are presented in the literature (Guezgouz et al. 2019; Bhattacharjee & Dey 2014). The most common HRES reliability indices terms applied are LOLP, LOLE, LOEP, and LOEE presented in Table 2.5.

Table 2.5: Reliability indices mostly used for HRES

Reference	**Reliability index**	**Key Equation**	**Remarks**
(Marsa et al. 2021; Maleki & Askarzadeh 2014)	LPSP	$$LPSP = \frac{\sum_{t=1}^{T} LPS(t)}{\sum_{t=1}^{T} E_{Load}(t)}$$ LPS denotes loss of power supply when the generated energy E_{Gen} could not meet the load demand E_{Load} at in each time interval t. T is usually the total number of hours in a year. $$LPS(t) = E_{Load}(t) - E_{Gen}(t)$$	LPSP is the probability of failure of the load supply by the HRES components and energy storage. LPSP should be minimized to achieve maximum security of supply in the standalone HES
(Freire-Gormaly & Bilton 2015)	LOLP	$$LOLP = \frac{\sum_{t=1}^{T} hours(E_s < E_d\ (t)}{T}$$ $E_s\ and\ E_d$ denote energy supplied and needed by the system at time t, and T the total number of simulation time or hours per year	LOLP occurs when the load on the system exceeds the power generation available for use; When the cost of the system is high, LOLP is low

Table 2.5 (continued)

Reference	Reliability index	Key Equation	Remarks
(Hadidian Moghaddam et al. 2019)	LOLE	$$LOLE = \sum_{n=1}^{N} E(LOL(t)$$ where $E(LOL(t)$ denotes expectation of loss of load at time t and it is obtained by: $$E[LOL] = \sum_{s\in S} T_s \times P_s$$ P_s is the probability of being in state s, S represents all possible states, and T_s represents time of load loss.	loss of load expected (LOLE) forecasts the number of days or hours that the load will exceed the power generation capacity in a year
(Mallikarjuna, Balachandra, Potli & Venugopal 2016)	LOEP	$$LOEP = \frac{EENS}{P_{load}}$$ where $EENS\ denotes$ the expected energy not supply, and P_{load} represents the total load demand.	Loss of Energy Probability (LOEP) is defined as a kWh that is likely not provided by the generating capacity of the system. Different sizes of the systems can be compared
(Hadidian Moghaddam et al. 2019)	LOEE	$$LOEE = \sum_{t=1}^{T} E[LOE(t)]$$ $E[LOE(t)$ is the expectation of the loss of energy in time interval t.	Loss of energy expected (LOEE) is also known as expected energy not served. It represents the predicted amount of electric generation that has not been supplied to satisfy the load demand.

2.3.5.3 Constraints for HRES optimization

HRES optimization solution is bounded by set of system constraints which must be satisfied to provide a feasible and optimal result. The restriction placed on some parameters are informed by the objective of the system, and they are based on real conditions observed around the problem space. These enforcements form set of constraints which ought to be met while satisfying the objective functions. When formulating HRES optimization problem with multiple conflicting objectives, some of them could be converted into a system constraint which is bound to be satisfied within the feasible solution space. Some commonly defined constraints for HRES include power generated, power balance, battery state of charge (SOC), and probability of power loss etc(Kaluthanthrige, Rajapakse, Lamothe & Mosallat 2019; Mohamed, Eltamaly & Alolah 2017).

The power generated constraint ensures that the power generated from each source cannot exceed the maximum capacity of the power generating components. Similarly, power balance constraint guarantees that the total power generated by the hybrid system makes up for total load demand, total power loss, and storage power. The battery constraints are set so that at any given time the SOC is maintained within a desirable threshold. When the battery's SOC falls below a minimum allowable limit it compromises the system reliability. The reliability criteria for power loss constraint of a hybrid system LPSP is usually defined between 0 and 1. When LPSP is evaluated as 1, it means the load will never be satisfied, and LPSP of 0 value means that the load will always be satisfied, hence the power loss constraint is modelled to have the least possible value but meeting the load demand often.

$$P_{gen}(i) < P_{gen;max}(i) \tag{2.14}$$

where i denotes the number of power generation sources

$$P_{Total} = P_d + P_l + P_s \tag{2.15}$$

Or

$$P_{generated} \geq P_{demand} \tag{2.16}$$

where P_{Total} denotes the total power generated by the system, $P_d, P_l,\ and\ P_s$ represent power demand, power losses and storage power respectively.

LPSP is given by:

$$LPSP = \frac{\sum_{t=1}^{T} LPS(t)}{\sum_{t=1}^{T} E_{Load}(t)} \tag{2.17}$$

LPS denotes loss of power supply when the generated energy E_{Gen} could not meet the load demand E_{Load} at in a given time interval t. T is usually the total number of hours in a year.

$$LPS(t) = E_{Load}(t) - E_{Gen}(t) \tag{2.18}$$

So, LPSP constraint is set to maintain high reliability in terms of power supply by:

$$LPSP \leq LPSP_{max} \tag{2.19}$$

where $LPSP_{max}$ denotes the maximum allowable value of LPSP specified by the system user.

It is crucial to perform both technical and economic analysis for a hybrid energy system to derive the best performance of the system. However, when a hybrid system has multiple generating units with many parameters to optimize, the process becomes cumbersome and complex. An optimal solution to such a problem requires proper tools or techniques. Some of the techniques used in HRES optimizations are discussed in the next section.

2.4 Optimization Techniques

Different papers detail the development and effective use of numerous optimization approaches and technologies. For hybrid renewable energy system sizing, in addition to standard methodologies, numerous meta-heuristic algorithms and hybrid techniques have been effectively deployed (Kalananda & Komanapalli 2021b; Mohseni, Brent & Burmester 2020b; Nabipour-Afrouzi, Yii, et al. 2018; Siddaiah & Saini 2016). In HRES optimization, optimization tools, such as software packages and computer methods, are commonly employed (Ram, Swain, Vallabhaneni & Kumar 2021; Motjoadi, Adetunji & Meera Joseph 2020; Katsigiannis, Kanellos & Papaefthimiou 2016; Sinha & Chandel 2014). Noted among these software tools are HOMER (hybrid optimization model for electric renewable energy), iHOGA (improved hybrid optimization by genetic algorithm) and Hybrid2 (Ram et al. 2021) however, some of these software simulation tools include deficiencies such as the usage of black box code, less data entry possibilities, platform dependence, etc (Ram et al. 2021; Sinha & Chandel 2014). To overcome these challenges, most authors have proposed using conventional (classical), non-conventional (metaheuristics), or hybrid methods. Each approach has its own pros and cons.

2.4.1 Classical/conventional techniques

To attain the best configurations of hybrid systems, several traditional approaches are employed. Graphical construction technique, least squares method, iterative and probabilistic approaches (Ridha et al., 2020), linear and mixed integer linear programming are the methodologies utilized by various writers (Singh, Singh & Kaushik 2016). These approaches are simple to use and comprehend, and they have a wide range of applications. Optimisations based on traditional approaches allow the discovery of optimal solutions for continuous and differentiable functions. These optimization techniques are also known as analytical, conventional, and traditional techniques. They use information such as the gradient or derivative of functions to solve an HRES optimization issue (Ganguly et al. 2018; Twaha & Ramli 2018).

Linear programming (LP), mixed integer linear programming (MILP), iterative technique, and trade-off approach are the most often used classical methods for HRES optimization. The employment of traditional approaches to optimize HRES is investigated, and their benefits and drawbacks are analysed in full in (Lip et al., 2017; Twaha & Ramli, 2018). Although these techniques are simpler to use and comprehend, they have a wide range of applications (Anoune, Bouya, Astito & Abdellah 2018; Singh, Singh & Kaushik 2016b). However, these strategies involve a substantial danger of being trapped in the local optimum as opposed to the global optimum (Sinha & Chandel, 2015). Table 2.6 provides a summary of the strengths and weaknesses of the most prevalent classical optimization strategies utilized to solve an optimization issue for a mini-grid or a standalone HRES.

Table 2.6: Advantages and disadvantages of classical optimization techniques for HRES

Technique	Highlights	Strength	Weakness
Graphical	A graphical illustration of the answer to the optimization issue.	straightforward to conceive, comprehend, and employ	Cannot model numerous choice factors, and some details cannot be recorded
Probabilistic	Depending on the unpredictable influences on system performance.	User-friendly and easy to use.	Representing the dynamic changes and performances of hybrid systems is problematic
Iterative	It is a recursive procedure that concludes when the optimal configuration according to the design requirements has been determined.	Simple to comprehend. Identifies problems at an early stage.	Each iteration step is rigorous and does not accommodate any intermediates by overlapping.
Linear programming	Based on linear equations and inequalities, model the system's mathematical relationships.	It is best for handling difficult problems that can be expressed in a linear fashion, is easy to apply and versatile, and can tackle a broad variety of issues.	There is a shift in the relationship between input, output, gain, loss, etc. There is a lack of linearity between variables, and the linear programming assumptions are therefore impractical.
Trade-off	Based on a circumstance involving the sacrifice of one characteristic or the acceptance of something in exchange for the acquisition of another quality or aspect	Easy to comprehend	Limited application in renewable energy systems

Source: (Sinha & Chandel 2015)

2.4.2 Non-conventional or Artificial intelligence techniques

The application of scientific and technological knowledge to the production of intelligent computer programs is artificial intelligence (AI). In general, AI strategies are applicable procedures that produce superior optimization outcomes. AI spans several disciplines, including Artificial Neural Networks (ANN), Fuzzy Logic (FL), Genetic Algorithms (GA), and Swarm Intelligence (SI), as well as hybrid approaches that may contain two or more of these branches in a single model. Utilizing AI technology appropriately leads in systems with

Table 2.7: Advantages and disadvantages of some nature-inspired algorithms for HRES optimization

Algorithm	Advantage	Disadvantage	Reference
PSO	Simple to program; rapid convergence; low storage required	It converges too quickly. Local optimum may be reached despite the difficulty of parameter design.	(Tezer, Yaman & Yaman 2017)
GA	Available in the MATLAB toolbox; capable of solving problems with many solutions	Calculation of the fitness function is performed for each generation. It may not converge on the global optimum if not executed with care and precision.	(Mandal 2020; Mohamed et al. 2017; Xiao, Pei, Dong, Kong & Wang n.d.)
ABC	It is simple to use and has both local and worldwide search capabilities.	As the number of decision variables increases, the convergence rate slows, and a global optimum may not be reached.	(Geleta & Manshahia 2021; Abd El-salam, Beshr & Eteiba 2018)
ACO	Local and global search performance is excellent; wide range of application domains.	Several parameters of an algorithm must be adjusted. Initialization is a random process.	(Sinha & Chandel 2015)
HGWOGA	combines the benefits of GWO with GA to enhance the search method; The code for MATLAB is available for testing	Complexity in design and implementation difficulties So many variables are involved.	(Geleta & Manshahia 2021; Abd El-salam et al. 2018)
BBO	Excellent converging	It may result in several impractical solutions.	(Kalananda & Komanapalli 2021a)
HS	Few parameter settings are necessary, and it can solve continuous and discontinuous functions; its exploitation and exploration capabilities are excellent.	It has a difficult solution procedure; implementation is difficult.	(Nazari-Heris, Mohammadi-Ivatloo, Asadi, Kim & Geem 2019)

superior performance or other qualities that may not be suitable to conventional methods (Dawoud et al., 2018). Their applications' adaptive search methodologies, including heuristics and stochastics, make AI approaches resilient (Kalananda & Komanapalli, 2021). To improve operational expenses and lifetime of energy storage and to increase system efficiency, heuristic-based techniques to optimization are utilized. Earlier researchers used several AI strategies to handle the component size and cost optimization concerns of hybrid energy systems in off-grid applications.

AI models can be built on either mathematical or natural intelligence, resulting in very successful nature-inspired or meta-heuristic algorithms (Mohamed et al., 2017; Twaha & Ramli, 2018; Zahraee et al., 2016). The application of evolutionary computing, swarm intelligence, and artificial immune systems in HRES optimization has improved the science of artificial intelligence (AI). Many researchers have incorporated AI techniques in a wide range of application area. Examples of common AI techniques include PSO, GA, ACO, BBO, DE, EP, ES, ABC, AIS, and HS, as Table 2.7 details the benefits and drawbacks of some of the most prevalent AI strategies employed in HRES optimization.

Role of Nature-Inspired Algorithms for Renewable Power Optimization

The family of optimization algorithms known as nature-inspired is based on the observed hunting or foraging strategies of various animals. Each creature's hunting techniques are unique, and they use a variety of techniques to find prey. Instead of individual strategies, the algorithms imitate the hunting abilities of groups of animals/birds (flocking). Collective foraging is used so that the algorithm can effectively explore the search environment, avoiding local solutions and reaching the best feasible global optimal solution (Kalananda & Komanapalli 2021).

Nature-Inspired Algorithms—A Brief Overview

An effective way to solve any sort of optimization issue is to implement the most efficient method from the vast number algorithms. While it is acknowledged that all nature-inspired algorithms work well, it is essential to emphasize that not every method properly optimizes every optimization problem (Wolpert & Macready 1997). This phenomenon is sometimes referred to as the no-free-lunch theorem, which states that the degree of optimization for various algorithms varies from issue to problem, with some techniques doing better than others. Modifications or tweaks are made to the algorithm so that the particular optimization job at hand is optimally optimized. Figure 2.7 contrasts the performance of metaheuristics with that of random and specialized systems.

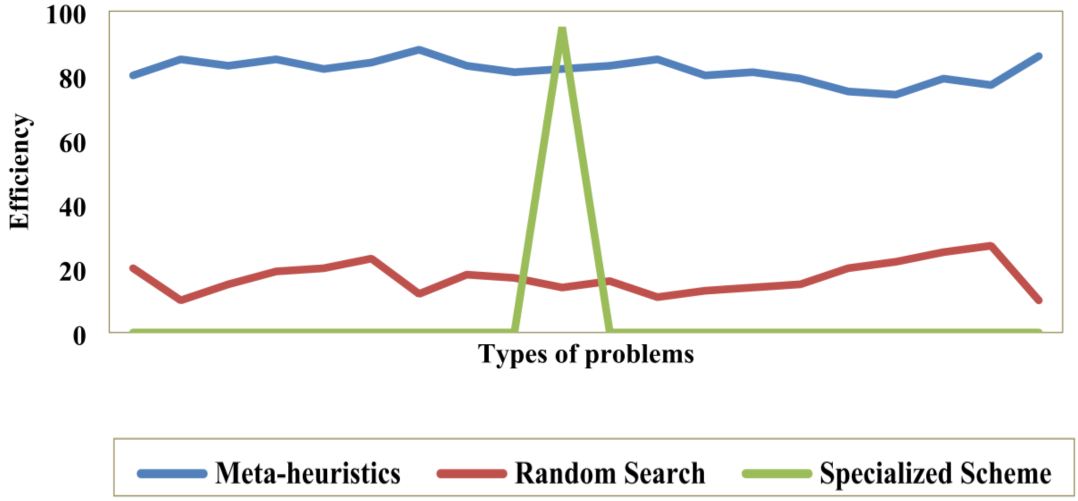


Figure 2.8: performance of meta-heuristics in relation to randomized schemes and specialized schemes

Source:.(Kalananda & Komanapalli 2021b)

It is obvious that meta-heuristics have the upper hand in creating optimum solutions to practically any type of issue, even when only minimal knowledge about the problem is available or when processing capacity is constrained. The meta-heuristic/nature-inspired algorithms (NIAs) are efficient, but the random search strategies may not be as effective. Specialized methods created for a particular application-oriented job may have the upper hand, but they incur greater computing costs and need comprehensive issue knowledge. includes electrical systems Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) lead this category with 6,1% and 3,1% of their total energy-related applications, respectively. Other prominent NIAs include the Artificial Bee Colony Optimization (ABC), the Firefly Algorithm (FA), the Bat Algorithm (BA), and the Whale Optimization Algorithm (WOA), among others.

Legacy of Nature-Inspired Algorithms—PSO and GA

In some sense, PSO and GA are related to swarm or evolution-based algorithms inspired by nature. These two concepts have established norms and continue to dominate optimization today (Ghorbani, Kasaeian, Toopshekan & Bahrami 2018; Sawle, Gupta & Bohre 2017). There are several applications of PSO and GA in the power domain, and different variations of these paradigms have been created to optimize their performance in specific applications. PSO is inspired by swarm theory, whereas GA is an evolutionary algorithm. However, both algorithms were in some manner influenced by the forces of nature. PSO is inspired by the swarming behavior of birds/fish, known as particles, whereas GA optimizes the solution through mutations and crossing of genetic material (DNA). Refer to Table 2.8 for a brief description of GA and PSO

Table 2.8: Brief description of PSO and GA

Details of algorithm	Algorithm	
	PSO	GA
Developers	James Kennedy and Russell Eberhart	John Holland originated the concept in 1960. David E. Goldberg created it.
Year	1995	introduced in 1960 and subsequently upgraded in 1989
Inspired by	Social behaviour of bird/fish Tuning	Charles Darwin's evolution hypothesis
Turning parameters	Weight of inertia (w), cognitive and social parameters (c1 and c2), population size (Np), and number of iterations (T)	Population size (Np), Number of iterations (T), crossover probability, mutation probability
Frequency of fitness assessments	Np × T	Np × T (approximately)

In addition to PSO and GA, there are other NIAs that contribute significantly to the optimization of renewable energies. Each NIA is different and employs different and intensified foraging tactics to explore and exploit the foraging environment. The uptake of NIAs in the renewable energy field has exploded in the last decade (Kalananda & Komanapalli 2021), with the number of publications increasing. Researchers and scientists prefer NIAs over other computational techniques because of the flexibility of the algorithm, which can be refined for reliable and optimal performance while handling both equality and inequality constraints with minimal computational effort and the algorithm's potential for success on higher-dimensional problems. The renewable energy field has seen an increase in applications of GA and PSO in different sub-sectors.

Besides PSO and GA, the Artificial Bee Colony (ABC) algorithm dominates renewable energy optimization, followed by Whale Optimization Algorithm (WOA) and Gray Wolf Optimization Algorithm (GWO). Other meta-heuristics and approaches are significant, but differential evolution (DE) is the undisputed leader, followed by TLBO. DE and TLBO have maintained their leadership in optimizing renewable energy (Aala Kalananda & Komanapalli 2021). A number of hybridization and extension forms of these models have been presented over time to solve the problem between exploitation and exploration. With DE's acceptance and ease of use among academics is the main reason for its success, and the tuning parameters play a crucial role. TLBO, on the other hand, is a relatively simple and effective paradigm that does not require adjustment of many parameters and also shows promising accuracy (Aala Kalananda & Komanapalli 2021). In addition to DE and TLBO, HS and Jaya algorithms have a significant efficiency level for single and multi-objective optimization problems (Aala Kalananda & Komanapalli 2021). To further increase the efficiency of these algorithms and achieve a perfect balance between opposing objectives, such as when constructing a near-optimal HRES, exploration and exploitation mechanisms must be harmonized with other search approaches to enhance optimization tactics in complicated settings.

Table 2.9: Advantages and disadvantages of optimization techniques

Optimization Technique	Advantages	Disadvantages
Classical Methods	The logical sequence between instructions and analyses is easy to follow. It is easy to write the code and has more applications.	Multiple mathematical or analytical processes significantly increase the computational difficulty. The application is troublesome when the constraint is satisfied: it does not handle constraints correctly. High propensities to become stuck in the local optimum as opposed to the global optimum.
AI Methods	Ability to skip local minima or maxima to find a near-optimal solution. It reaches the global optimum with minimal computational effort. Good calculation speed Effective and robust Ability to manage numerous constraints. Compatible with multiple decision factors. Applicable to many academic disciplines. The literature is widely available and is spreading rapidly	May converge too quickly. Can take some time to depart from the local optimum. It is difficult to code complicated issues. With several choice factors and limitations, reaction time might be exceedingly slow.
Hybrid Methods	Utilizes the potential of individual tactics to become more competitive	It is difficult to evaluate because of its complex structure.
Software tools	Free and paid application programs with intuitive interfaces. Useful for on-the-fly multi-target and single-target optimization issues and techno-economic system analysis. May include several system components	Domain codes that are confined to a particular application are inaccessible for study or assessment.

2.4.3 Hybrid techniques

Existing nature-inspired algorithms are frequently combined with other evolutionary-based algorithms to improve optimization result in several disciplines. Over time, improved, enhanced, and more advanced versions of the current NIAs are introduced (Sultan et al. 2021; Chen et al. 2019; Moghaddam et al. 2019; Jo & Kim 2018). Although the optimization strategies are effective in addressing the difficulties of the hybrid renewable energy system, the studied literature gives more potential hybrid solutions (Karve, Kurundkar & Vaidya 2019; Saiprasad, Kalam & Zayegh 2019). Hybrid-based strategies (combining two or more algorithms) are potential methods for overcoming the limits of single algorithms (Frimpong, Millham & Agbehadji 2021). SA taboo search, Monte Carlo Simulation PSO, hybrid iterative/GA, MODO/GA, artificial neural fuzzy interface system (ANFIS), artificial neural network/GA/MCS, PSO/DE, and evolutionary algorithms are examples of hybrid approaches (Singh, Singh & Kaushik 2016b; Sinha & Chandel 2015). These techniques provide better solutions for the HRES. Although hybrid optimization approaches improve overall optimization efficiency, they are not without drawbacks. The optimism of hybrid MCS part-PSO, hybrid iterative/suboptimal GA solutions, random modification of evolutionary algorithm inertial weight, and optimization coding complexity are examples (M.M. Ashraf & Malik, 2020).

2.4.4 Advancement of NIAs for HRES optimization

In recent years, a growing number of research projects in computer science, mathematics and biology have focused on computations inspired by nature. These algorithms are innovative approaches based on the ideas and inspirations of nature's biological evolution or physical or chemical events to create new yet robust search methods. Evolutionary computation (EC) and swarm intelligence (SI) are the two most prominent types of well-known nature-inspired computational approaches (Nguyen et al., 2020b). Evolutionary Computing (EC) refers to optimization problem-solving strategies that mimic evolutionary notions. The Genetic Algorithm (GA), a well-known EC meta-heuristic technique (Jo & Kim 2018), mimics evolutionary principles (survival of the fittest) and genetic inheritance schemes between successive generations (crossover, mutation) to enable search operators to do the exploring the search space of an optimization problem effectively. Swarm intelligence (SI), on the other hand, efficiently uses the collective behavior of many species (e.g. ants, bees, flocks of birds) and constructs a group of agents with basic interaction rules. These operational concepts produce efficient decentralized search algorithms with balanced exploration and exploitation capabilities.

SI search strategies share traits of natural inspiration, sociality, and repetition. The agents investigate and use the search space in different ways. Particle swarm optimization (PSO) and ant colony optimization (ACO), in addition to other current heuristics, are well-known methodologies for nature-inspired computing. Meanwhile, other algorithms are now very popular, for example due to their increasing use in optimization. Artificial bee colony (ABC), bat algorithm (BA), cuckoo search (CS), gray wolf optimization (GWO), firefly algorithm (FA), social spider algorithm (SSA), and kestrel-based search algorithm (KSA) and many more (Agbehadji, Millham & Fong 2017; Yu & Li 2015a; Akay 2013; Slowik 2011; Socha & Dorigo 2008).

For the goal of improving hybrid energy systems, several algorithms have been updated or improved to generate specialized versions or upgrades. Commonly examined parameters include the class/type of optimization issue, the set of choice variables, the computing time and space requirements, and efficiency. To identify the best solution for HRES optimization issues, nature-inspired algorithms are utilized. Due to the vast working range of the NIA, it is prudent to develop or enhance HRES optimization models. In benchmarking studies, these algorithms performed well. Despite different applications, no algorithm solution is superior in all hybrid system optimization problem (Wolpert & Macready 1997). Nature-inspired optimization algorithms are influenced by algorithmic structure, selection of hyperparameters, and other considerations (Faccio et al. 2018). To produce a high-quality output, it is essential to use reliable data, as all algorithms are data-driven.

Current technologies such as Internet of Things (IoT), Edge Computing, Computational Intelligence and Big Data Analytics etc. make it possible to study technical advances that promote reliable sustainable energy production (Hadi, Lawey, El-Gorashi & Elmirghani 2018; Padma & Ilavarasi 2017). The Internet of Things can be used to improve energy efficiency, increase the share of renewable energy, and reduce the environmental impact of energy consumption. Using the Internet of Things, the authors of (Mar Myint Aung, Win & Win Zaw 2018; Padma & Ilavarasi 2017) have described a monitoring and control system for the output voltage of a solar panel stored in a remote location and monitoring its output power from the servers (IoT). A related work (Sarswat, Yadav, and Maurya 2019) presents a system architecture for real-time monitoring of solar photovoltaic (SPV) system parameters using Internet of Things (IoT) technology. Using sensors, essential properties of the SPV system such as voltage, current and plate temperature are measured and used to determine the SPV output power. Alhmoud & Al-Zoubi (2019) studied wind resource assessment and lifetime estimation of wind power models using IoT technologies while using IoT sensors and related technologies to monitor biogas power plants (Ahmed et al., 2017; Dedgaonkar et al., 2018; Farhan et al., 2018; Huo et al., 2019). In the next part, we briefly describe the IoT platform and how its components contribute to the diffusion of technologies in the energy sector.

2.5 IoT and edge analytics

The Internet of Things (IoT) is a network of everyday objects that can exchange data over wired or wireless connections. The Internet of Things connects physical devices or things over the Internet (Adhya, Saha, Das, Jana & Saha 2016). Examples of physical things that can be connected using IoT technology are home appliances, office supplies, and machines. With the right sensors and communication networks, these devices can provide meaningful data and provide individuals with a variety of applications (Ioannides et al. 2021). The Internet of Things includes applications across consumer electronics and appliances (Marinakis & Doukas, 2018), such as smart homes, smart campuses (Eltamaly, Alotaibi, Alolah, & Ahmed, 2021), smart automobiles, healthcare, industrial security, and smart cities, among others (Alhmoud & Al-Soubi, 2019; Motlagh, Mohammadrezaei, Hunt, & Zakeri, 2020; Alhmoud & Al-Soubi, 2019); drone-based services; effective building energy management; and environmental monitoring have seen undergone massive development with IoT (Ioannides et al. 2021).

On the IoT platform, transmission protocol is among the important components which support applications and service delivery. Due to the heterogeneity of sensor devices, the protocol is required to establish effective data transmission between multiple devices. Depending on the needs of the application, the protocol creates a space where different devices can interact and share their data with controllers or decision-making centres (Wu, Wu, Guerrero & Vasquez 2021). ZigBee, Bluetooth, Wi-Fi, and cellular technologies such as LTE 4G and 5G networks are examples of protocols that enable IoT applications on multiple devices (Motlagh, Mohammadrezaei, Hunt & Zakeri 2020).

It is essential for a data driven IoT application to effectively manage the sensor data collected. In practice, the sensors create a large quantity of data, necessitating an efficient data storage facility for their utilization (Motlagh et al. 2020). The last component of IoT applications is data analysis based on acquired data. After data has been stored, it is possible to do data analysis in real-time or offline (Kolajo, Daramola & Adebiyi 2019; Mohammadi, Al-Fuqaha, Sorour & Guizani 2018). During the offline analysis, the acquired data is initially visualized locally using visualization tools(Motlagh et al. 2020). Cloud or edge servers, such as Stream Analytics, deliver real-time analytics visualizations (Agbehadji, Frimpong, Millham, Fong & Jung 2020). Decisions about how to run the program are made through data analysis. The many elements of an IoT platform are shown in Figure 2.9.

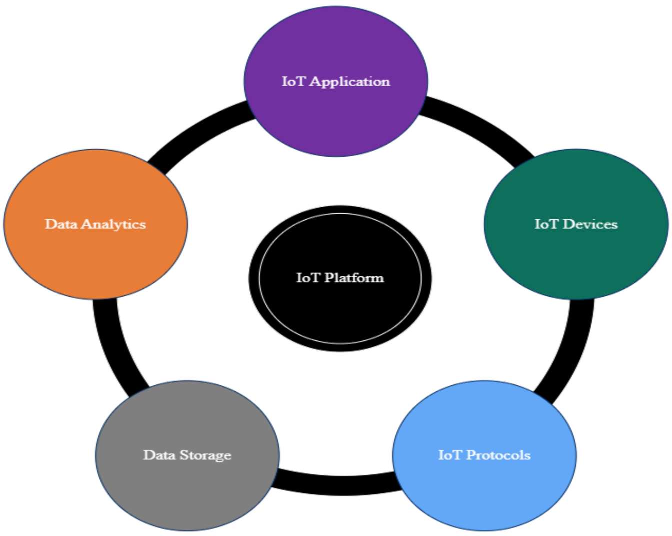


Figure 2.9: Components of an IoT platform

Source: (Motlagh et al. 2020)

2.5.1 Hardware and architecture based IoT system

The choice of IoT components, such as sensor devices, communication protocol, data storage and processing must be suitable for the intended application when creating an IoT application(Chawla, Singhal & Garg 2020; Motlagh et al. 2020). IoT hardware, such as sensors, actuators, and gateways, is essential to collecting, sending data (stimuli) for further analysis (Chawla et al. 2020; Al-Ali 2016). Special devices gateway facilitates bidirectional connection between IoT hardware and the cloud or data centre (Motlagh et al., 2020), thus, allowing data to flow on the IoT platform. Therefore, in an IoT architecture, the hardware deployment and the design of the high-level system model is crucial for the successful implementation of any IoT-based system. Accordingly, the following components required for the standard architecture of any IoT system are as shown in Figure 2.10:

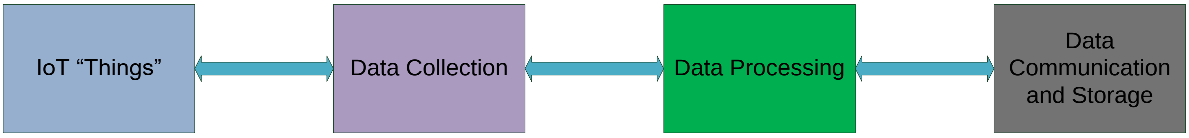


Figure 2.10: Architecture of an IoT system (Gorrepotu, Swaroop, Chandu & Deb 2020)

IoT things: Sensors and actuators are used to monitor and manage things. The smart devices have these components fully integrated (Allhoff & Henschke 2018). Applications for sensors that track physical conditions include automation, healthcare, consumer goods and industrial infrastructure, etc(Gorrepotu, Swaroop, Chandu & Deb 2020).

Data Collection: Data collection is the process of gathering information from numerous sensors in the packet structure described. The packet's type-length value can be user-defined or follow a standard format. A microcontroller/microprocessor is used for data acquisition (Gad & Gad 2015; Anwari, Arief, Hamid & Taufik 2003; Koutroulis & Kalaitzakis 2003). The microcontroller can be battery operated because it consumes little power.

Processing: Data collected from sensors is processed by gateway microcontroller-based devices (Gill, Behbood, Ramadan-Jradi & Beydoun 2017). The ability of gateway devices to process input from many sources should be improved. The gateway stores the data locally after processing and manages the process (Gorrepotu et al. 2020).

Communication and storage: The most important component of the IoT architecture in terms of hardware is the connectivity module. This circuit enables communication with the cloud platform (Motlagh et al. 2020). The data package contains sensor data from multiple communication ports including SERIAL, MODULE, CAN and I2C. The radio technologies for wireless communication such as Lora, WiFi and ZigBee are included in the gateway to cloud server communication (Gorrepotu et al. 2020). The data stored on a cloud server can be accessed from anywhere in the world via the Internet. You can access the collected data on any smartphone or laptop.

In addition to the hardware architecture on which IoT applications are based, the vision and scope of the Internet of Things is currently expanding due to the recent rise and convergence of a variety of digital technologies, including analytics, big data, blockchain, cloud, mobile, social, machine learning, commodity computing and so on (Rehman, Naz & Razzak 2021). The Internet of Things automates more and more systems. Companies are aware of the benefits of statistical data for their business as the digital revolution is already in full swing. The interdisciplinary use of IoT applications to improve service quality is well documented in the literature. For example, the temperature and position of ladle vessels for metallurgical purposes are recorded with an Arduino sensor system that has been set up and put into operation. The Arduino microcontroller is coupled to several modules including a type-K thermocouple, a GPS shield, a real-time clock, and a Bluetooth module. The technology has undergone extensive testing to show that it can measure 1220°C for 22 hours (Chang & Martin 2021). The authors have shown that the Material Processing Institute's use of the industrial IoT service is an excellent case study for integrating Industry 4.0 technology (Chang & Martin 2021).

An IOT data acquisition system has been proposed for long-term data acquisition of PV system variables. Four NODEMCU boards, a pyranometer (PYRA300), a temperature and humidity sensor (DHT22), an air pressure sensor (INA 219), a temperature sensor (LM35), an anemometer, a dust sensor and ThingSpeak make up the system. ThingSpeak estimates, collects, processes and displays PV system variables including generated voltage, current, module temperature, humidity, ambient temperature and generated power. Other customer elements such as mobile devices, tablets, and internet-connected workstations can access the information stored by a device from anywhere using Thing Speak APIs (Gupta, Sharma, Pachauri, & Babu 2021). Over the course of 28 days, the performance of the proposed IoT-enabled data collection system under difficult environmental conditions was examined. The proposed data collection system is suitable for harsh outdoor environments and for monitoring and collecting operational data of the PV system to analyze its performance based on real-time test results.

Another study proposes a Raspberry Pi-based hardware platform for data acquisition, monitoring and energy management of a hybrid PV/WT/battery system (Lazgheb et al. 2019). A Raspberry Pi 2 board is to serve as the central control for the hybrid PV/WT/BT system to collect energetic data (system status data and meteorological data). In a related study, a new low-cost IoT-based method of remotely monitoring a photovoltaic array for performance evaluation was performed. This enables real-time monitoring in addition to the historical examination of the system, fault diagnosis and preventive maintenance (Adhya, Saha, Das, Jana & Saha 2016).

2.5.2 IoT in energy sector

Power generation, transportation of products and countless other crucial human activities are all supported by the energy industry. IoT in the energy sector has enhanced knowledge about how this market space operates. The adoption of IoT and associated technologies in the energy industry has enabled a smart energy management system by consistently delivering energy effectively and enabling improved load-balancing strategies. (Motlagh et al. 2020). The majority of IoT projects in the energy sector focus on on-demand applications. However, a properly deployed IoT application brings infinite benefits for optimizing the entire value chain and optimizing all phases of the energy supply chain, namely power generation, transmission, and distribution. Appendix D describes the applications of the IoT in the energy sector by contrasting the different areas of application with the advantages that the IoT offers in the energy supply chain.

As energy systems grow increasingly complex and decentralized, IoT applications enhance the visibility and responsiveness of networked equipment. The Internet of Things collects and transmits real-time data using sensors and communication technologies, allowing for rapid computations and effective decision-making. In addition, IoT can aid the transition of the energy sector from a centrally controlled, intelligent, and integrated energy system to a distributed, intelligent energy network. This is crucial for the deployment of local, decentralized renewable energies like wind and solar, as well as the transformation of countless small energy users into prosumers, the aggregation of their supply, and the optimization of their demand whenever it is advantageous to the grid (Eltamaly, Alotaibi, Alolah & Ahmed 2021; Abid, Lghoul & Benhaddou 2017).

The optimization of renewable energy sources is another significant use of the Internet of Things in the energy industry. Energy users may optimize and perhaps minimize their energy usage by installing intelligent monitors that automatically regulate the temperature of a plant, room, or office. In addition, businesses and organizations may install smart sensors in buildings to activate and deactivate energy usage based on the occupancy of a room or building. This application is extremely advantageous for the energy sector, since it not only prevents significant quantities of energy from being misused but also connects the whole sector to the Internet, leading to the improvement in operations. IoT solutions, such as intelligent gateways, also provide basic components for fundamental systems that enable integration, minimize development costs, and accelerate the deployment of innovative emerging technologies. These technologies are essential for generating new and more efficient renewable energy (Eltamaly et al. 2021; Ioannides et al. 2021; Abid et al. 2017).

In the energy ecosystem, the introduction of smart meters and a smart grid has enabled the application of IoT for efficient energy system management. The term "smart grids" refers to a network of electrical circuits that facilitate reversible energy transfer and can self-diagnose and repair in the event of maintenance concerns. Furthermore, another aspect of smart grids is that they enable energy users to become equal partners 'prosumers' in the energy market as they can redirect excess energy to where it is needed most. Consequently, wise consumption is encouraged (Ioannides et al. 2021). In terms of monitoring and evaluating the energy consumption, smart meter installation technology may assist in identifying the regions where the most energy is spent and the locations where energy can be saved considerably (Abid et al. 2017).

IoT-based smart meters may be installed in homes and businesses to provide consumers with an in-depth analysis of their energy consumption trends (Eltamaly et al. 2021; Abid et al. 2017). It is vital to highlight that the concept of smart grids predates current events, and one of the most innovative IoT applications in this industry, smart grids are the future (Ioannides et al. 2021). Microgrids have recently gained a substantial amount of interest. Microgrids are independent energy networks that may operate in island mode or grid mode (Alsmadi et al. 2019). In grid mode, households can distribute energy to grids, which can then be consumed by other units. If a home does not intend to distribute energy, the Internet of Things can turn off its energy circuits automatically. In addition to conserving energy, microgrids and smart grids help direct electricity to where it is necessary.

In addition, IoT in the energy sector can install a preventive repair mechanism that sends alerts and warning signals if a circuit is disrupted, or equipment requires maintenance (Adekanbi 2021). This application has been shown to save industrial maintenance costs significantly and is a speedy problem-solving mechanism. In contrast to a year before, when the circuits could not self-mend, the intelligent circuits of today are completely capable of informing the energy maintenance departments about the repair job. IoT-based systems automate, integrate, and control processes with communication and sensor technology. Large-scale data gathering and the deployment of sophisticated algorithms for real-time data analysis can aid in monitoring energy production or consumption patterns of various users and equipment over a range of timeframes, hence supporting more efficient operational management (Adekanbi 2021; Marinakis & Doukas 2018). Appendix E presents capabilities of IoT in energy management.

IoT applications deployed on public wireless communication networks such as GSM for data transmission might be too expensive in terms of operating and maintenance expenses, rendering the system unviable for its intended purpose. A further obstacle to IoT adoption is the high data growth rate in IoT applications caused by the huge number of networked sensor devices. In order to maximize the use of data resources in IoT systems through effective data management, data pre-processing and data reduction solutions have been proposed (Pioli, Dorneles, de Macedo & Dantas 2022; García, Ramírez-gallego, Luengo, Benítez & Herrera 2016). In Table 2.10 the solutions that IoT technologies offer to the varying concerns and challenges in the energy ecosystem are presented.

Table 2.10: IoT solutions to some challenges in the energy sector (Motlagh et al. 2020)

Challenge	Issue	Example Solution	Benefit
Architecture design	Providing a reliable end-to-end connection	Using heterogeneous reference architectures	Interconnecting things and people
	Diverse technologies	Applying open standard	Scalability
Integration of IoT with subsystems	IoT data management	Designing co-simulation model	Real-time data among devices and subsystems
	Merging IoT with existing systems	Modelling integrated energy systems	Reduction in cost of maintenance

Table 2.10 (Continued)

Challenge	Issue	Example Solution	Benefit
rStandardization	Massive deployment of IoT devices	Defining a system of systems	Consistency among various IoT devices
	Inconsistency among IoT devices	Open information models and protocols	Covering various technologies
Energy consumption	Transmission of high data rate	Designing efficient communication protocols	Saving energy
	Efficient energy consumption	Distributed computing techniques	Saving energy
IoT security	Threats and cyber-attacks	Encryption schemes, distributed control systems	Improved security
User privacy	Maintaining users' personal information	Asking for users' permission	Enables better decision-making

The proliferation of sensors and distributed data sources has greatly increased the amount of data created, processed, and stored in an IoT application. The process of serving and receiving large amounts of data is complicated because the data size can grow exponentially in a very short time. Accordingly, data pre-processing and reduction are plausible means to manage this data effectively (Pioli et al. 2022).

The idea of edge computing, which processes data closer to the source of generation (Dias de Assunção, da Silva Veith & Buyya 2018) before transferring it to the cloud, has emerged as an effective option to support data pre-processing. This design improves data efficiency and decreases cloud bottlenecks by processing raw data closer to the point of creation (Pioli et al. 2022). It also limits the transmission of unnecessary data over the network, freeing it for data cleansing and consistency. This component is typically placed between the raw data and cloud servers employing advanced hardware technologies. Gateways, servers, routers, and switchers are some of the hardware technologies utilized as edge hardware mediators (Dias de Assunção et al. 2018).

2.5.3 Data pre-processing and future of IoT in energy systems

The set of techniques used before applying a data mining method is called data pre-processing and is an important topic for knowledge discovery from data (Garca et al., 2016).

Pre-processing the raw or sensor data at the edge before it reaches the cloud involves data preparation and data reduction techniques that transform high-dimensional data into compact data. The former consists of data transformation, integration, cleaning, and normalization, whilst the latter seeks to minimize the data's complexity by feature selection, instance selection, or discretization (Garca et al., 2016). After data is reduced at the edge layer, it might be used directly by AI solutions in the cloud, since it is a trustworthy and adequate source for data mining algorithms and data-driven applications. The concept of applying data reduction at the edge can bring many benefits when dealing with IoT sensor data. For example, bandwidth network latency can be reduced in a gateway, eliminating I/O bottlenecks across network connectivity (Mohammadi et al. 2018).

Future of IoT in the Energy Sector

There are enormous benefits of using modern IoT technologies to offer energy efficient solutions in the energy sector. To increase IoT performance and overcome the related problems as discussed in Table 2.10, IoT deployment in the energy sector requires new ideas and approaches to meet evolving challenges. Blockchain technology and green IoT are two strategies identified to mitigate the foreseen difficulties within the energy sector (Motlagh et al. 2020).

Blockchain

Most IoT solutions used today are based on a centralized cloud infrastructure (Wang, Zhong & Souri 2021; Ahmadi et al. 2019). Most IoT applications require numerous IoT machines and devices to be connected, which is difficult to synchronize (Motlagh et al. 2020; di Martino et al. 2018). Furthermore, since the IoT is centralized and of server-client design, if a server is vulnerable, all connected objects are easily compromised, bringing security risks for the system and privacy concerns for consumers (Adekanbi 2021). Fortunately, blockchain can offer a solution to this problem (Minoli & Occhiogrosso 2018). Without the need for outside intervention, blockchain provides a decentralized and democratic platform. Each IoT node must prove to the blockchain's consensus platform that it has the same goals as other nodes. In addition, information about verified transactions is kept in the form of a block linked to the previous block, so it can never be deleted. In addition, each node's transaction history can be logged and made available to all (Minoli & Occhiogrosso 2018).

Blockchain technology's distributed ledger makes it possible to synchronize thousands of IoT devices. A secure distributed database can be offered through the peer-to-peer network-based blockchain consensus methods (Wang et al. 2021; Minoli & Occhiogrosso 2018). Blockchain can therefore provide a decentralized, private Internet of Things that can ensure privacy (Wang et al. 2021). Blockchain can also store and distribute software updates between objects, which is more important (Motlagh et al. 2020). As a new node, updates are checked for correctness by nodes checking for harmlessness, which also ensure their safety from threats. Once an update has been inserted into the blockchain as a valid block, it cannot be removed or modified. Blockchain can be used to offer updates, availability, and security for IoT-based platforms (Samizadeh Nikoui, Rahmani, Balador & Haj Seyyed Javadi 2021).

The use of blockchain in the energy sector will increase the effectiveness of the IoT by providing distributed power generation and storage systems with a decentralized platform that improves renewable energy generation security and efficiency (Adekanbi 2021; Motlagh et al. 2020). Without the intervention of a third party, devices can openly exchange real and high-quality data, and consumers can receive energy information immediately (Motlagh et al. 2020; Bedi, Venayagamoorthy, Singh, Brooks & Wang 2018). Energy can easily be exchanged between neighbours. Therefore, avoiding government intervention not only increases public confidence, but it can also reduce many of the costs associated with this connection to centralized networks. Another benefit is that blockchain will allow power distribution to remotely control the flow of power to a specific area by tracking an area's usage statistics (Motlagh et al. 2020). In addition, blockchain-based IoT systems are helpful for diagnosing and maintaining smart grid devices. Currently, it is difficult to directly implement blockchain technology in an IoT-based system due to limited processing capacities, bandwidth, and the need to save power. However, cloud and fog computing platforms may make it easier for IoT to adopt blockchain services (Samizadeh Nikoui et al. 2021; Motlagh et al. 2020; di Martino et al. 2018).

Green IoT

Due to the high proliferation of IoT applications and related technologies, the power consumption of IoT devices becomes a concern as the technology is expected to be widely deployed (Samizadeh Nikoui et al. 2021; Bedi et al. 2018). A significant amount of energy is required to power the billions of devices connected to the internet. The proliferation of

IoT devices will result in significant e-waste production (Samizadeh Nikoui et al. 2021; Allhoff & Henschke 2018). Addressing these issues requires a low-carbon and effective communications network preferably powered by renewable energy system (Adekanbi 2021; Xhafa in press). Consequently, these requirements have sparked interest in the development of Green IoT (G-IoT) for efficient use of the IoT throughout its life cycle, including design, production, deployment and finally disposal are its key features (Motlagh et al. 2020). Various IoT technologies can leverage the G-IoT cycle. For example, RFID tags use radio frequency identification. The size of RFID tags is being reduced to reduce the amount of material that is difficult to recycle (Zhu, Leung, Shu & Ngai 2015).

A new phase of the energy transition is imminent. A system-wide, integrated strategy is required to reduce the socio-economic and environmental impacts of energy systems, given the widespread use of various renewable energy in distributed energy systems and the desire for energy efficiency (Vahidinasab, Ardalan, Mohammadi-Ivatloo, Giaouris & Walker 2021; Bibri & Krogstie 2017). In this respect, cutting-edge technologies such as the Internet of Things (IoT) can help the energy sector make the transition from a centralized, hierarchical to a decentralized, intelligent and optimized supply chain (Adekanbi 2021; Motlagh et al. 2020). The future of the energy industry will be shaped by IoT applications at different scales and levels, including smart grids, smart buildings, and intelligent energy management in the context of the energy supply chain (Wang et al. 2021). However, there are several challenges in integrating the IoT into the energy sector, including the challenge of element identification, huge data management, connectivity issues and unpredictability of some renewable energy sources, subsystem integration, security and privacy issues, and power requirements of IoT devices (Samizadeh Nikoui et al. 2021; Vahidinasab et al. 2021; Elshawi, Sakr, Talia & Trunfio 2018). Several solutions to these problems, such as blockchain technology and green IoT, are envisaged as potential future research areas (Motlagh et al. 2020).

2.6 Research gap

Assembling IoT devices to collect environmental data for further analysis to provide a near-optimal solution for power generation from hybrid renewable energy systems requires myriad techniques and tools to extract quality data from the collected lot. This process includes some of the techniques enumerated in the previous sections, particularly in relation to the data pre-processing aspects to ensure that the optimization algorithm has adequate but high-quality data at its disposal. Unfortunately, previous work is limited to a subset of monitoring and controlling hybrid energy systems with IoT applications (Adhya et al., 2016; Ioannides et al., 2021). Therefore, a self-adaptive optimization method is proposed that considers the underutilized renewable energy resources across Africa. The system outlines a framework for both the assessment of the renewable potential at the site and the techno-economic analysis of the intended hybrid system. At the heart of this framework is the analysis of IoT data to inform energy production in reliable quantities. To help in the optimal system sizing configuration and preliminary evaluation, a metaheuristic algorithm: a bio-inspired search technique is integrated into the proposed framework to optimize HRES power generation.

2.7 Conceptual framework

Using IoT technologies in renewable energy generation could be advantageous in monitoring and maintaining of power production units. For example, IoT devices like weather sensors can sense and communicate climatic weather data such as wind speed, ambient temperature, solar irradiance, etc to optimize the overall performance and stability of renewable based system which depend on these parameters. An IoT-integrated system of this type makes good use of real-time data and enables multiple sensors in wide range of feasible domains to communicate, presenting significant potential for gaining insight into the data moving through the network. The application of the IoT and related technologies in renewable energy systems includes monitoring the operation of PV systems (Sarswat et al. 2019; Babu, Rambabu, Rajesh Naidu, Prasad & Gopi Krishna 2018; Padma & Ilavarasi 2017), IoT-based monitoring of wind turbines (Fran, Anitha & Mohan 2017), biogas analysis and monitoring (Huo et al. 2019; Dedgaonkar et al. 2018; Farhan et al. 2018) and so on.

The conceptual structure underlying the proposed system is shown in Figure 2.11. IoT sensors are deployed at locations where renewable power generation systems are installed or would be installed to collect and communicate energy data for efficient system management or optimal system design. The schematic diagram depicts a three-layer framework: the basement is the boundary layer where the acquisition, transmission and acquisition of sensor data takes place; the second layer is an intermediate component between the edge and cloud layers. This layer collects streaming data from the basement. The incoming data is stored on an edge device for pre-processing and further analysis. Once, sufficient data is collected and pre-processed the refined data is given as an input among other parameters to optimization algorithm to determine an optimal configuration size or optimal power output for a hybrid energy system. Before the processed data is transferred from the intermediate layer to the fog cloud layer, there are checks and balances at this stage to meet predefined optimization goals. The machinery for this process is called the Check- Reduce-Improve (CRI) component.

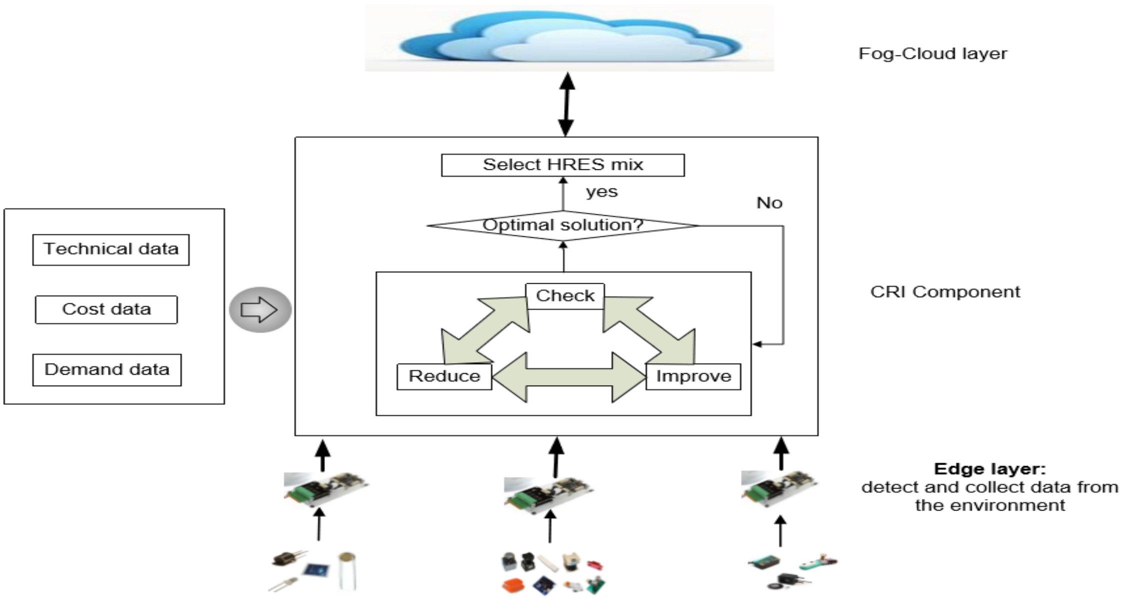


Figure 2.11: Framework for HRES optimization with edge computing capability.

The CRI component aims to address the energy trilemma by reviewing climatic weather data during a feasibility study and mapping it to the optimal system design. In addition, a performance check of the system configuration parameters including the obtained renewable resource data is performed. Then, using the optimization algorithm, an improved solution to the optimization problem is evaluated. The algorithm keeps improving the optimal solution until the lowest cost (reduction) for the system is found. These operations are aligned with the optimization goals and constraints. Thus, the CRI component provides an intelligent way to balance the load demand with the power generated at a given point in the optimization process to prevent power loss for the HRES. Consequently, the output is returned to make an informed decision. However, the processed data and the optimal solution could be transferred to the fog cloud layer for future use.

The fog cloud layer stores the data generated from the HRES environment for further processing and analysis. Several applications including asset monitoring, maintenance, historical data analysis, inspection planning and other decision-making applications could be easily implemented using the resources from the fog cloud layer. Although these applications are not the subject of this study, if integrated into the hybrid renewable energy system, they would contribute immensely to the overall performance of the system. In addition, the weather data can help in weather forecasting, while the energy and technical data could be used to improve the efficiency and reliability of energy production.

2.8 Chapter summary

It is necessary to conduct an environmental feasibility study for the site of an HRES project to produce sustainable and self-sufficient renewable energy at an affordable price. In addition, the exact dimensioning of the hybrid system components contributes significantly to the economic and technological advantages of the HRES projects. This chapter contains an extensive literature review on the optimization of hybrid renewable energy systems. The study examined the integration of three renewable energy sources - a solar array, a wind turbine and biomass energy in conjunction with a battery storage system for reliable power generation. The aspects to consider when sizing a hybrid system, including technical data, climate/weather data and cost information, the methods for system optimization and cost analysis. In addition, a framework based on advanced IoT analysis for collecting real-time environmental data is specified, which assumes a true reflection of the renewable energy resources on site.

CHAPTER 3: DEVELOPING METHODOLOGICAL FRAMEWORK

3.1 Introduction

The combined use of wind and solar energy as a hybrid energy system has proven to be more efficient and economical than their respective energy systems, especially for stand-alone applications (Khan 2020; Yong & Shaowu 2020). Introducing biomass into a PV-wind based hybrid system improves system reliability due to the uncertainties of both solar and wind resources (Kharrich et al. 2021; Singh, Singh & Kaushik 2016). Furthermore, complementing a purely hybrid renewable energy system with a battery storage system stabilizes the system to be more efficient and reliable to meet the energy demand of the load (Mouachi, Jallal, Gharnati & Raoufi 2020; Ayodele, Misra, Damasevicius & Maskeliunas 2019). This work therefore aims to optimize hybrid PV-wind-biomass-battery system by accurately dimensioning the system's components for stand-alone operation. Optimal dimensioning of the hybrid system components is a practical approach to achieve the study objective. The optimization process ensures that a certain level of system reliability is maintained by keeping the LPSP below 0.1 while minimizing the total annual system cost. This chapter introduces the strategies used by the researcher to dimension the HRES hybrid system.

After creating the optimization scheme that describes the many aspects of the system, it is important to evaluate and test the hybrid system (Khan, Pal, and Saeed, 2018). As a result, a framework was created that describes the solution to the problem. The process of processing the optimization of HRES power generation is specified in the framework. Starting with a preliminary study of the feasibility of the hybrid system configuration, the process continues until the optimal, or even better, near-optimal solution to the problem is found. The system data, namely the meteorological, technical and economic data, have a significant impact on the best solution of the HRES (Sinha and Chandel, 2015). The sizing, price and reliability of the system components are all directly affected by the data. As a result, real-time sensor data is collected from the environment to enable accurate HRES sizing and costing. Since the real-time data collected was not sufficient to draw a meaningful conclusion, historical but benchmark data was experimented with. The research was conducted at the Ritson campus of Durban University of Technology in Durban, South Africa

In this chapter, the researcher applies the mathematical formulation as a method (Lian et al. 2019; Lip, Shiun, Shin, Hashim & Tin 2017; Siddaiah & Saini 2016; Bhandari et al. 2015) to identify the specifically relevant and interesting behaviors modeling social spiders and their prey on the social web. The model is then translated into an optimization algorithm (Agbehadji, Awuzie, Ngowi, Millham & Frimpong 2021; Frimpong, Millham, Agbehadji & Jung 2021) that is used to find the near-optimal solution of power generation from hybrid renewable energy systems. The modeled behaviors are tied to the establishment of hybrid renewable power generation characteristics. From the researchers' perspective, the random variables in the HRES power generation system can be effectively managed using an intelligent optimization algorithm, hereinafter referred to as Social Spider and Prey (SSP).

SSP uses the vibration propagated via the social web by either an artificial spider or a prey to make an intelligent movement towards the vibration source, considering the intensity, frequency, damping and amplitude of the vibration. These properties represent the unique features of SSP and have been aligned to the hybrid power generation scenario for an optimal solution. Although SSP is modeled and tested on renewable power generation systems, in this case the dynamics of its operating mechanism and the randomization of parameter settings make it a global optimization algorithm that can search a hyperdimensional search space for an optimal solution (Frimpong et al., 2021).

The methodology for conducting the study and addressing the identified gaps in the existing body of knowledge is discussed in the next section. The conceptual model that emerged at the end of Chapter 2 is mapped directly to and aligned with the framework. Therefore, this chapter provides examples of how to fill research gaps outlined in the previous chapter.

3.2 Methodological framework

An overview of the research approach, design, and methods, collectively referred to as research methodology, guides the flow of activities, the selection of appropriate measurement tools, and evaluation and evaluation criteria to place the study on a scientific footing. There are multiple scientific approaches to a given problem, however, a researcher's philosophical worldview influences the choice of approach and hence the methodology for an investigation (Creswell and Creswell, 2018). Due to the subjectivity of scientific methods, it is very important that a methodology is explicitly defined to inform the intended audience of how data was collected, analysed and interpreted in order for a claim to be either confirmed or rejected based on the results (Creswell 2013).

According to Creswell, there are four key inquiries that might aid in researchers' comprehension of research design(Creswell and Creswell, 2018). The first, what theory of knowledge informs research (is it objectivism or subjectivism)? The second question, which theoretical perspective is behind the relevant methodology? There are several plausible answers to this question: positivism, empiricism, post-positivism, interpretivism or critical theory, etc. These perspectives relate to the epistemological and methodological frame of reference. This frame of reference determines the researcher's attitude and relationship to data production and the selection of research tools and methods (Adam, 2014). The next question aims to identify the methodology based on which a study is conducted, i.e., the action plan and strategies that link methods and results. This survey could be an example of predetermined inquiry, in which causation are thought to dictate outcomes or consequences, from a postpositivist viewpoint. Therefore, the issues that postpositivist study are issues that require evaluating and identifying the factors that influence experiment results (Creswell and Creswell, 2018).

However, to circumvent the context problem, positivism assumes that data is of good quality and appropriate if it can be measured (Adam, 2014). Furthermore, positivism sidesteps the problem of context by focusing on the numerous variables and the correlations that exist between them. First, it is based on the heavy reliance on quantification and the highly technical nature of the release; Second, it typically derives from statistical (multivariate) methods used in a study and no attempt is made to triangulate the data. Finally, the analysis of the results could be based on a single data set or very limited data sources, so that the results are largely viewed categorically, and the problematic results are less emphasized (Adam, 2014; Weideman, 2018). More generally the positive worldviews are expressed as described scientific research or empirical study that uses tools aimed at reducing ideas to a smaller, discrete, measurable set-in order to test or confirm their validity, such as the variables that comprise hypotheses and research questions research (Creswell and Creswell, 2018). This positivist philosophy is rooted in a quantitative research methodology that uses experimental manipulations as a scientific tool to measure variables to answer research questions and/or hypotheses (Creswell and Creswell, 2018). Research questions are concisely addressed with the required quantitative assessment tools and study designs. Research design is a tool for investigation within a qualitative, quantitative, or mixed strategy that specifies processes in a research project (Creswell and Creswell, 2018). Research designs are viewed as investigative strategies that guide the flow of studies. The concepts and methods employed under a research design provide the foundation on which the study posits to address the research problem (Apuke and Programmes, 2017; Creswell and Creswell, 2018).

Therefore, the positivist worldview in this study provides the researcher with a lens to perceive the energy issues discussed in the previous sections. Therefore, to find the best combination of different renewable technologies to generate electricity, a quantitative research methodology is used. Quantitative techniques focus on carefully measuring (or experimentally treating) a set of variables to address theory-driven research questions and hypotheses. Quantitative research methods involve estimating and evaluating numerical values to draw conclusions (Creswell and Creswell, 2018). It is important that the system components are properly sized to consider the correct sizing of the solar PV panel, wind turbines, biomass engine and battery storage system to stably power the associated load to provide a near-optimal solution to reach HRES. Although oversizing the system can increase system security by producing more current than the load, it incurs additional costs, but power reliability would be compromised if system components are undersized. Therefore, the reliability index to be met and the system costs must be considered in the estimates for the respective renewable technologies.

This chapter describes how the near-optimal power generation of an HRES is solved to meet the fluctuating demand of the system. The optimal system configuration is determined using the SSP swarm-based meta-heuristic algorithm. In addition, methods for checking the results of the optimization solution are discussed. First, a methodological framework is introduced that shows the different phases of the optimization problem formulation up to the solution. The phases range from the feasibility analysis of the hybrid system through the optimization process to the decision analysis based on the optimization solutions obtained. Central to the optimization process is the data used and the technique used, so the chapter explains the process used to collect both sensor and historical data and how the SSP algorithm that uses this site was developed and tested. Finally, the criteria and reasons for choosing comparison algorithms are given along with the software tools (programming platform) used to design and implement the algorithm and to visualize the results.

The need to thoroughly investigate renewable energy resources in the catchment area of the proposed system cannot be overemphasized. Depending on the energy needs of the end user (energy consumer/electricity producer), it is necessary to identify a coherent, efficient and appropriate energy planning framework. (Wu et al., 2021). The framework must be based on the collaboration of decision analysis and optimization engineering to build a reliable, resilient and cost-effective mini-grid system that uses locally accessible resources for an autonomous energy system. (Wu et al., 2021). In view of such a development, the framework must have three distinct phases.

First, feasibility analysis considering different criteria (technical, economic, and environmental) which are mainly data attributes serving as input to the selection process of suitable energy alternatives to support the design of the mini grid. Second, the optimal size of the various components of the system to determine the ideal mix of renewable energy technologies for a given situation, and finally an optional analysis method used to evaluate the best sustainable hybrid energy system based on specified criteria such as reliability and cost. Based on this analogy, a framework model to solve the HRES optimization problem was improved and adopted from (Jyoti Saharia, Brahma and Sarmah, 2018; Wu et al., 2021) to help solve the HRES optimal power generation problem as shown in Table 3.1 on the next page.

Then the framework is used to design an appropriate hybrid system for an idealized community in South Africa, Durban with varying loads using real-time climate data and secondary data. The feasibility assessment of HRES power generation using the proposed methodology demonstrates competence not only in determining the near-optimal size of a hybrid standalone mini-grid, but also in reducing the annual cost of the system and thereby minimizing the levelized energy cost (Maradin, 2022). The proposed methodological framework consists of three phases, namely feasibility and decision analysis, optimal sizing of HRES and decision analysis based on the optimization solution. Table 3.1 shows the different phases, descriptions, activities and data or algorithms that form the methodological framework.

Table 3.1:Phases of optimal power generation for HRES with advanced IoT analytics at the edge

Phase	Description	Activity	Data/Algorithm/tool
Phase 1: Feasibility and decision analysis for hybrid renewable system	Preliminary stage of designing the hybrid system. It involves analysing the energy generation potential of the available renewable resources for example, solar, wind and biomass	Collection of renewable energy data from primary and secondary sources. Deploy sensors to collect climate data from the environment	Solar energy data (temperature, irradiation) Wind energy data (wind speed) Biomass (estimation of the bio-energy potential such as the amount of input material per day) Load and economic data are obtained from literature and the Internet
Phase 2: Optimal sizing of HRES	Solar energy data (temperature, irradiation) Wind energy data (wind speed) Biomass (estimation of the bio-energy potential such as the amount of input material per day) Load and economic data are obtained from literature and the Internet	Define the optimization problem, objective function(s) and constraints. Declare problem variables and set all parameters of the algorithm. Apply an optimization tool to solve the problem	As inputs for the optimization algorithm, the technical data of the renewable energy technologies i.e., wind turbine, solar panel, and biomass engine specifications; meteorological data, and economic indicators are taken as optimization parameters or inputs variables.
Phase 3: Decision analysis based on optimization solutions	In the last phase, the result obtained from the optimization phase is evaluated and the most suitable option is selected in terms of cost efficiency and a better reliability index of the hybrid system	Arrange plausible solutions to the problem given by the optimization algorithm/technique. Use an analysis tool to choose the best solution that meets the needs of the hybrid system	Evaluation and statistical analysis of the optimization result using comparative metaheuristic algorithms, namely PSO, TLBO and SSA, against the performance of SSP.

The first phase is the preliminary stage, which deals with the feasibility assessment of the site in terms of the renewable technologies that should be deployed to harness usable energy (electricity) with the lowest investment costs. To do this, data on renewable energies from the surrounding area is collected using IoT and sensor technology. The sensor data collected complements historical data retrieved from a secondary source, (National Renewable Energy Laboratory (NREL), a renewable energy data repository) to perform the feasibility analysis. After the preliminary analysis of the site and the renewable energy potential has been assessed, the next phase is carried out. Thus, Phase 2 includes the optimization process. With the help of the SSP algorithm, the component dimensioning of the hybrid PV-wind-biomass-renewable energy system is derived. The optimal solution is based on the techno-economic analysis (Tezer, Yaman and Yaman, 2017) of the hybrid system. It is worth noting that several combinations of the hybrid system components are possible. Eventually, this leads to different system configurations with different costs and sizes in Phase 2. Finally, in Phase 3, all candidate solutions from the previous phase are ranked. A decision analysis technique is then used to make an informed decision to select the most appropriate outcome for the optimization problem.

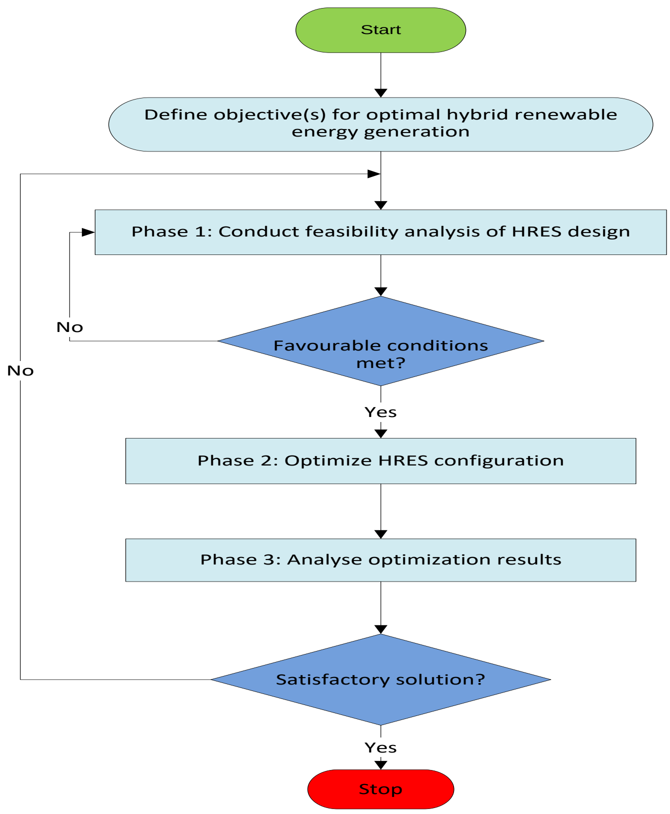


Figure 3.1: Flow chart of the methodological framework for HRES optimization

Figure 3.1 is a flowchart of the framework adopted for hybrid renewable power generation optimization. It presents the optimization processes for dimensioning based on a techno-economic evaluation of the hybrid renewable energy system from a high level.

3.2.1 Phase 1: Conduct feasibility analysis of HRES design

As with most system designs, a feasibility analysis is central to configuring a hybrid renewable energy system to reliably power the connected load (Kumar et al., 2018; Kalananda and Komanapalli, 2021). An effective approach to cost-effectively generate a reliable power supply from the hybrid system is to optimize the components of the hybrid system. Optimizing a hybrid renewable energy system is a multidimensional problem. There could be multiple but conflicting targets and myriad random variables (Kumar et al., 2018) as HRES encompasses multiple renewable energy systems. For example, solar PV, wind turbines and biomass engines (gasifiers) were considered in this study. Furthermore, the battery storage system was considered as an integral part of the hybrid system to create different scenarios and numerous alternatives for the optimal power configuration. Incorporating multiple renewable resources into HRES requires different technologies with different standards to generate a reliable power supply for the assigned load. The diversity of renewable technologies amidst the random nature of the decision variables complicates the design of HRES. This makes HRES optimization a very difficult problem (Tezer, Yaman and Yaman, 2017; Yong and Shaowu, 2020) that can be tackled but with little success using traditional optimization approaches such as graphical engineering or linear programming (Fister et al., 2013).

Recent reviews of models and methods to assess an optimal configuration of HRESs are presented in (Faccio et al., 2018; Frimpong, Millham and Agbehadji, 2021). Several techniques or approaches for the preliminary assessment of HRESs include commercial software (e.g. HOMER), hand-made approaches and computational tools including AI techniques (e.g. PSO, GA, TLBO) as discussed in Chapter 2. AI methods have been popularized in recent studies relating to optimization as researchers look for efficient ways of addressing complex problems such as HRES optimization.

The first stage of solving HRES problem involve conducting a preliminary evaluation of the HRES system design. A site-by-site assessment of the HRES system is very important, so a survey of the target site is conducted to collect various data such as meteorological data (wind speed, temperature, irradiance, humidity, etc.) and load profile (which describes the local load demand for electricity). Depending on the availability and potential of on-site renewable energy sources, a viable energy system could be designed and implemented to meet the community's energy needs (Lip et al., 2017; Twaha and Ramli, 2018).

In line with the study objectives, real-time weather data was collected and processed to determine how feasible it would be to implement a PV-wind-biomass hybrid system within the study area. The sensors used in this study included a wind speed sensor, a temperature and humidity sensor, and a light intensity sensor. The sensors were deployed at different times of the day in and around the area surrounding the Durban University of Technology, Ritson campus, for two months (April and May 2022). Although the sensor data did not provide an adequate representation of the annual climatic conditions of the case study area, they served as a tool for real-time data collection. In addition, the sensor data provided the researcher with a validation mechanism for the secondary data retrieved from the internet. The next section explains how sensors were used to collect renewable data for hybrid system design.

3.2.2 Sensor data collection and edge analytics

The two most important input parameters for a hybrid PV wind energy system are solar irradiance and wind speed (Ohunakin, Adaramola, and Oyewola, 2011). These are the indicators and measure of the renewable potential of such a hybrid system. There are other climatic attributes such as wind direction, air density, humidity, insolation, etc. related to solar and wind energy that can be useful in hybrid system design estimation (Lipu et al., 2021). However, using all these parameters when designing hybrid systems complicates the model but adds insignificant precision to the accuracy or efficiency of the system (Khan, Pal, and Saeed, 2018). Therefore, for the estimation of wind energy resources, wind speed data was collected with a wind anemometer sensor, and two different temperature sensors were used to collect ambient temperature data. The temperature data was then used to estimate the solar radiation using the Hargreaves model (Irwan et al. 2013).

Hargreaves Model

Since weather data is scarce in distant regions and fully instrumented meteorological stations are expensive to set up and operate, simple correlations are practical. The information on solar radiation is decisive for estimating the performance of photovoltaic systems. Any projection of solar radiation must be accurate over the long term for that location. In the absence of long-term solar radiation data, the Hargraves model could be used to estimate solar resources(Irwan et al. 2013). Latitude and daily minimum and maximum temperatures serve as the base for this estimation technique. Current sensor readings and/or historical location information are used to determine solar irradiance. The idea that solar Irradiance (I_S) may be computed from the difference between the highest and lowest air temperatures (Irwan et al. 2013) was originally propagated by Hargreaves and Samani in 1982:

$$I_s = \alpha \times R_a (\Delta T)^{1/2} \tag{3.1}$$

where ΔT denotes the difference in air temperatures for each day, in °$\boldsymbol{C}$, R_a is the co-efficient of extra-terrestrial radiation and, it depends on latitude and the day of the year; α is constant (0.16 for inland and 0.19 for coastal).

The value of R_a is given by

$$R_a = (\frac{1440}{\pi}) \times c \times e \times (\cos\theta \,.\cos\delta \,.\sin\gamma + \gamma.\sin\theta \sin\delta) \tag{3.2}$$

where c denoting solar constant is 1367 W/m^2, e denotes orbital eccentricity correlation coefficient, and it is calculable using the equation:

$$e = 1.0 + 0.033.\cos\big(2\pi(d/365)\big) \tag{3.3}$$

θ represents the latitude (L) of location, and it is given by:

$$\theta = L.\pi/180 \tag{3.4}$$

and δ represent solar declination angel which can be estimated by the equation:

$$\delta = (23.45\pi/180).\sin\,(2\pi(284 + d/365) \tag{3.5}$$

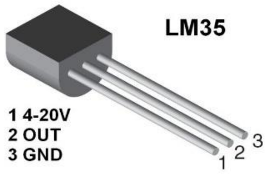
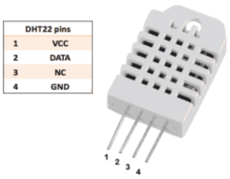
and γ is the mean sunrise hour angle which can be calculated by:

$$\gamma = \cos^{-1} - tan\theta\; tan\delta \tag{3.6}$$

The value of R_a depends on Julian day (d) of the 365 days, and the value of I_s is proportional to the difference between $T_{max}\; and\; T_{min}$ (ΔT), and its value is directly proportional to R_s, hence, should ΔT increase the value of R_s will increase.

Table 3.2 gives an overview of the sensors used in collecting the real-time experimental data.

Table 3.2: Sensors used in collecting and transmitting environmental stimuli

Sensor/device	**Description**	**Remarks/Reference**
Temperature sensor 	With an output voltage corresponding to the temperature in Celsius, the LM35 series of quality integrated temperature sensors. It is a chip that provides a linearly proportional voltage output to temperature in °C, so it is very easy to use with an Arduino. The LM35 sensor is reliable, non-degradable, used in a range of climatic conditions, and it does not need any other parts to work. Additionally, the LM35 sensor does not need to be calibrated and has a 1°C accuracy across the whole temperature range of -55°C to +150°C. The sensor has an incredibly low self-heating since it runs from a 4V to 30V supply and uses less than 60A during active temperature conversion (less than 0.08C in still air).	The only downside to the LM35 is that it needs a negative bias to measure negative temperatures. Therefore, it is highly recommended to use the TMP36 instead when measuring temperatures from -40°C to 125°C. (Mar Myint Aung et al. 2018)
DHT22 	The DHT22 is a simple, low-cost digital sensor for measuring temperature and humidity. It monitors the surrounding air with a sensor and a capacitance humidity sensor and delivers a digital signal on the data pin. Specifications: Energy: 3-5V; maximum current of 2.5mA; Humidity: 0 to 100% 2.5% to 5%, and accuracy of temperature can range between -40°C to +122°C with $\pm$0.5 degrees accuracy	The DHT22 sensor does not require analog input ports and may communicate over considerable distances. (Fezari & Dahoud 2018; Sarswat et al., 2019)
Wind speed sensor 	An anemometer is a sensor device used to measure wind speed. It calculates the analog voltage, which may be between 0.4 and 2.0 volts (0 m/s of wind velocity) equivalent to a wind speed of 32.4 meters per second.	The anemometer is programmed to produce a voltage between 0.4V and 2V. A number 0.4V indicates no wind, while a value of 2V indicates a wind speed of 32.4 m/s. The relationship between voltage and wind speed is linear, which means that each 0.1V increase corresponds to a 2.025 m/s increase in wind speed.

3.2.2.1 Setup for sensor data collection: Primary dataset

In the initial phase of the experiment, each sensor was configured independently by connecting it to the Arduino UNO microcontroller with jumper wires directly or via a breadboard. A module code was written in Arduino IDE to test each sensor's output on an integrated serial monitor within the IDE. The code was then downloaded from a PC to the microcontroller. Using the Arduino UNO microcontroller, a USB connection was made between the PC and the UNO to collect the captured and streamed data to the PC. After that, each sensor module was tested in the laboratory. After a successful test case, all sensors (anemometer, LM35 and DHT22) were integrated into one device component. This made it possible to read/collect different climate data at the same time. Finally, Microsoft Excel Data Streamer was used to record the streaming data from the sensors. The data was pre-processed and used as a test case for the feasibility assessment of the renewable potential for the study area.

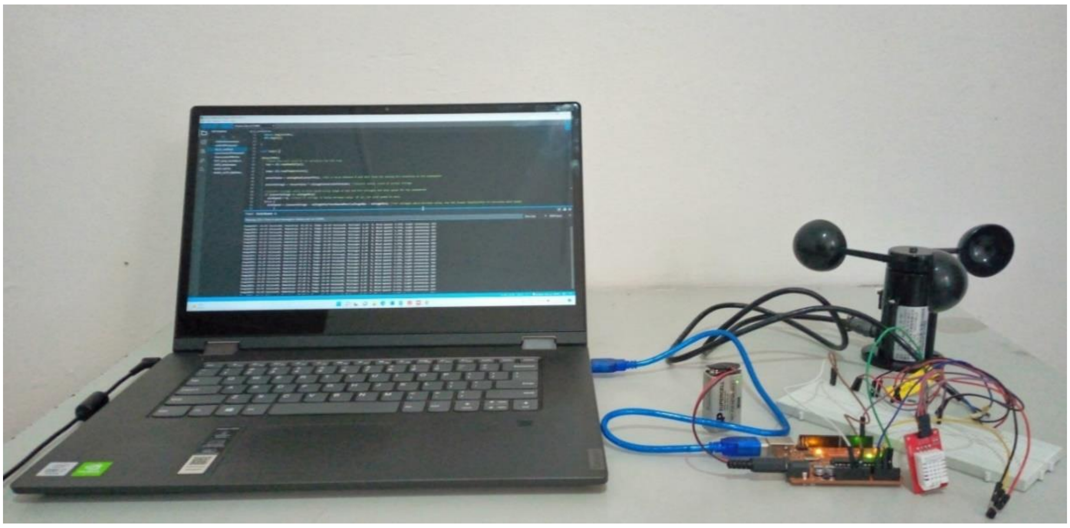


Figure 3.2: Setup used in collecting real-time environmental data

3.2.2.2 Data Pre-processing

The process of converting unstructured data, in this case data collected from the environment, into a format that can be understood is known as data pre-processing. Data pre-processing is very important in data mining because raw data is useless until properly structured. Before algorithms are applied to the data for analysis, they should be validated for quality (Garca et al., 2016).

3.2.2.3 *Why is data pre-processing important?*

The pre-processing of data primarily involves assessing the quality of the data in order to make an informed decision based on this dataset. Accuracy, completeness, consistency, timeliness, and interpretability are some of the attributes used to assess data quality (Mishra et al., 2020). The accuracy attribute of quality data determines whether the data entered is accurate and ensures that the data represents exactly what it is intended to explain. The presence (availability) or lack of access (unavailability) of data is described by the data completeness attribute. All required attributes must exist in a complete data instance. The freshness attribute also determines whether a record has been correctly updated to reflect changes. This property wants to know if sensors collect and transmit data instances correctly for sensor data gathered from the environment. Data interpretability dictates that datasets are understandable, readable, and available in the correct format to facilitate data utilization for other applications. Therefore, these data qualities result from performing certain tasks or activities to prepare data for all forms of application (Dias de Assuno, da Silva Veith and Buyya, 2018). The main tasks of data pre-processing are briefly discussed in the next subsection.

The primary tasks in data pre-processing are cleansing, reduction, integration, and transformation of data (Dias de Assuno, da Silva Veith and Buyya, 2018; Cardellini et al., 2019).

3.2.2.4 *Data cleansing:*

This process involves removing incorrect (erroneous data), inaccurate, and/or incomplete data from data sets, and finding good replacements for missing values (Garca et al., 2016). The term noisy data describes useless data value that is read or captured into a data set. Both noisy data and missing values must be corrected when preparing the data set for effective analysis. Therefore, the sensor data that had string literals appended to it was cleaned up so that it contained only the numeric values needed for the analysis. Data cleaning techniques mainly focus on dealing with missing values from datasets or dealing with noisy data.

Handling missing values:

Missing values from a dataset can compromise data integrity, so it is important to fix the missing value for an attribute to reflect the correct representation of the data instance. Common values such as not available (NA) can often be used to fill in the gaps. Another technique, but not recommended for a large data set, is to enter the missing values manually. For particularly large datasets, a default value can be used instead. If the data are normally distributed, the mean of the attribute can be used to fill in the missing value; Alternatively, if the data are not normally distributed, the median value of the attribute can be used. When using regression or decision tree approaches, it is also possible to replace the missing value with the most probable one (Zlobaite and Gabrys, 2014).

Handling Noisy data:

Outlier is an example of a noisy data set that contains random errors or unnecessary data points. The experimental data showed that several data points were outside the usual range of values when considered in the context of the streaming data pattern. It is possible that this was caused by inaccurate sensor readings. In such a development, the noisy data could be contained by binning, regression analysis or clustering (Rajput & Vinoth Babu 2018; Younis, Krunz & Ramasubramanian 2006).

Binning is a method that relies on sorting data points to eliminate noise. The information is sorted first, and then the sorted values are divided and kept in bins. Data in the bin can be rounded in three different ways. In the smoothing by class mean technique, the class mean takes the place of the class values. While smoothing by bin boundary substitutes the closest border for the missing data entry, smoothing by bin median replaces the values in the bin with the median value. In this method, the bin values are replaced with the closest limit after accounting for the lowest and maximum values of the bin values (Garca et al., 2016).

Another method for finding unnecessary data in a data set is regression, a type of data smoothing technique. The approach establishes a mathematical connection between dependent and independent variables (Mohammadi et al. 2018). Regression analysis is used to determine or evaluate the optimum data point to represent a certain data characteristic or variable (Mohammadi et al. 2018). Clustering is another technique for locating outliers in data sets. Clustering is often used in unsupervised learning. In the literature on computer and networks, clustering has been widely studied (Agbehadji, Millham, et al. 2021; Rajput & Vinoth Babu 2018; Younis et al. 2006).

3.2.2.5 Data integration:

Creating a single dataset by combining the data from multiple sources is called data integration. The process of data integration is one of the aspects of data management that is one of the most important processes in data management. There are a few things to consider when integrating data. First, schema integration (Wachowicz, Arteaga, Cha & Bourgeois 2016), which deals with metadata definitions from different sources. Different data sets have attribute definitions in different formats, data types, sizes, or default values. This description of data about data should be harmonized in a single data set for a common purpose. On the other hand, the problem of entity or instance identification also affects the integration of different data sets (García et al. 2016). Should the attribute descriptions of the same entity differ in different database systems, data engineers must make rigorous efforts to streamline the different entity groups from multiple databases to get a better view of the integrated dataset for effective analysis (Kolajo, Daramola, and Adebiyi, 2019).

3.2.2.6 Data reduction:

This approach helps reduce data volume and simplify analysis while maintaining the same or nearly the same results. This reduction of data also helps save disk space, which is important for efficient data management. Data reduction strategies include dimensionality reduction, redundant data removal/reduction, and data compression. Since the data volume for real applications is huge, a dimensionality reduction method is required (Zlobaite and Gabrys, 2014). In order to decrease the dimension of a data set, random variables and characteristics are minimized by merging data characteristics without compromising their original qualities (Zlobaite and Gabrys, 2014). This also adds to the reduction of storage space and calculation time. In data compression, however, compression can be lossless or return loss of data. In lossless compression, no information is lost during the process of compression. While lossy compression decreases data size by eliminating irrelevant features/information from the data set (Wu, Tan, and Xiong, 2016).

3.2.2.7 *Data Transformation:*

Data transformation is the process of altering the format or structure of data. Depending on an application's requirements, this step may be simple or challenging. Methods used in data transformation include smoothing, aggregation, discretization and normalization (Mohammadi et al., 2018). By removing noise from a data collection, smoothing makes it easier to use algorithms to locate the significant features of the data set. Even tiny adjustments that improve the prediction of a given dataset can be found through smoothing. Another technique for transforming data is aggregation. This tactic involves compiling and presenting information in a compressed format. The description of data analysis involves collecting data from multiple sources. This is an important stage as the quantity and quality of the data will determine how accurate the data will be. Results are more significant when the amount and quality of data are high. In addition, the discretization technique for data transformation continuously modifies the data by segmenting data into intervals. The data size is reduced by discretization. For example, a period could be specified instead of the lesson time. Another method of transforming data is data normalization, which uses scaling to represent a variety of data qualities so that it can be represented more compactly (Mohammadi et al., 2018).

3.2.2.8 *Real-Time Sensor-Generated dataset*

After setting up a working data collection system, the IoT devices were deployed in the area to collect solar and wind energy data. The streamed data was observed and recorded in the Microsoft Excel spreadsheet application. Using Excel's Text (String) and Numerical (Mathematical) functions, the streamed data was processed to extract key data values from the respective sensor columns on the worksheet. The hourly mean values of the data were derived from the collected data and the estimate of the mean values for a typical day was used in the hybrid system design. Since sufficient information/data is needed to make an accurate renewable energy forecast (Dufo-López et al. 2017; Ghofrani & Hosseini 2016), the researcher used secondary data to complement the real-time data generated by sensors. Both sets of data were used to find the near-optimal value for the HRES optimization problem studied.

In this study, the impact of atmospheric humidity on both solar and wind power generation was not considered (Nandakumar, Vaghasiya, Yang, Zhang & Tan 2020; Danook, Jassim &

Hussein 2019). Meanwhile, the ambient temperature estimate used in the model was derived from averaging the readings from the two temperature sensors (Kalma, McVicar & McCabe 2008; Liao & Dexter 2004).

3.2.2.9 Secondary dataset used and reason for the choice

The secondary dataset was retrieved from the National Renewable Energy Laboratory (NREL) website. The website is equipped with a search tool that helps generate a desired result from the NREL database. A request for the Durban data set was therefore made via the search engine on the website. The result of querying the database presented two downloadable Excel files for hourly and monthly distribution of solar resources. Both files were in CSV (comma-separated values) format. In the files was a brief description of the location for which the data was provided; The description includes information such as Weather Data Source: (INTL) Johannesburg, South Africa, Latitude: 26.13S and Longitude: 28.33E. The Solar Resource dataset contains the solar data and other meteorological data, including ambient temperature, and wind speed describing the climatic weather and site conditions. Figure 3.3 provides an overview of the hourly data file for the specified location retrieved from the NREL database in September 2021. The data set uses a set of weather data compiled from the NREL Database. NREL hosts the collection of data from other sources for the rest of the world. The data set uses hourly typical annual meteorological data, which is a year's worth of data representing solar and wind resources over a multi-year period. The dataset provides, among other things, the monthly and annual average values for solar radiation in kilowatts per square meter per day, the wind speed in meters per second and the temperature in degrees Celsius. There are 8760 data instances representing the total hours in a year.

```
PVWatts: Hourly PV Performance Data
Requested Location:,"Durban"
Location:,"JOHANNESBURG, SOUTH AFRICA"
Lat (deg S):,"26.13"
Lng (deg E):,"28.23"
Elev (m):,"1700"
DC System Size (kW):,"4"
Module Type:,"Standard"
Array Type:,"Fixed (open rack)"
Array Tilt (deg):,"20"
Array Azimuth (deg):,"0"
System Losses:,"14.08"
Invert Efficiency:,"96"
DC to AC Size Ratio:,"1.2"

Month,"Day","Hour","Beam Irradiance (W/m^2)","Diffuse Irradiance (W/m^2)","Ambient Temperature (C)","Wind Speed (m/s)","Plane of Array Irradiance (W/m^2)",
1,"1","0","0","0","18.5","0","0","18.5","0","0"
1,"1","1","0","0","17.6","0","0","17.6","0","0"
1,"1","2","0","0","16.9","0.5","0","16.9","0","0"
```

Figure 3.3: Overview of NREL dataset retrieved for Durban in September 2021

The rationale for using NREL datasets is that they represent a standard benchmark dataset for experimental research, as used and referenced in several scholarly articles (Singh, Singh, and Kaushik, 2016; Pookpunt, 2019). It also has a year of continuous data that the primary data collected with the sensors could not provide. Therefore, using the NREL dataset was an appropriate for this study.

Moreover, other historical dataset retrieved from literature (Ntlela & Davidson 2022; Govindasamy & Chetty 2018) and the National Aeronautics and Space Administration (NASA) data repository ("POWER | Data Access Viewer" n.d.)were used to complement the sensor data to extrapolate the real-time sensor data for an entire year period. The extrapolated dataset was also used alongside the NREL dataset to estimate the near optimal HRES power generation for the proposed system. Figure 3.3 and Figure 3.4 monthly averages from Ntlela & Davidson (2022) and brief description NASA dataset used to extrapolate the missing values for the real-time sensor dataset.

Table 3.3: Monthly solar irradiance for Durban

Month	Clearness index	Daily Radiation (kWh/m^2/day)	Solar Irradiance (W/m2)
Jan	0.475	5.67	236.25
Feb	0.500	5.51	229.58
Mar	0.531	5.03	209.58
Apr	0.582	4.40	183.33
May	0.639	3.81	158.75
Jun	0.653	3.40	141.67
Jul	0.659	3.65	152.08
Aug	0.620	4.25	177.08
Sep	0.557	4.84	201.67
Oct	0.472	4.93	205.42
Nov	0.455	5.30	220.83
Dec	0.468	5.69	237.08

Source: (Ntlela & Davidson 2022)

	A	B	C	D	E	F	G	H	I	J	K
2	NASA/POWER CERES/MERRA2 Native Resolution Hourly Data										
3	Dates (month/day/year): 01/01/2022 through 09/30/2022										
4	Location: Latitude -29.8469 Longitude 31.0047										
5	Elevation from MERRA-2: Average for 0.5 x 0.625 degree lat/lon region = 15.2 meters										
6	The value for missing source data that cannot be computed or is outside of the sources availability range: -999										
7	Parameter(s):										
8	ALLSKY_KT CERES SYN1deg All Sky Insolation Clearness Index (dimensionless)										
9	T2M MERRA-2 Temperature at 2 Meters (C)										
10	WS10M MERRA-2 Wind Speed at 10 Meters (m/s)										
11	CLRSKY_SFC_SW_DWN CERES SYN1deg Clear Sky Surface Shortwave Downward Irradiance (Wh/m^2)										
12	CLRSKY_SFC_PAR_TOT CERES SYN1deg Clear Sky Surface PAR Total (W/m^2)										
13	-END HEADER-										
14	YEAR	MO	DY	HR	ALLSKY_KT	T2M	WS10M	CLRSKY_SI	CLRSKY_SFC_PAR_TOT		
15	2022	1	1	2	-999	22.48	4.99	0	0		
16	2022	1	1	3	-999	22.5	5.42	0	0		
17	2022	1	1	4	-999	22.58	5.92	0	0		
18	2022	1	1	5	0.42	22.83	6.43	56.8	24.88		
19	2022	1	1	6	0.6	23.24	6.9	258.95	120.3		
20	2022	1	1	7	0.68	23.66	7.28	482.65	225.77		
21	2022	1	1	8	0.72	24.12	7.98	698.45	327.98		
22	2022	1	1	9	0.73	24.44	8.71	868.02	404.52		
23	2022	1	1	10	0.73	24.7	8.89	996.1	461.52		
24	2022	1	1	11	0.72	24.81	8.8	1057.27	489.3		
25	2022	1	1	12	0.73	24.8	8.7	1053.33	488.15		
26	2022	1	1	13	0.72	24.73	8.54	984.6	457.33		
27	2022	1	1	14	0.72	24.63	8.09	856.1	399.12		
28	2022	1	1	15	0.68	24.52	7.3	675.33	317.6		
29	2022	1	1	16	0.51	24.33	6.43	462.33	218.85		
30	2022	1	1	17	0.41	24.3	5.51	237.65	112.05		
31	2022	1	1	18	0.13	24.33	4.49	43.17	19.05		

Figure 3.4: Overview of NASA dataset retrieved for Durban in August 2022

3.2.3 Phase 2: Optimize HRES configuration

Proper sizing of HRES is very important in providing energy consumers with cost-effective, reliable power. In order to avoid failures in HRES projects, mainly due to incorrect sizing of the system components, it is crucial for hybrid system designers to effectively optimize the system components based on the potential of renewable resources at the site in order to satisfy the stakeholders (power consumers). Therefore, efficient optimization techniques for sizing and control of energy resources are needed to make the whole system reliable and sustainable in order to maximize system performance. Figure 3.5 shows the schematic diagram of hybrid PV-wind-biomass system. The various components that would help in generating electricity from renewable resources include solar PV panels, wind turbines, biomass generators, inverters/converters that would be connected to the load. Battery storage system is a complementary component of the system to enhance the hybrid system reliability. Batteries are therefore charged when renewable energy production exceeds demand. On the other side, the battery bank will send electricity into the system to satisfy the load when the load demand exceeds what the renewable energy system can deliver.

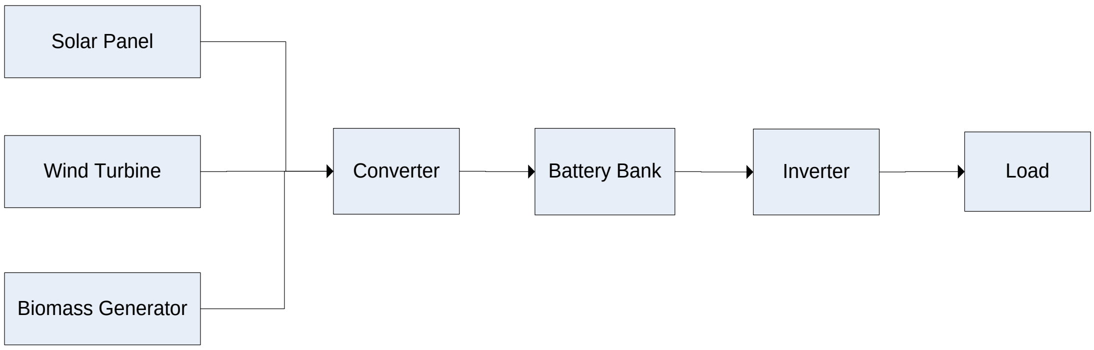


Figure 3.5: Block diagram of hybrid PV-Wind-Biomass system model with battery bank

The benefits of HRES optimization are numerous, but in most cases energy engineers and researchers try to achieve specific goals when designing the system. The goal of optimization can be to significantly reduce emissions into the environment and at the same time lower the costs of energy production. Thus, it is possible that the optimization problem has multiple goals, some of which may be contradictory, making optimization a difficult problem. In these situations, there is only one global optimal point that can be reached as a compromise between several local optimal points corresponding to the different goals. Analytical methods cannot be used to tackle such optimization problems, which are challenging if not unattainable. Such problems can be solved using multi-objective heuristic optimization approaches. (Barakat, Ibrahim & Elbaset 2020; Lu, Wang, Zhang & Cheng 2017).

In a hybrid system where PV arrays, wind turbines, and biomass engines power a load at a remote site, where national grid connectivity is impractical, optimizing the system such that the load is powered as much as feasible by energy generated by the system is keen. The primary purpose of this research is to discover a cost-effective and reliable PV-wind-biomass hybrid energy system. Evaluation and sizing of photovoltaic panels, wind turbines, battery banks, and biomass gasifiers are the most influential decision variables. The next part describes the mathematical models of the different renewable energy systems, such as solar photovoltaic (PV), wind turbines, and biomass gasifiers. In addition, a computation of the energy required for battery storage based on the battery system's charge level is presented. The system operation strategy details the power flow to coordinate all functions of the proposed hybrid system for effective power management. Last but not least, the objective function of the optimization issue and the approach (algorithm) employed are discussed.

3.2.3.1 Solar PV Model

The amount of energy generated by a Photovoltaic panel at a specific time frame, when the influence of temperature is neglected, is calculated as (Singh, Singh & Kaushik 2016):

$$P_{SP}(t) = P_{RSP} \times \eta_{SP} \times \frac{I_R}{I_{std}} \tag{3.7}$$

where P_{RSP}, η_{SP}, I_R *and* I_{std} represent rated power of solar panel, efficiency of solar panel, solar irradiance and rated solar irradiance at standard conditions. Table 3.4 provides the parameter setting for the PV model used in the simulation of the HRES configuration.

Solar panel parameters used in simulation of the HRES configuration.

Table 3.4: Solar panel parameters used in optimization of the HRES

Parameter	Variable	Value (Unit)
Rated PV power	P_{RSP}	1 kW
Efficiency of PV panel	η_{SP}	90%
Solar irradiance	I_R	W/m2
Standard irradiance	I_{std}	1000 W/m2
Capital cost of PV	CC_{PV}	R 1500
Replacement cost	RC_{PV}	0.7 * CC_{PV}
Maintenance cost	MC_{PV}	R100/year
PV Lifetime	PV_{life}	20

3.2.3.2 Wind Turbine Model

The power output of a wind turbine at a given point in time is estimated as follows (Sanajaoba Singh & Fernandez 2018):

$$P_{WT}(t) = \begin{cases} 0, & v(t) < v_{cin} \; or \; v(t) > v_{cout} \\ P_{RWT}, & v_R \le v(t) \le v_{cout} \\ P_{RWT} \times \dfrac{v(t) - v_{cin}}{v_R - v_{cin}}, & v_{cin} \le v(t) \le v_R \end{cases} \tag{3.8}$$

where P_{RWT} represents the rated power of the wind turbine, $v_{cin,}$ v_{cout}, and $v(t)$ denote cut-in wind speed, cut-out wind speed, and the measured wind speed at a hub height. $v(t)$ is calculated as:

$$v(t) = v_R(t) * \left(\frac{H_{WT}}{H_R}\right)^{\propto} \tag{3.9}$$

where $v_R(t)$ denotes the wind speed at reference height, H_{WT}, H_R, $\propto$ represent wind turbine hub height, reference height, and surface roughness value is usually given as 1/7 or ranged between 0.1-0.4.

Table 3.5: Wind turbine parameters used in optimization of the HRES

Parameter	**Variable**	**Value (Unit)**
WT Rated power	P_{RWT}	1 kW
Rated wind speed	v_R	11 m/s
Wind speed at time t	$v(t)$	m/s
Cut-in speed	v_{cin}	2.5 m/s
Cut-out speed	v_{cout}	45 m/s
Wind turbine hub height	H_{WT}	10
Wind speed reference height	H_R	2
Surface roughness constant	$\propto$	1/7
Capital cost of wind turbine	CC_{WT}	R 5700
Replacement cost wind turbine	RC_{WT}	0.7 * CC_{WT}
Maintenance cost wind turbine	MC_{WT}	R1000/year
Wind turbine efficiency	η_{WT}	28%
WT Lifetime	WT_{life}	20 years

3.2.3.3 Biomass Model

Solid biomass-to-electricity conversion technology first converts the solid state into gaseous fuel, which is eventually used to power a biomass generator. The amount of biomass electricity that could be generated by the biomass gasifier per year (Das & Mahanta 2019; Singh, Singh & Kaushik 2016)is given by the equation:

$$P_{bmg} = P_{R\_bmg} \times (8760 * CUF) \tag{3.10}$$

P_{R_bmg} denotes the biomass gasifier rating, CUF represents the gasifier capacity utilization factor. The assessment of available biomass takes into consideration the annual biomass volume (tons) and the gasifier's operating hours. The relationship between the rating of a biomass gasifier P_{R_bmg} and the other important variables is defined as follows:

$$P_{R\_bmg} = \frac{Total\ biomass\ \left(\frac{Ton}{year}\right) \times 1000 \times CV_{bm} \times \eta_{bmg}}{365 \times 860 \times Operating\ hours/day} \tag{3.11}$$

where $CV_{bmg}\ and\ \eta_{bmg}$ denote the biomass calorific value and overall conversion efficiency of the gasifier respectively.

Table 3.6: Biomass gasifier parameters used in simulation of the HRES configuration

Parameter	**Variable**	**Value (Unit)**
Biomass gasifier power rating	P_{R_bmg}	5 kW
Capacity utilization factor	CUF	1.97%
Calorific value of biomass	CV_{bm}	18 MJ/kg
Conversion Efficiency of gasifier	η_{bmg}	25%
Capital cost of biomass gasifier	CC_{BMG}	3500 R/kW
Replacement cost gasifier	RC_{BMG}	0.7 * CC_{BMG} R/kW
Maintenance cost gasifier	MC_{BMG}	10 R/kW
BMG Lifetime	BMG_{life}	15000 hrs

3.2.3.4 Battery storage system

The measurement of the power delivered by the battery storage system is determined by the state of charge (SOC) of the battery as a function of time when the battery is to deliver energy or store energy. When the battery is charged, the SOC is calculated as follows (Askarzadeh 2017):

$$SOC(t) = SOC(t-1) + \frac{(P_{batt} \times \Delta(t))}{1000 \times C_{batt}} \tag{3.12}$$

When the battery is in discharge mode, the SOC is also indicated by:

$$SOC(t) = SOC(t-1) - \frac{(P_{batt} \times \Delta(t))}{1000 \times C_{batt}} \tag{3.13}$$

SOC(t-1) denotes the previous state of charge of the battery before the current time t, SOC(t) is the current state of charge, P_{batt} represents the battery power, $\Delta(t)$ denotes the time steps to charge or discharge the battery, and C_{batt} represents the nominal capacity of the battery The maximum charging or discharging capacity of the battery storage system can be calculated as follows:

$$P_{batt\_max} = \frac{N_{batt} \times V_{batt} \times I_{max}}{1000} \tag{3.14}$$

where, $N_{batt}, V_{batt,}$ and I_{max} denote the number of batteries, the voltage of each battery and the maximum charging current.

Table 3.7: Battery storage parameters used in the optimization of the HRES

Parameter	**Variable**	**Value (Unit)**
Power of battery	P_{batt}	Wh
Capacity of battery	C_{batt}	150 Ah
Voltage of single battery	V_{batt}	12 V
Maximum charging current	I_{max}	150 A
Maximum state of charge	SOC_{max}	100%
Minimum state of charge	SOC_{min}	30%
Battery efficiency	η_{batt}	95%
Capital cost of battery	CC_{Batt}	R 4000
Replacement cost of battery	RC_{Batt}	0.4 * CC_{Batt}
Maintenance cost of battery	MC_{Batt}	100 R/year
Battery lifetime	$Batt_{life}$	5 years

3.2.3.5 Power Converter model

Power converters are required to regulate the power supply to the load when its AC and DC components are present in the system (Nagalakshmi, Babu & Prashanth 2014). It should be noted that solar PV panels and batteries produce DC output power (Singh, Singh & Kaushik 2016a), however the series of gears in wind turbines increases the rotational speed of the blade in varying proportion from about 18 rpm to around 1800 rpm with wind speed (Fran, Anitha & Mohan 2017). Accordingly, wind turbine generators produce an alternating electrical current. The size of the converter or inverter depends on the peak load requirement (P_{load}) and the efficiency of the device (η_{inv}), which is calculated as follows:

$$P_{inv_R}(t) = {}^{P_{load}(t)}/_{\eta_{inv}} \tag{3.15}$$

where $P_{inv_R}(t)$ denotes the rating of the inverter at a given time t.

Table 3.8: Inverter settings for HRES configuration

Parameter	**Variable**	**Value (Unit)**
Rated power	P_{inv_R}	100 kW
Efficiency (Rectifier & inverter)	η_{inv}	90%
Capital cost of inverter	CC_{inv}	3000 R/kW
Replacement cost of inverter	RC_{inv}	0.4 * CC_{inv}
Maintenance cost of inverter	MC_{inv}	1200 R/kW
Inverter lifetime	Inv_{life}	15000 hours

3.2.3.6 Operational strategy of the proposed PV-Wind-Biomass-Battery HRES

The operational strategy of HRES describes the flow and management of the renewable energy sources. To ensure system reliability in a hybrid power system, adequate power management is vital. The biomass engine is used in this system as a backup when the solar PV, wind turbines, and battery bank are unable to supply the load requirement. The following steps describe the operating strategy for the hybrid system, which is also shown schematically in Figure 3.6.

- The load demand is fulfilled by renewable sources when the combined power produced by solar panels and wind turbines is adequate and the wind energy is less than the load. Excess power can be sent to the battery bank once the load has been satisfied.
- The leftover power (from both the solar PV and the wind turbine) can be put into the battery bank if the load requirement can be met entirely by electricity produced by wind turbines in excess.
- When wind turbines and solar PV panels cannot provide enough electricity, the battery can provide the necessary balancing power.
- The biomass engine provides electricity to the load when solar and wind energy are insufficient and batteries are also unable to produce the required amount of power to fulfil the load requirement.

Consequently, the model makes this crucial decision by considering these circumstances and trade-offs throughout the optimization process. The main goal is to improve the performance of the hybrid system while achieving the optimization goal considering the specified conditions.

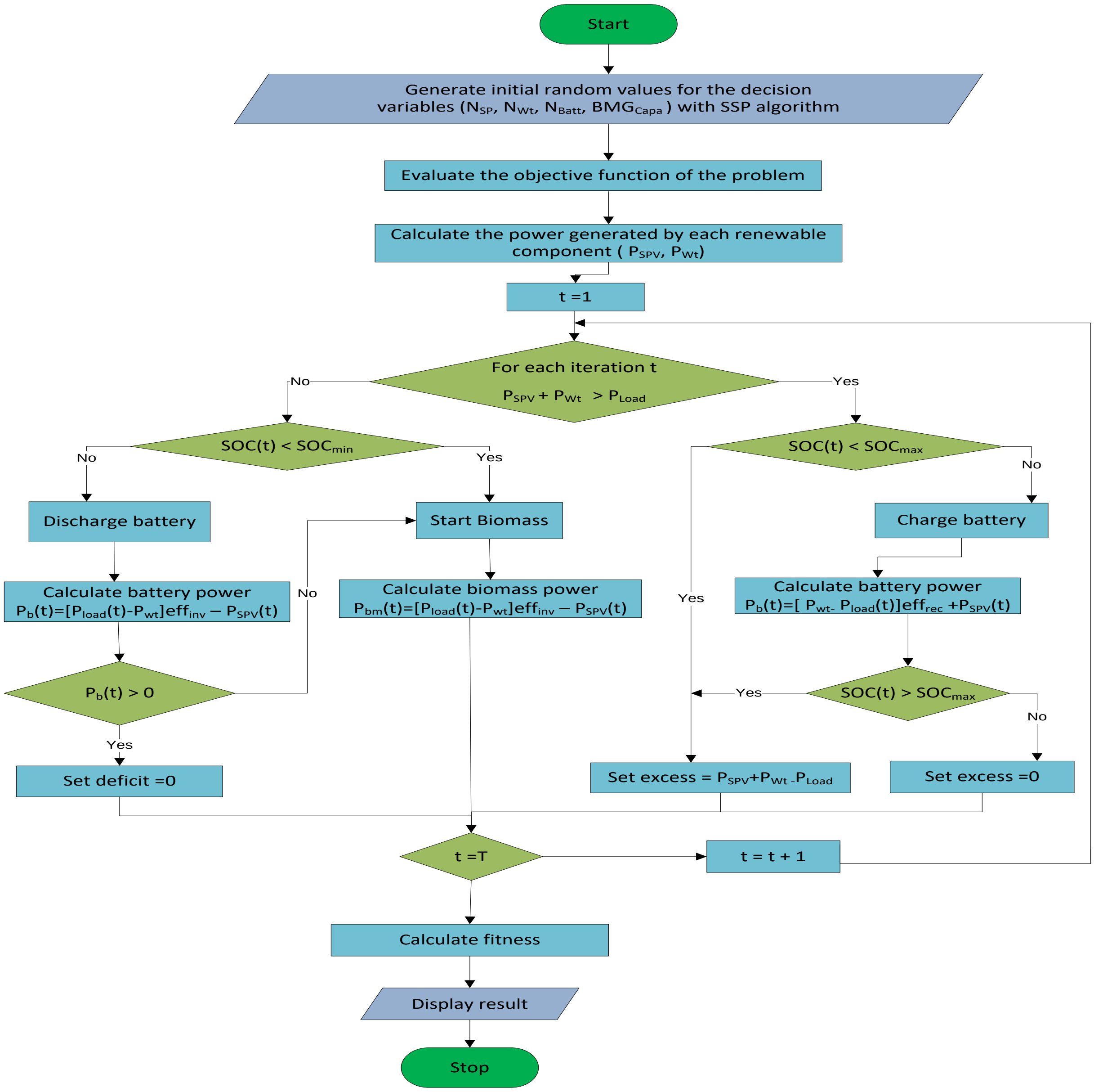


Figure 3.6: Operational strategy for the proposed hybrid renewable energy system

3.2.3.7 Optimization Objective

This study's primary objective is to lower the proposed hybrid system's total NPC, ASC, and COE while retaining the optimum energy flow feasible in terms of system reliability (LPSP). For the optimal system architecture, the number of wind turbines, solar panels, batteries, and the rated power of the biomass gasifier was chosen as four choice factors. In economic analysis, annualized system cost (ASC) is employed. Therefore, the optimal solution is the one that satisfies all criteria and optimization restrictions and has the lowest ASC (optimum). A *goal function* is the total system costs, which consist of the operating and maintenance costs of the components, the replacement costs, and the total capital costs. The installation and construction expenses are included in the capital costs when calculating the unit energy cost of a component. It is anticipated that the significant target function, the monetary worth of the entire system, also accounts for a significant portion of the hybrid system's power output. Therefore, the goal function for improving the HRES is given by:

Minimize: ASC

$$\text{ASC} = \sum_{i=1}^{K} N_i C_i \tag{3.16}$$

K represents the total number of HRES components, N_i denotes the quantity or rating of a particular component, C_i denotes the cost of the component which includes solar PV (C_{PV}); wind turbine (C_{WT}), battery (C_{batt}), inverter ($C_{inv)}$), and gasifier (C_{bio}).

The installation component of ASC is made up of several sub-components, including capital and installation costs (C_{Cap}), replacement costs (C_{Rep}), annual maintenance and operating costs ($C_{O\&M}$), and recycling/salvage costs (C_{Sal}). As a result, each component's overall ASC may be stated as follows.:

$$C_{PV} = C_{PV\_Cap} + C_{PV\_Rep} + C_{PV\_O\&M} - C_{PV\_Sal} \tag{3.17}$$

$$C_{WT} = C_{WT\_Cap} + C_{WT\_Rep} + C_{WT\_O\&M} - C_{WT\_Sal} \tag{3.18}$$

$$C_{batt} = C_{batt\_Cap} + C_{batt\_Rep} + C_{batt\_O\&M} - C_{batt\_Sal} \tag{3.19}$$

$$C_{bio} = C_{bio\_Cap} + C_{bio\_Rep} + C_{bio\_O\&M} - C_{bio\_Sal} \tag{3.20}$$

$$C_{inv\_con} = C_{inv\_Cap} + C_{inc\_Rep} + C_{inv\_O\&M} - C_{inv\_Sal} \tag{3.21}$$

The capacity recovery factor (CRF) is a formula that can be used to determine the annual cost of any component. Cash value of money is calculated using CRF which can be provided by:

$$CRF(r, \text{L}) = \frac{r(1+\text{r})^L}{(1+\text{r})^L - 1} \tag{3.22}$$

where L is the project life expectancy in years, and r shows the yearly interest rate.

A set of constraints for the optimization problem are:

$$1 \leq N_{PV} \leq N_{PV\_max} \tag{3.23}$$

$$1 \leq N_{WT} \leq N_{WT\_max} \tag{3.24}$$

$$1 \leq N_{batt} \leq N_{batt\_max} \tag{3.25}$$

$$1 \leq N_{bio} \leq N_{bio\_max} \tag{3.26}$$

$$0 \leq LPSP \leq LPSP_{max} \tag{3.277}$$

where N_{PV_max} denotes the maximum number of solar PV modules, N_{windT_max} is the maximum number of wind turbines, N_{batt_max} is the maximum number of batteries, $N_{biomass\_max}$ is the maximum power rating of the biomass engine, SOC_{batt} represents the state of charge of the battery, and SOC_{min} and SOC_{max} are the minimum and maximum values of battery SOC.

In a perfect system, where energy is always produced to meet the load demand, LPSP = 0, while in a system, where the load is never met, LPSP = 1. To guarantee that LSLP is below a certain limit, this optimization first concentrates on the capacity of the biomass engine, batteries, and near-optimal size of PV modules, wind turbines, and batteries (0.2). It is crucial to optimize the system for the lowest overall yearly system cost because renewable energy systems are more expensive than fossil fuels (Yang, Cheng, and Yao 2019; Foster et al. 2017).

In brief, the overall cost consists of the initial investment, the yearly operating cost, and the cost to maintain the system throughout time. The number of PV modules utilized, the number of wind turbines used, and the capacity of the biomass engine are modifiable variables that influence the cost and LPSP. These form the variables to be optimized by SSP in the optimization phase of the framework. The PV modules, wind turbines and biomass engines must then be examined as to how they can be mapped in this optimization about their energy production and additional costs for the systems. Therefore, the optimal hybrid system configuration selected based on the Levelized cost of electricity (LCOE) and reliability is estimated using the annualized system cost (ASC). The LCOE is the average price per kWh of valuable energy produced by the hybrid system and can be calculated as follows:

$$LCOE = \frac{ASC}{Total\ useful\ energy\ served} \tag{3.288}$$

The cost evaluation helps establish the different expenses, such as capital, operations, maintenance (O&M), cost of electricity (COE), etc., which are crucial for attracting possible investors to the energy project (Frimpong, Millham & Agbehadji 2021; Wu et al. 2021). Due to the increasing complexity of energy planning, optimization methods have evolved from single-target to multi-target optimization (Abd El-salam et al., 2018) (Ghorbani et al., 2018). Based on available data and information about generation, load, financial parameters (e.g., interest rate), geographic factors, desired system reliability, cost requirements, and other case-specific information, generation technologies and their sizes can usually be optimized to meet specific objective functions such as minimizing environmental impact, installation and operating costs, payback periods of investment, and maximizing reliability (Nehrir et al. 2011; Alsmadi et al., 2019).

For completely cost-effective dimensioning of the energy system, optimization methods, models, or software tools can be utilized, depending on the feasibility evaluation. When annual load growth is considered, component sizing is frequently substantial, which increases upfront expenses. The next stage of the methodological framework is to analyse the optimization result to gain a general sense of what to anticipate from the system.

3.2.4 Phase 3: Analysis of optimized results

Following a thorough techno-economic analysis of the energy system, the results are thoroughly analysed using a decision-based approach in line with the study's goals. When using a software-based optimization tool like HOMER, the optimization process runs until a termination condition is satisfied repeatedly, and the results of each iteration are collated for additional study (Motjoadi, Adetunji & Meera Joseph 2020; Lu et al. 2017). Based on the NPV results, potential options for the hybrid system setup are ranked (Motjoadi et al. 2020). This examination would provide light on the hybrid system's durability, dependability, and cost-effectiveness. The goal of the problem, the availability of data, the key performance indicators for the evaluation, practical considerations considering the problem, etc., are the primary factors that influence the selection of the right decision analysis approach. Sometimes, expert input is also considered (Ram et al. 2021).

An optimization algorithm is a tool that helps to make a good decision under the complex and challenging circumstances offered for this study. The behaviour of social spiders and their prey is discussed in the following subsection along with some of their distinctive traits, the mathematical formulation that captures those traits, the assumptions underlying the mathematical formulation, and the development of ground rules for each identified trait. These steps represent the steps in developing the SSP optimization algorithm. As a result, these stages are applied to the specified optimization problem as part of the proposed HRES search algorithm.

3.3 Social spider and prey algorithm for solving HRES optimization problem

Although social spiders reside in a structured group in a social web, these arthropods have long lagged in bionics research (Yu & Li 2015b; Nentwig 1985), maybe because most spiders are solitary (Whitehouse & Lubin 1999). Spiders like Mallos gregalis and Oecobius civitas, however, have been shown to live in communities and interact with one another (Cangialosi 1990). In response, the first swarm intelligence system based on the behavior of social spiders was created to address optimization issues (Cuevas, Cienfuegos, Zaldvar, & Pérez-Cisneros 2013). In 2015, Yu and Li created the social spider algorithm for global optimization.

Spiders are widespread organisms throughout the entire planet, and they may be found on every continent. They constitute one of the broadest groups of animals. Although colonies of spiders are extremely uncommon, those that create and maintain the social web, which serves as a dwelling and a tool for seeking food (Pruitt & Avilés 2018; Cangialosi 1990; Nentwig 1985), demonstrate social features. The social web also acts as a channel of communication for spiders. Spiders use a range of foraging techniques when they hunt, with the majority detecting prey through vibrations (Pruitt & Avilés 2018). Spiders are extremely sensitive to vibrations, as web vibrations indicate the capture of prey, as has long been known.

Spiders attack the vibration source when the vibrations fall within a particular frequency range. Social spiders can also tell the difference between vibrations coming from their prey and those coming from other spiders (Pruitt & Avilés 2018; Nentwig 1985). Because they passively pick up vibrations produced by other spiders in the same web, social spiders have a precise understanding of their web. One of the distinguishing features of social spiders and other species is this. The latter often actively transfer data, decreasing information loss but increasing energy consumption per transmission.

To identify the search pattern of the algorithm, various behavioural traits of social spiders and their prey are represented in this section. The concept is recognized to have originated from earlier studies (Yu & Li 2015b; Cuevas et al. 2013), however they have been expanded to incorporate a model for the prey that is essential to the topic at hand. The coordinated movement of the spiders to the food source is what distinguishes the foraging activity of a social spider. Spiders detect vibrations carried by the web and analyse them to predict where a food source is likely to be (Yu & Li 2015b). SSP optimizes the search space by taking use of this natural behaviour (Agbehadji, Awuzie, et al. 2021; Frimpong, Millham, Agbehadji, et al. 2021). Prey and artificial spiders' disturbance of the social web provide a meaningful indicator for managing the dynamics of the search space. To choose what to monitor in specific conditions, consider the frequency and amplitude of the vibration source (from the prey if it is under a predetermined threshold, emphasizing the freshness and stability of the vibration) (Frimpong, Millham, Agbehadji, et al. 2021).

The search strategy described by SSP considers the random oscillation of the prey in the social spider web. Thus, a captured prey broadcasts its presence across the web and upsets the balance of the social web by causing the web to vibrate. This vibration is unique compared to that generated by social spiders. In addition, the vibrations of prey provide information about its weight. It is important to note that many preys can be caught in the web at the same time. This premise underpins the latest advances in optimizing the search process. Consequently, the following traits and qualities of the prey are condensed as follows:

1. Artificial spiders on the search space are recognized based on their location (position), and each spider on the web has a definite location.
2. The present position of each spider determines its fitness on the web
3. A captured prey stuck on the social web is also identified by its position (location)
4. Web vibrations produced by prey are spread across the search area.
5. The vibration frequency, which is related to the weight of the prey, determines the freshness and stability of the prey.

3.3.1 Mathematical model of the SSP

The vibration intensity transmitted across the web is given by Equation (3.29) as:

$$I_{Prey} = \begin{cases} \frac{1}{1+f(X_i)}, & f(X_i) \geq 0 \\ 1+abs\big(f(X_i)\big), & f(X_i) < 0 \end{cases} \quad (3.29)$$

where $f(X_i)$ denotes the prey's fitness value X_i. The frequency of the prey's vibration propagated throughout the web ξ which signifies the freshness and sustainability of the prey on the web, as given in equation (3.30)

$$\xi = \frac{1}{2}\pi\sqrt{\frac{k}{m}} \times rand \quad (3.290)$$

where k denotes the maximum intensity, m is the intensity of the prey, and rand $\in (0,1)$ represents captured or fleeing prey. Equation (3.31) gives the location of a prey on the social web.

$$X_{Prey,i}^{r} = X_i^r + \xi\big(X_{best,prey}^{r} - X_{avg,prey}^{r}\big), \quad (3.301)$$

where $X_{Prey,i}^{r}$ is the location of the ith prey at present, $X_{best,prey}^{r}$ is the position of the best-found prey and $X_{avg,prey}^{r}$ is an estimated prey with the average value of prey along the decision variables with the best value.

Information about captured prey is broadcast via the social network to instruct spiders of the necessary activities. SSP's prey phase is comparable to that of artificial bee colonies (Omkar et al., 2011). The last phase involves manipulating artificial spiders to find prey in the social web, a hyperdimensional search space. Each spider records its position, vibration, and other search-controlling data. Each vibration that a spider detects has a source and strength. The equation for the vibration intensity I created and experienced by other spiders at time t is as follows:

$$I(P_a, P_b, t) = log(\frac{1}{f(P_s) - C} + 1) \quad (3.312)$$

where $I(P_a, P_b, t)$ denotes the source intensity between search agent a and b, $f(P_s)$ is the spider's assessed fitness value, C is a constant assumed to be smaller than any fitness functional value and P_a, P_b denote the vibration's source and target. The 1 norm distance measure is Manhattan distance representing the rate of vibrational attenuation over distance and its destination. For high-dimensional data mining applications, the Manhattan distance is preferred than the Euclidean distance metric (Aggarwal, Hinneburg, and Keim, 2001), and this is also true for the HRES optimization issue. Therefore, the distance-dependent attenuation is given by:

$$D(P_a, P_b) = \|P_a - P_b\|1. \tag{3.323}$$

Now the vibration intensity received by a spider is calculated according to equation:

$$I(P_a, P_b, t) = I(P_a, P_a, t) \times \exp\left(\frac{-D(P_a, P_b)}{\sigma \times r_a}\right), \tag{3.334}$$

where r_a represents an adjustable variable that governs the rate of vibration attenuation with distance, and σ is the measure of the spread of all spider locations along the measure of dimensions. In addition, spiders employ dimensional mask (*dm*) switching and random walk to travel from one point to the next using the following equation (3.23). The *dm* consists of a binary vector whose members are 0s and 1s, and it corresponds to the optimization problem dimension. The *dm* is initialized with zeros, but in each iteration, a spider modifies the value of its mask with a probability of $1 - P_c^n$ where $P_c^n \in (0,1)$. If the mask is decided to be changed, each bit of the vector has a probability of P_m to be assigned with a 1 and $1 - P_m$ to be assigned a zero.

$$P_{k,follow,(r)}^t = \begin{cases} P_{k,target,(r)}^t & if\ m_{k,(r)}^t = 0 \\ P_{k,random,(r)}^t & if\ m_{k,(r)}^t = 1 \end{cases}, \tag{3.345}$$

Each spider undertakes a random walk after the next position has been determined (Yu & Li 2015) using equations (3.24) and (3.25) as follow:

$$P_k^{t+1} = P_k^t + PM_k \times rand_k + (P_{k,follow}^t - P_k^t) \odot R \tag{3.356}$$

$$PM_k = P_k^t - P_k^{t-1} \tag{3.367}$$

where R represents a matrix of evenly distributed random values from 0 to 1, and $\odot$ represents element by element multiplication, as explained in (Yu & Li 2015).

3.3.2 SSP Input Parameters

SSP generates an initial solution set for the decision variables of an optimization problem once given the required parameters and the problem definition. There are only a few parameters that need to be set for SSP to run. These parameters include the population size, the number of iterations, the maximum and minimum decision values, and the number of decision variables. Upon receiving these input parameters, the algorithm iteratively refines the coefficients of the decision variables with intelligent operators. The objective functions serve as a yardstick to measure the suitability of a candidate solution among the solutions specified at each iteration, and once a stopping criterion is met, the algorithm exits and returns the best result found.

For the optimal HRES power generation problem as described in the previous section, the parameters and their respective values used to solve the problem are listed in Table 3.9.

Table 3.9: SSP parameter values for the HRES optimization problem

Parameter	Value
Population size	100
Maximum number of iterations	200
Maximum decision value (upper bound)	500
Minimum decision value (lower bound)	0
Number of decision variables	4

3.3.3 SSP alignment with HRES optimization

The social web is compared to the independent mini grid, where artificial spiders are acting as the energy generating units (mainly the renewable energy technologies). Praying are the climatic weather conditions that occur randomly with different intensities. The vibration properties such as intensity, frequency, attenuation /amplitude are related to renewable energy sources and their availability/freshness and strength (intensity), presence in any time frame (frequency) and stability/suitability (attenuation/amplitude) of the resources.

The SSP algorithm is structured to show how each search agent, artificial spiders, on the social web work together to achieve a common goal. This collaboration between the search agents leads to two phases of the search technique in SSP, namely neighbourhood search and global search. SSP randomly picks the prey(s) based on the number of search agents after the initial population has been produced using the upper bound, lower bound, and size of the problem. When the population size of the search agent is large, thus greater, or equal to 100 SSP, randomly choose 30% of the initial population as prey; otherwise, the algorithm prefixes the prey size in the range 1-3. By modifying one of the decision factors, a prey encourages a neighbourhood search (intensification/exploitation). After the prey phase, spiders in the neighbourhood detect the vibrations of prey and move towards it. By modelling the spider- or prey-caused vibrations spreading across the social web, SSP can discover a robust solution to a global optimization issue.

The presented framework is implemented to solve an optimal hybrid PV-wind-biomass generation of renewable energy. In this study, the optimization algorithm that goes through all the phases described is the SSP, an intelligent algorithm to carry out the analysis of the design and configuration of the hybrid system. SSP is a nature-inspired algorithm that mimics the foraging behavior of spiders and prey on the social web. Table 3.2 provides a bird's-eye view of the study methodology and shows how the conceptual model from the previous chapter and the methodological framework converge to address the research problem. The table outlines the study objectives and the instrument used to achieve these objectives.

Table 3.10: Convolution of the methodological framework, conceptual model and study objective

Conceptual Model	Methodological Framework	Study objective	Tool
Edge and sensor layers	Phase 1: Conduct feasibility analysis of HRES design	Deploy IoT technology (sensors) on-site where HRES will be implemented to collect real-time renewable energy data from the surrounding area for feasibility assessment and optimization	Use IoT sensors to collect solar and wind energy data. Retrieve secondary/historical renewable energy data from the web
CIR Component	Phase 2: Optimize HRES configuration	Estimate the viable amount of energy each production unit (renewable energy technology) could produce from historical and real-time sensor data	Use the modelled SSP algorithm
	Phase 3: Analysis of optimized results	Find near-optimal power generation for local load demand	Use comparison algorithms (TBLO, PSO and SSA) to analyze the results obtained

3.4 General procedure for using metaheuristic algorithm in global optimization problem

In solving an optimization issue with a metaheuristic, the problem must be described, and the objective function(s) and constraints must be given. The algorithm then interacts with the optimization issue to identify the ideal solution (Kalananda & Komanapalli 2021; Jyoti Saharia, Brahma & Sarmah 2018). The link between a metaheuristic method and an optimization issue is depicted in Figure 3.3. The algorithm (metaheuristic method) generally generates candidate solutions or a single solution (search agent) with the exact dimensions as the optimization problem's choice variables. The search agent or agents undergo a series of iterative refining procedures and assessments. After each iteration, the solution(s) are evaluated against the objective function to determine their adequacy compared to their previous iteration value. The algorithm's refining mechanism determines whether a solution is accepted and kept in memory or rejected depending on its appropriateness (Ezugwu, Adeleke, Akinyelu & Viriri 2020). This cycle is repeated, and the algorithm improves the search agents using intelligent operators. This procedure is performed until a termination criterion is satisfied.

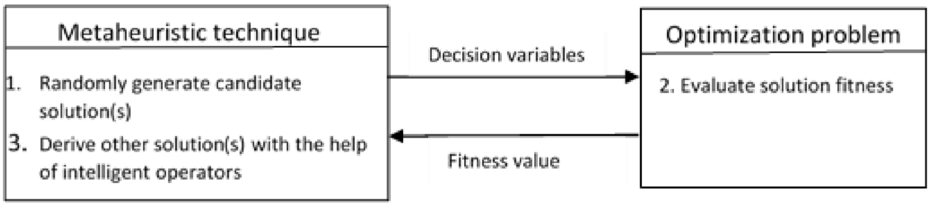


Figure 3.7: Interaction between metaheuristic technique and optimization problem

The process given provides an overview of the steps of the proposed bio-inspired model. In accordance with the methodological framework recommended in Table 3.1 for the bio-inspired model to solve the HRES optimization problem, the phases of the experiment in the study followed as indicated below. The relevance of the experiment is that after examining the data set and using the SSP algorithm, the near-optimal solution to the problem was determined. The best result was chosen after assembling multiple results from running the algorithm multiple times. Although each bio-inspired/meta-heuristic algorithm contains initial parameters (user provided), the stages outline how the optimal approach was chosen.

Step 1: Mathematical modelling of some interesting behavioural traits of social spiders and prey.

Step 2: Translating the mathematical model into the proposed agent-based search algorithms.

Step 3: Implementing the proposed algorithm using MATLAB.

Step 4: Conducting an experiment by testing the implemented algorithm against selected comparative algorithms on a dataset. The results of the experiment are presented and discussed in later chapters.

Step 5: Analyzing the performance results to select the best-found result. The analysis results are presented in later chapters.

3.5 Comparative algorithms

Here we compare the performance of different methods used in the approach. Three nature-inspired swarm intelligence-based algorithms, namely TLBO, SSA, and PSO, are selected for comparative studies. These algorithms have been used extensively in literature for solving different optimization problems including HRES optimization (M. M. Ashraf & Malik, 2020; A. Khan & Javaid, 2019; Khare & Kumar, 2016). Furthermore, since they are all population-based search techniques, the selected algorithms share a similar structure and mechanism, making them ideal for comparative analysis. Although TLBO is a recent technique, it is used on several optimization issues, such as HRES sizing (Kalananda & Komanapalli 2021; Kajela & Manshahia 2017). Similarly, as claimed by the creator, SSA is highly effective when solving hybrid functions when distinct dimensions of the objective functions cannot be coupled and no extra information, such as a correlation matrix, is given (Yu & Li 2015). In addition, PSO is one of the most researched swarm intelligence-based algorithms and has been used to hybrid renewable energy optimization issues (Malaquias & Souza 2019; Salehi & Askarzadeh 2018; Singh & Fernandez 2017). To discover the optimal/near-optimal solution to a given issue, all particles in PSO follow both global and personal best positions.

Table 3.11: Parameter settings for comparative algorithms

PSO algorithm	TLBO Algorithm	SSA Algorithm
Number of decision variables: 4	Number of decision variables:4	Number of decision variables:4
Number of search agents: 30	Number of search agents: 30	Number of search agents: 30
Total iteration: 60	Total iterations:60	Total iterations:60
Initial weight: 0.4		Attenuation Rate ra: 1.0
Final weight: 0.9		Mask Changing Probabilities pc and pm: 0.7 and 0.1
Weighting factors (C1 and C2): 2		

The proposed algorithm would be compared to the comparison algorithms using the historical dataset retrieved from the Internet. Since the nature of various bio-inspired algorithms may make them better suited for certain tasks than other algorithms, their internal organizational control mechanism is not considered in the discussion, rather their parameter settings are given for the sake of clarity. The experimental results were output to a text file and/or to the MATLAB output screen using an appropriately selected set of metrics generated by the comparison algorithms implemented in MATLAB.

3.6 Programming language and other software packages

In order to achieve a desired outcome for a specific problem, it is imperative to thoroughly evaluate the appropriate tools for a specific activity. This section provides a description of the software packages and tools used in the investigation. First, the basic mathematical formulas generated from the behavioural traits of the social spider and its prey required the use of an appropriate software application for experimental purposes. That mathematical statements can be converted into executable algorithms, MATLAB (2022a) is used for the development and implementation of this algorithm. MATLAB's built-in functions and toolboxes enable a wide range of activities from mathematical calculations to graphical display, making it easy to view data and gain significant insights. These built-in functions help perform basic numeric operations and matrix-based calculations, encourage easy interactivity (expressions entered by the user are evaluated immediately and results are displayed), and have a comprehensive set of programming constructs that make it easy to customize a program. Because of the built-in features and capabilities, the computational mathematics of the proposed bio-inspired/metaheuristic method, which was later used to optimize HRES power generation, was expressed using MATLAB as a convenient software tool. Likewise, the comparative study of the different algorithms was carried out within the same MATLAB environment.

On the other hand, Arduino IDE was used to program IoT devices to collect environmental data. The integrated development environment (IDE) provided simplified blocks of code for creating Arduino code that could communicate with sensors via an Arduino UNO microcontroller connected to all sensors. The IDE environment consists of two main components: the editor and the compiler. The editor is used to write the code needed while the compiler is used to compile the code and upload it to the supplied microcontroller. Finally, streaming sensor data was collected using the Data Streamer add-in for Microsoft Excel spreadsheet software. Continuous streams of data are ubiquitous and represent such a large volume of data that they may not be able to be stored on disk, but sometimes it is important to examine them in real time. Stream processing is a programming paradigm that processes them quickly and allows for continuous analysis. MS Excel data streamer add-in provides visualization of live streams, live programming to calculate new streams and export of calculations to be performed on a server where they are shared with other users and stored beyond the lifetime of the spreadsheet be able.

3.7 Summary

In this chapter, the knowledge claim was based on positivism because it facilitates understanding of the theory underlying animal (spider and prey) behavior and the mathematical expressions used to model it. The mathematical tools allow for the dynamic formulation of the numerous behavioural aspects of the animals under consideration. This factor contributed to the development of a two-phase algorithmic structure that was studied along with the global optimization search technique. The different animals and their actions were matched to the different vibrations they generated on the social web, characterized by their intensity, frequency, and amplitude. These properties are essential for individual search agents to achieve the global optimization goal. Prey vibration due to its web constriction has been linked to neighbourhood searching, while spider vibration and movement represent a global searching mechanism.

In their web, two of the most important behaviours of social spiders are capturing their prey and exploiting a foraging area for food. This chapter explores these phenomena to explain how such behavior could be used to optimize the HRES optimization problem. As indicated by the methodological framework, the general outline provided general guidance in the form of phases for translating the mathematical formulation based on the bio-inspired behavior into the relevant algorithms in each phase of the mainly bio-inspired framework. And with the help of built-in functions and mathematical expertise, MATLAB was chosen as the perfect software to create the computational model. In the following chapter, the same strategy is used to experimentally evaluate the algorithm using several benchmark functions. The exercise examines the resilience of SSP to global optimization problems. To improve the visual representation and user understanding, the results are combined in graphical representations. In the following chapter, SSP is used to optimize hybrid renewable energy generation.

CHAPTER 4: TESTING OF SSP ALGORITHM AND EXPERIMANTAL SIMULATION OF HRES OPTIMIZATION PROBLEM

4.1 Introduction

The purpose of this chapter is to experimentally verify the effectiveness of the proposed methodology, discussed in Chapter 3, on sample global optimization problem. Hence, with the help of both benchmark functions and experimental test scenarios the proposed algorithm namely SSP is subjected to series of trials and validations against comparative algorithms. Therefore, in this chapter the proposed methodology has been utilized to optimize hybrid renewable energy generation. There are three main sections; First, the SSP algorithm is tested as a global optimization algorithm on five benchmark functions. This exercise demonstrates the effectiveness of SSP for solving diverse and complex optimization problems with different dimensions. The second and third sections show experimental results of SSP and comparison algorithms (TLBO, SSA and PSO) on the optimization problem. While Section 2 provides details of the historical dataset for the simulation, the latter, section 3 presents results from extrapolated real-time sensor data collected from the environment. The results for the testing of the SSP algorithm and the simulations of the HRES optimization problem have been presented in tables and graphs to facilitate understanding.

4.2 Testing SSP algorithm on Benchmark functions

SSP algorithm is designed as a global optimization technique to solve complex optimization problem including problems with random variables as well as several decision parameters (Agbehadji, Awuzie, Ngowi, Millham & Frimpong 2021; Frimpong, Millham, Agbehadji & Jung 2021). This section describes the experiment conducted to test the effectiveness of SSP algorithms as a strategy for global optimization. The benchmark functions Sphere, Griewank, Sulfur 2.22, and Levy were chosen to evaluate SSP (Ke, Xiaodong, P. N., Zhenyu, and Thomas, 2010). The characteristics of the chosen benchmark functions are presented in Table 4.1. These functions were chosen based on their scalability (dimensionality) of the decision variables to verify the convergence capability of SSP with different set of optimization problem. Accordingly, the selected functions range from unimodal to multimodal, separable, and non-separable, however, all the test functions were continuous and differentiable.

Table 4.1: Benchmark functions used to test SSP algorithm

Function name	Mathematical expression	Description/properties of function
Sphere	$f(X) = \sum_{i=1}^{d} x_i^2$ d is the problem dimension	It is a continuous function, with differentiable, separable, and unimodal properties. Subject to $-100 \leq x_i \leq 100$ The global minima is located at $x^* = f(0, \dots, 0)$.
Griewank	$f(X) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	This is also a continuous, differentiable, non- separable, scalable multimodal function. Subject to $-100 \leq x_i \leq 100$, and The global minima is located at $x^* = f(0, \dots, 0)$, $f(x^*) = 0$
Schwefel's 2.22	$f(X) = \sum_{i=1}^{d} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$ d is the problem dimension	This possesses the qualities of being continuous, differentiable, non-separable, scalable, and unimodal. Subject to 500, x-i.500 The global minimum is situated at, x-.=f(0,...,0).
Levy	$f(X) = sin^2(\pi x_1) + \sum_{i=1}^{n}\left[\left(1 + 10(sin^2 x_{i+1})\right)\right] + ((x_n - 1)^2(1 + sin^2(2\pi x_n)),$ $x_i = 1 + \frac{1}{4}(X_i + 1)$	The Levy function is continuous, differentiable, non- separable, scalable multimodal. Subject to $-10 \leq x_i \leq 10$ Global minima is located at $x^* = f(0, \dots, 0)$, $f(x^*) = 0$

Figures 4.1 through 4.4 depict the convergence qualities of SSP to the test functions based on the test findings. The convergence graphs illustrate the search technique's progress in locating the best function value after 50 iterations. In addition to the convergence curve, the semilogy plot and search landscape are also illustrated. The semilogy charts illustrate the pace of logarithmic convergence. Figures 4.5 through 4.7 illustrate the convergence features of SSP for several high-dimensionality situations. With iterations ranging from 30 to 500, the variables n = 2, 3, 4, 5, 10, 20, and 30 were evaluated. However, due to space constraints, not all test results are published in this section; hence, just a handful are provided.

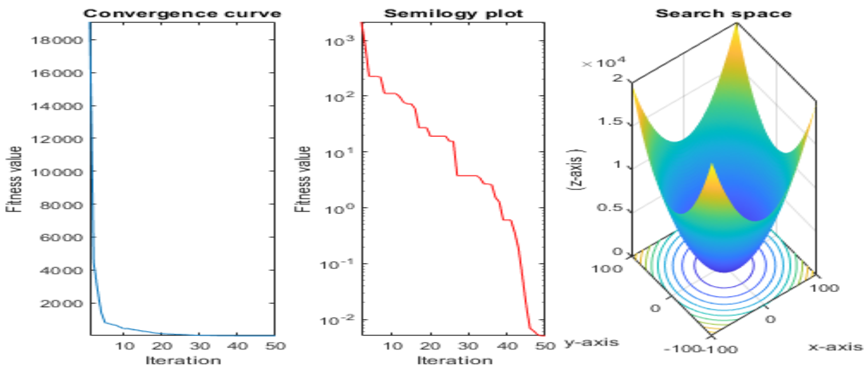


Figure 4.1: Convergence curve generated by SSP using Sphere function

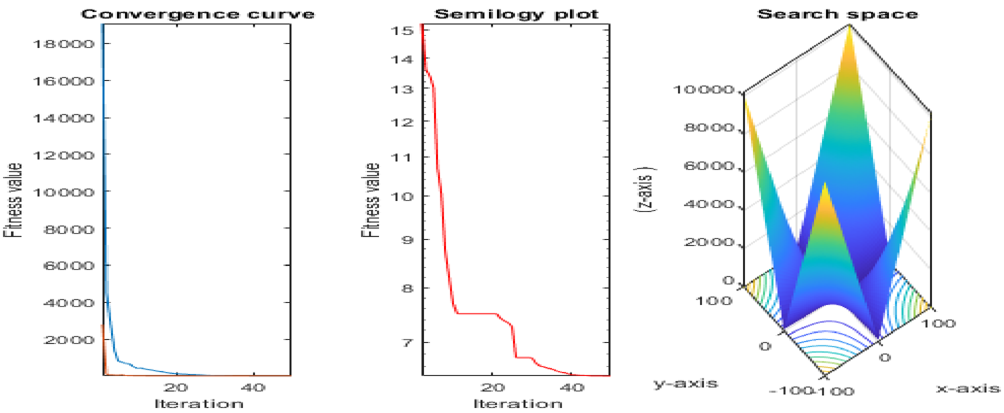


Figure 4.2: Convergence curve generated by SSP using Schwefel's function

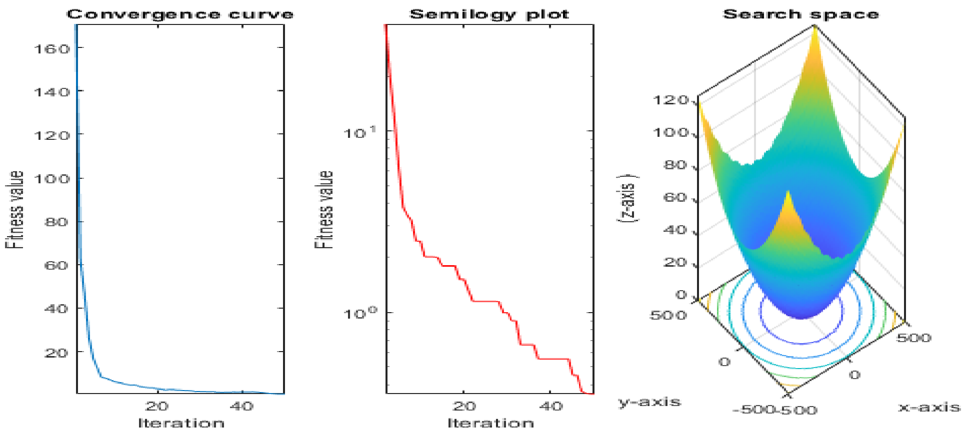


Figure 4.3: Convergence curve generated by SSP using Griewank's function

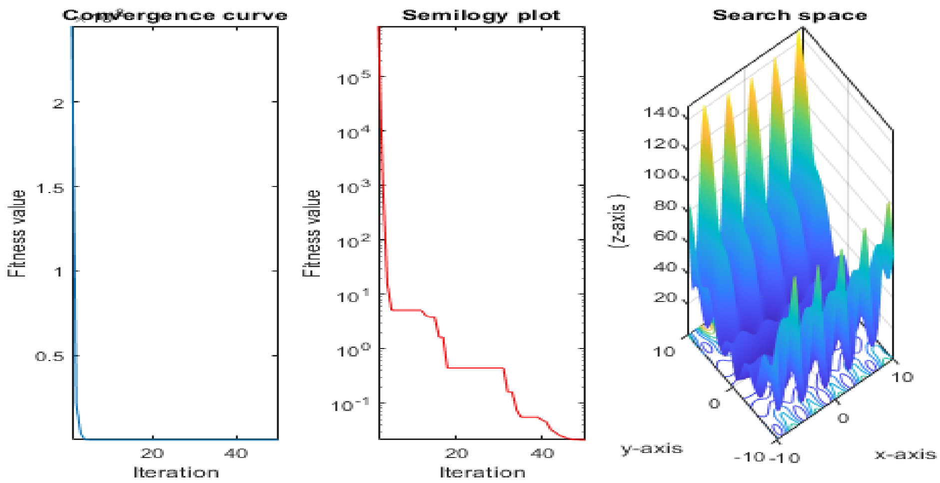


Figure 4.4: Convergence curve generated by SSP using Levy function

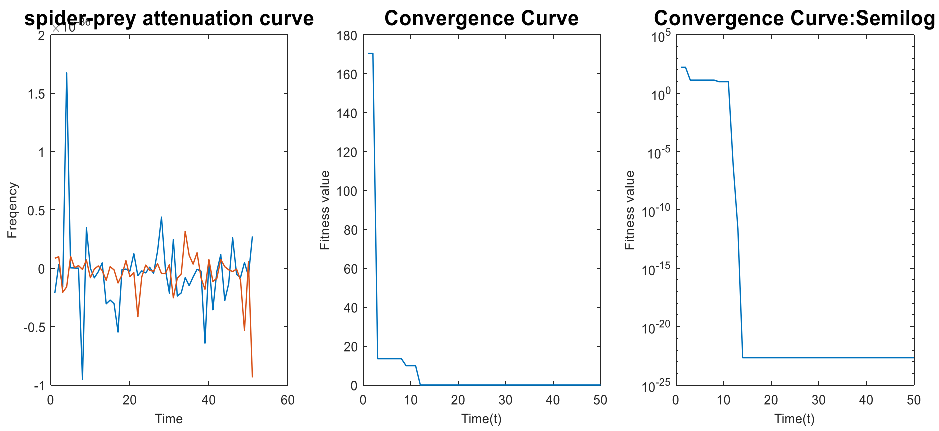


Figure 4.5: SSP convergence curve in a two-dimensional search space

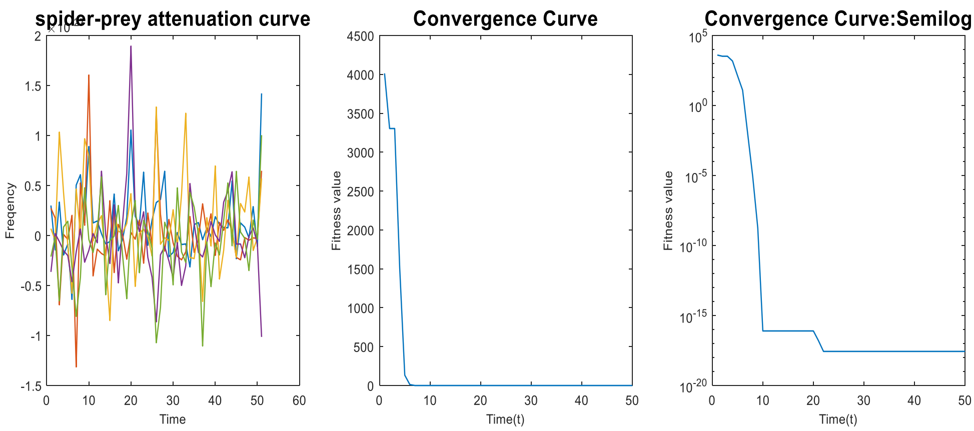


Figure 4.6: SSP convergence curve in five dimensions search space

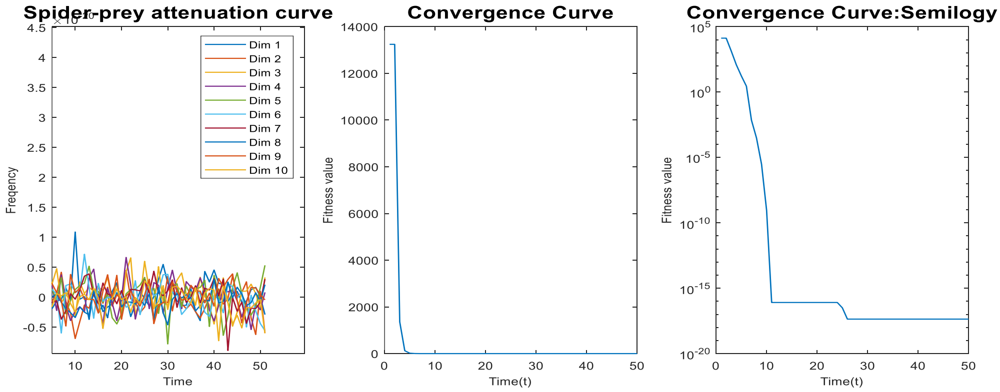


Figure 4.7:SSP convergence curve in ten dimensions search space

SSP demonstrated remarkable performance on the chosen test functions evaluated in the studies (Frimpong, Millham, Agbehadji, et al. 2021). First, the spherical function, which is scalable and converges at zero was evaluated using SSP. To constrain the decision variables, a lower limit of minus one hundred and an upper limit of one hundred were established. After a termination criterion of 40 cycles later, SSP converged at1.102×10^{-18}. Correspondingly, the converging curves created by SSP utilizing the other benchmark functions, namely Schwefel's 2.22, Griewank and Levy, are shown in Figures 4.2, 4.3 and 4.4, with convergence values 2.301×10^{-21}, 1.709×10^{-19}, and 1.111×10^{-22} respectively. Before reaching the terminating condition, it was noted that the SSP method was able to enhance the search results in a monotonic fashion, from the original solutions to an improved solution.

The next set of graphs (Figures 4.5, 4.6, and 4.7) illustrate the performance of SSP on global optimization problems with varying dimensions. These graphs illustrate the convergence of SSP, which has excellent convergence qualities on various problems with varying dimensions. Figures 4.1- 4.4 depict the scaled-up graphs of the spherical function for dimensions 2, 5, and 10. The leftmost graph in each illustration depicts the rate of change along the various dimensions. The random pattern of the graphs illustrates the motions of spiders and their prey towards convergence in the search space. The second and third graphs in each scenario depict convergence curves and the semilogy plot. Like the preceding trend of monotonic development in experimental outcomes towards the global optimum, SSP exhibited the same pattern across a variety of dimensionality sets of data.

In the test round, just 50 iterations were regarded as a termination criterion due to the simplicity of the sphere function. Even with a smaller number of iterations, SSP demonstrates a remarkable capacity to achieve extremely good convergence for all test cases. As illustrated in Figure 4.1, the best-found value for a particular dimension is 1.128×10^{-38}. Although fewer iterations were required, cooperation between spiders and their prey(s) was crucial to achieving a near-optimal solution without sacrificing exploration and exploitation strategies. Figures 4.6 and 4.7 illustrate the best-observed values for dimensions 5 and 10, which are 1.123×10^{-27}, and 1.18005×10^{-20} respectively.

The experimental results indicate that SSP may successfully advance towards the optimal global solution. This suggests that SSP will likely converge to the optimal value after a few repetitions.

4.3 Simulation of SSP on HRES Optimization

The methodology developed has informed a design of stand-alone PV-Wind-biomass-battery HRES to supply power to a varying load attached to the system. This model reveals the overall system performance over a year, including the number of photovoltaic panels, wind turbines, and battery storage capacity, as well as the contribution of biomass gasifiers to supply the attached load effectively. Using the SSP algorithm, the power delivered by each energy source over the year is thoroughly examined in terms of economic impact, and the reliability of the power delivered. This is an advantageous way to check how the system is being powered and which power source is best powering the load by analysing the economic implications associated with the hybrid system power supply.

4.3.1 Simulation of HRES Optimization Problem

The optimization problem, including the objective function and constraints, is defined in the previous chapter. In this part, the evaluation techniques are applied to the optimization issue. SSP is the main algorithm used to study the research problem. The other comparison algorithms are run in parallel for evaluation and comparison purposes. To verify the approach used to collect environmental data for the experiment, the researcher simulated the optimization on two different datasets. The data used to conduct the experiment are presented in subsections 4.3.2 and 4.3.3.

In subsection 4.3.2, the HRES was stimulated by using historical datasets. The load characteristics and details of the data set can be found in the section. SSP and the comparison algorithms (PSO, TLBO, and SSA) run the data to find the best (near-optimal) solutions. Four different scenarios were built using a combination of the renewable technologies, namely solar PV, wind turbine, biomass gasifier and battery storage system. The results of the experiment are tabulated and presented with graphs. Similarly, in subsection 4.3.2, a repeated series of experiments was performed using real-time sensor data collected from the environment. Since year-round data could not be collected for the intended purpose, the sensory data was extrapolated to provide a sufficient time-series dataset for the simulation. All four algorithms were used to run the extrapolated dataset to find the near-optimal result and the results of the simulation are presented in tables and graphs.

4.3.2 HRES optimization using historical data

The SSP algorithm is used to simulate a near-optimal standalone PV wind biomass battery HRES to generate reliable power supply for the load connected to the system. The load has a varying distribution characteristic as shown in Figure 4.5 with an estimated peak load requirement of 25 kW. The method used in this research derives the optimal size of each renewable technology, combinations of which would optimally meet the load, using economic and reliability indicators as a benchmark. It is worth noting that the output power of the hybrid system is directly related to the energy cost using equation (3.29). The objective function is to minimize the economics of the proposed hybrid system while maintaining a maximum of 1% LPSP. The optimization results therefore consisted of the total number of assessed PV modules, the number of wind turbines indicated, the number of batteries and the assessment of the maximum capacity of the biomass gasifier. The inverter was not considered as a decision variable, however an estimate of the inverter using the peak load demand value was set at 25 kW to maintain load flow balance.

Data: As described in Chapter 3, solar irradiance and wind speed data for the research location were collected from the NREL and NSA databases. The simulation and optimization methods employ hourly data; Table 4.2 displays the monthly mean values of the climatic data and the monthly mean values of the load (kW). The trend of ambient temperature, solar radiation and wind speed are shown in the graphs in Figures 4.8 – 4.12.

Table 4.2: Average monthly climatic, biomass resources and load data

Month	Solar Irradiance (W/m^2)	Ambient Temperature (°C)	Wind speed (m/s)	Available Biomass (tonnes/day)	Load (W)
January	260.94	19.94	1.71	2.5	5121.98
February	232.65	19.38	2.96	2.4	8576.98
March	203.16	18.61	2.64	2.5	7984.87
April	153.03	15.73	3.57	2.7	8992.78
May	113.11	13.63	1.61	1.8	9848.13
June	92.26	10.13	2.92	2.6	11153.96
July	102.96	10.00	3.25	2.6	9832.46
August	141.33	12.70	4.36	2.5	9985.43
September	185.31	15.99	3.70	1.9	10481.81
October	226.14	17.16	4.06	2.5	10975.64
November	247.59	17.83	3.78	2.7	10825.68
December	273.04	19.30	3.98	2.4	10254.72

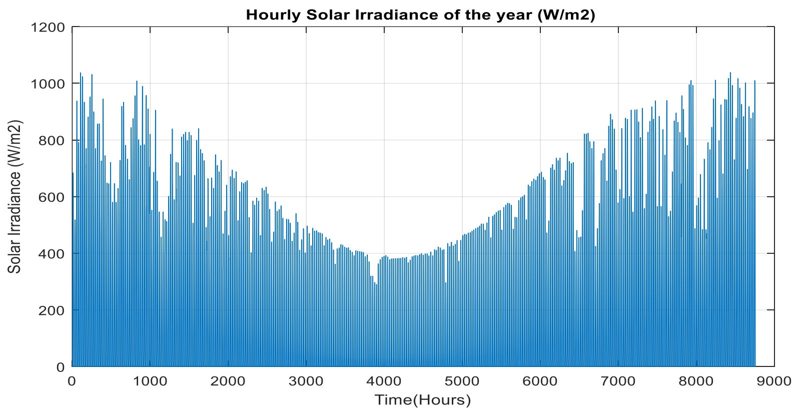


Figure 4.8: Hourly solar irradiance for one year period

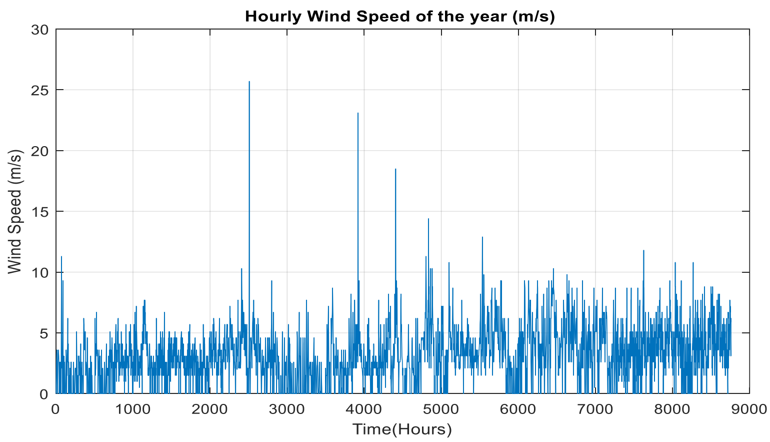


Figure 4.9: Hourly wind speed for one year period

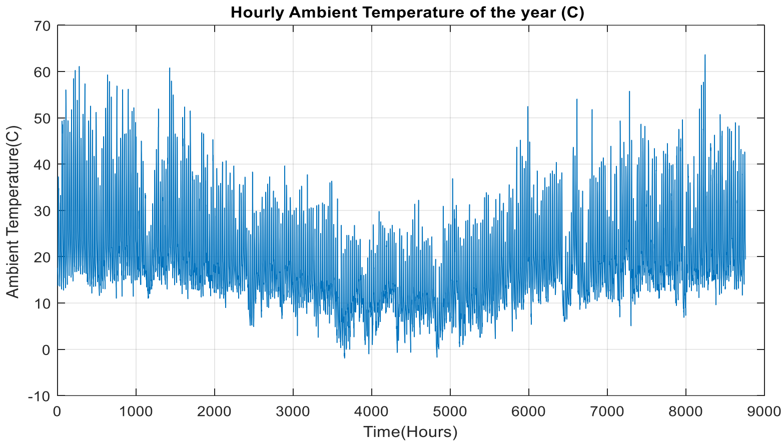


Figure 4.10: Hourly ambient temperature for one year period

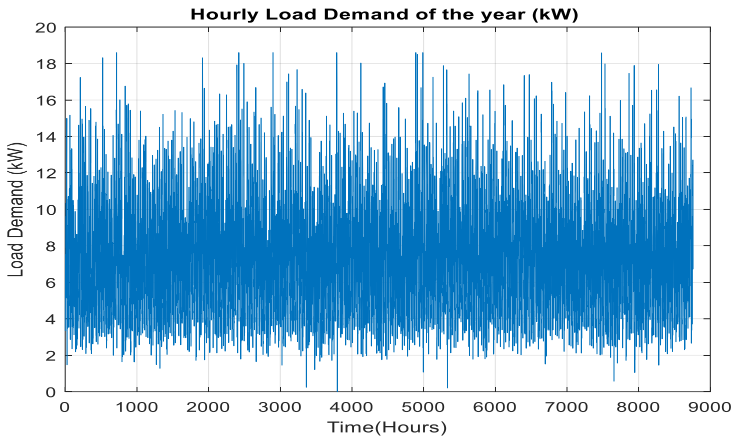


Figure 4.11: Hourly load demand for one year period

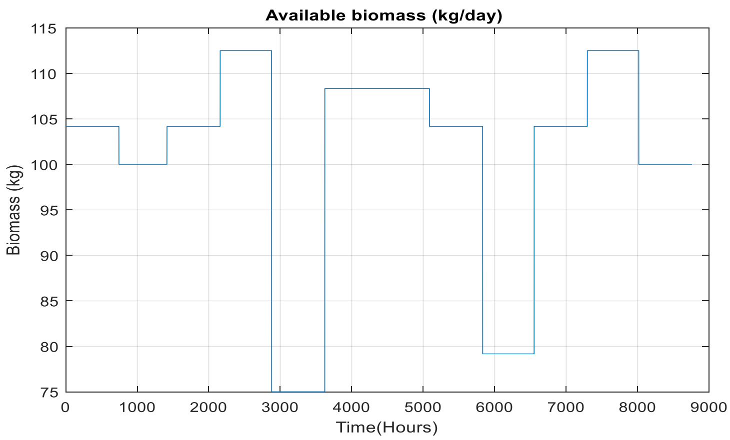


Figure 4.12: Available biomass in kg/day for one year period

The maximum number of PV panels, wind turbines, batteries as well as maximum capacity rating of biomass gasifier were set to 500, 500, 1000, and 50 respectively. Different scenarios were set with different combinations of the components (renewable energy technologies) to identify the best combination for the defined optimisation problem. Each algorithm was applied under each scenario. There were four test case scenarios which include Wind-biomass-battery, PV-wind-biomass, PV-biomass-battery, and PV-wind-biomass-battery. The time step for the simulation is considered for one hour and it was run on one year period dataset. The results of the simulation on case-by-case basis are presented in the next section.

4.3.2.1 Case 1: Wind-biomass-battery

This case is set to check the potential of wind energy resource together with available biomass at the location to reliably power the attached load. Moreover, battery storage system is considered as a backup for the hybrid system. For each algorithm the simulation of the optimization problem was run 10 times with an iteration of 60 per each run and their average results are computed and presented.

Table 4.3: Comparative results of the proposed HRES sizing with various optimization techniques for Case 1

Algorithm	PV	Wind Turbine	Number of Batteries	Biomass Gasifier Rating	Biomass Running (h)	LPSP	NPV (R)	ASC (R/yr)	COE (R/kWh)
SSP	0	107	315	9	587	0.011	15994131.58	3431512.26	5.1781
TLBO	0	118	311	11	613	0.008	17332250.36	3718603.24	5.6113
SSA	0	115	321	11	592	0.004	17339678.57	3720196.95	5.6137
PSO	0	118	317	9	599	0.005	16504173.07	3540940.75	5.3432

The result obtained by the various optimization techniques under Case 1 is presented in Table 4.3, and the minimum cost of energy is estimated as R5.1781 per kWh by SSP algorithm. The respective estimation for PSO, TLBO, and SSA are 5.3432, 5.6113, and 5.6137. In this case, the hybrid system configuration did not consider solar PV module. The number of wind turbines, number of batteries, and rating of the biomass gasifier as obtained by the various techniques are shown under their respective columns. SSP algorithm found the best result in terms of cost, and for the reliability index, SSA gave a better value of 0.004. The convergence curve of the comparative algorithms with respect to the levelized cost of energy are shown in Figure 4.13

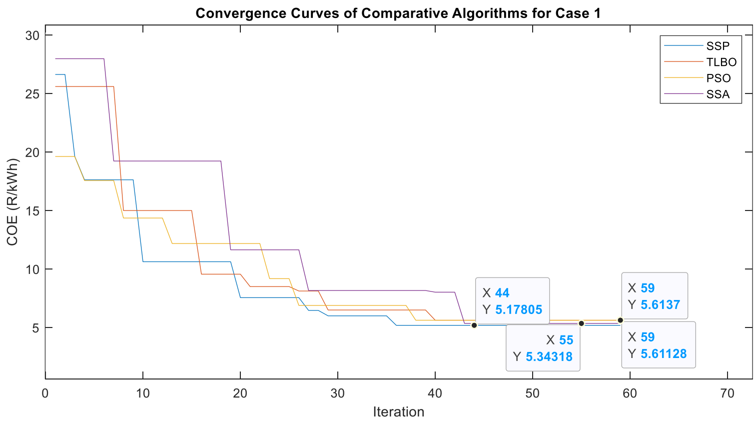


Figure 4.13: Convergence curves of comparative algorithms for Case 1

Table 4.4: Breakdown of NPC and ASC obtained by SSP algorithm for the proposed hybrid system under Case 1

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	Gasifier Running Hours	NPC	ASC
PV	0.00	0.00	0.00	0.00	0.00	0	0.00	0.00
WT	2728500.00	0.00	1050541.77	0.00	0.00	0	3779041.77	810786.64
BG	226800.00	274512.62	2273743.58	-18202.39	1143045.46	587	3899899.27	836716.40
Battey	1102500.00	1470690.54	5670000.00	0.00	0.00	0	8243190.54	1768561.75
Inverter	72000.00	0.00	0.00	0.00	0.00	0	72000.00	15447.47
Total	4129800.00	1745203.16	8994285.35	-18202.39	1143045.46	587	15994131.58	3431512.26

Table 4.4 lists the cost elements of the components involved that add up to the net present value of the hybrid system. For each component, the capital cost, replacement cost, operation and maintenance cost, and recycling cost were estimated by each algorithm, but due to space limitations only the optimal cost solution is presented. In addition to the four cost factors of the hybrid system, the fuel costs for the biomass gasifier are also considered and depend on the operating hours in a year.

The next subsection shows a graphical representation of the various components and their contribution to the total power delivered to the electrical load connected to the hybrid system.

Various components contribution to total power supply for Case 1

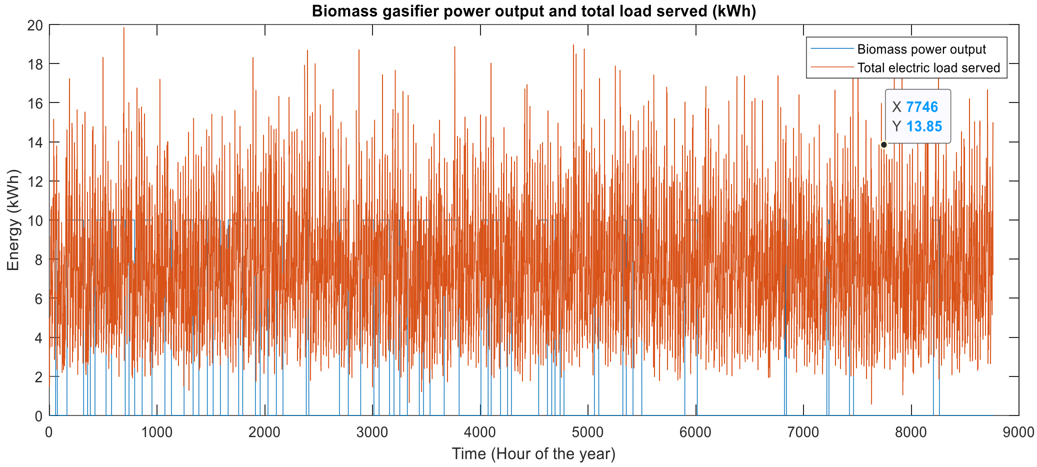


Figure 4.14: Biomass power output and total load served under Case 1

The gasifier has been observed to be used sparingly throughout the year, but its contribution to providing reliable energy cannot be overlooked. The biomass gasifier as a power conservation unit provided power to consumers when the primary source (wind) and storage system (battery) could not meet demand.

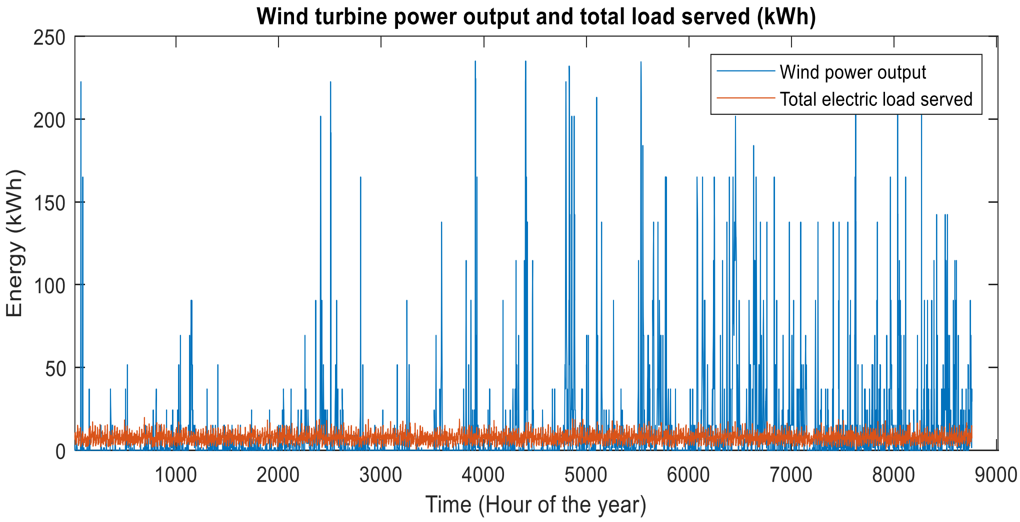


Figure 4.15: Wind turbine power output and total load served under Case 1

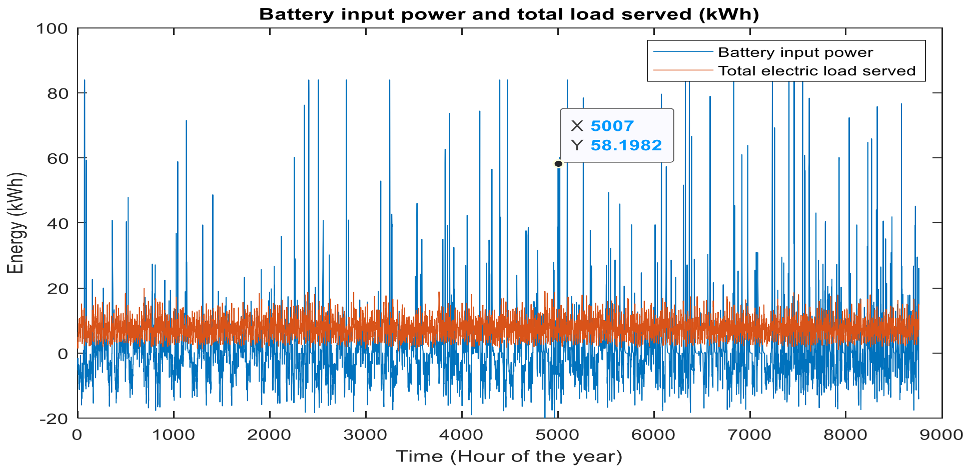


Figure 4.16: Battery input power and total load served under Case 1

The distribution of the battery input power indicates that the storage was heavily used for most of the year as a lot of power was drawn from it. This is shown in the graph in the negative direction. On the other hand, we see that the hybrid system could charge the battery when the power exceeds the load as shown in Figure 4.17.

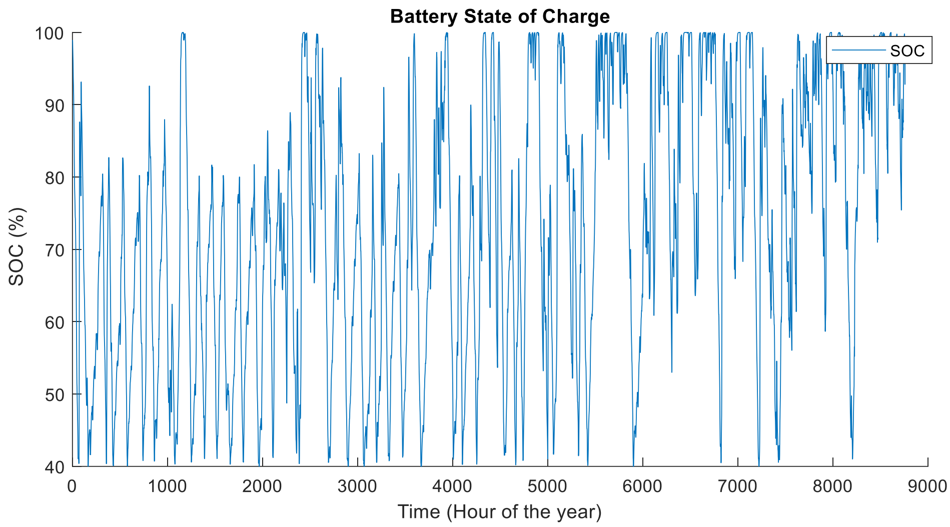


Figure 4.17: Battery state of charge for Case 1 scenario

4.3.2.2 Case 2: PV-wind-biomass

In Case 2, no battery storage system was connected to the hybrid power sources. Therefore, the renewable energy sources, namely solar PV, wind turbine and biomass gasifier were the only energy sources. Table 4.5 shows the optimal solution for the hybrid system configuration considered for Case 2 using the various algorithms.

Table 4.5: Comparative results of the proposed HRES sizing with various optimization techniques for Case 2

Algorithm	PV	WT	Gasifier Rating	Gasifier Running (h)	LPSP	NPV (R)	ASC (R/yr)	COE (R/kWh)
SSP	189	101	9	462	0.031	11884474.5500	2549792.7100	3.8476
TLBO	189	99	10	459	0.028	12137761.9200	2604135.0600	3.9296
SSA	191	100	10	449	0.021	12246260.6800	2627413.2700	3.9647
PSO	187	98	11	455	0.021	12293751.0000	2637602.1700	3.9801

The result obtained by the different optimization methods in Case 2 is presented in Table 4.5 and the minimum energy cost is estimated by the SSP algorithm to be 3.8476 R per kWh. The respective estimates for TLBO, SSA and PSO in R per KWh are 3.9296, 3.9647 and 3.9801. In contrast to the Case 1 scenario, the hybrid system configuration in this case considered all three renewable energy sources but no battery storage system. After simulating the optimization problem, the results for the optimal dimensioning of the hybrid system component for reliable power supply according to the different techniques are presented in Table 4.5. The number of solar PV, wind turbines and the evaluation of the biomass gasifier as obtained through the different techniques show that the SSP algorithm found the best result in terms of costs with 3.8476 R/kWh as the leveled energy costs. SSP and TLBO estimated the LPSP index factor to be 0.031 and 0.028, respectively. SSA and PSO each scored LPSP of 0.021. The convergence curve of the comparison algorithms regarding the LCOE for Case 2 is shown in Figure 4.18.

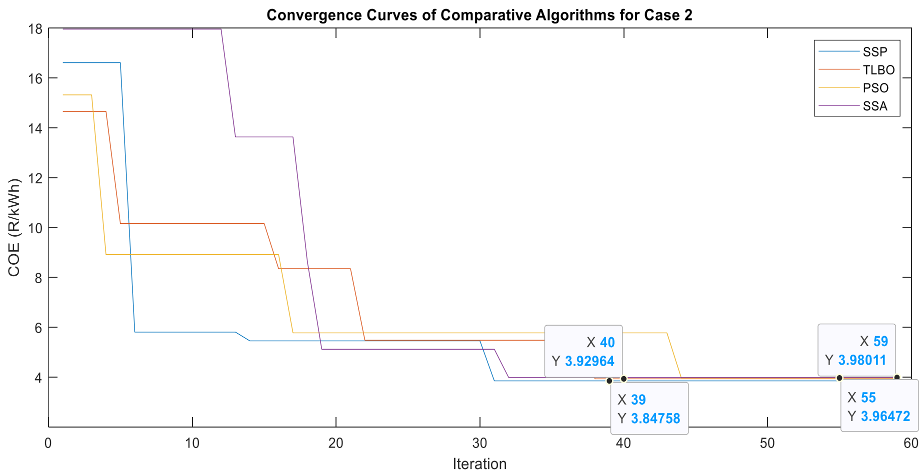


Figure 4.18: Convergence curves of comparative algorithms for Case 2

Table 4.6: breakdown of NPC and ASC obtained by SSP algorithm for the proposed hybrid system under Case 2

Component	Capital cost	Replace cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC
PV	3307500.00	0.00	1855629.86	0.00	0.00	0	5163129.86	1107740.26
WT	2575500.00	0.00	991632.89	0.00	0.00	0	3567132.89	765321.97
BG	226800.00	0.00	2041192.85	-85418.18	899637.14	462	3082211.80	661283.02
Battey	0.00	0.00	0.00	0.00	0.00	0	0.00	0.00
Inverter	72000.00	0.00	0.00	0.00	0.00	0	72000.00	15447.47
Total	6181800.00	0.00	4888455.59	-85418.18	899637.14	462	11884474.5	2549792.71

Table 4.6 shows the costing constituents of the components involved, which add up to the cash value for Case 2 hybrid system. For each component, the capital cost, replacement cost, operation and maintenance cost, and recycling cost are presented.

The diagrams in Figure 4.19 through Figure 4.21 represent the different components and their energy contribution to the total power delivered to the electrical load connected to the hybrid system for the present case studied.

Components contribution to total power supply for Case 2

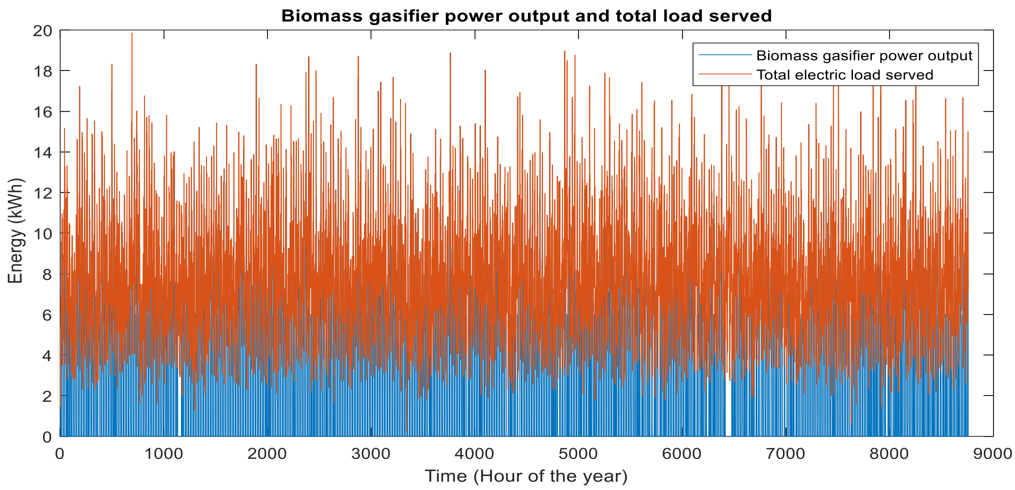


Figure 4.19: Biomass power output and total load served under Case 2

The biomass gasifier was utilized frequently in Case 2 perhaps for reason that no battery storage facility was available to provide power when it was needed.

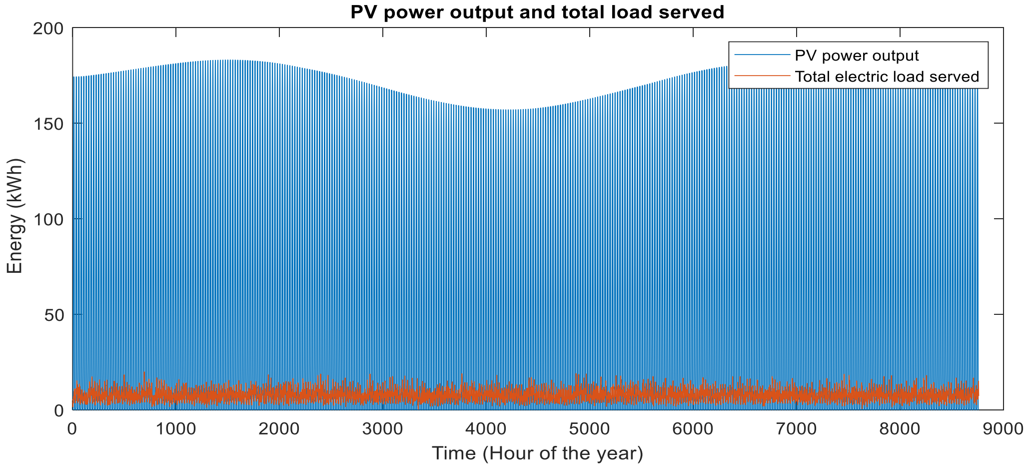


Figure 4.20: Solar PV power output and total load served under Case 2

From Figure 4.20 it can be observed that in the second case scenario the solar PV system generated a significant amount of solar energy whenever the sun was available.

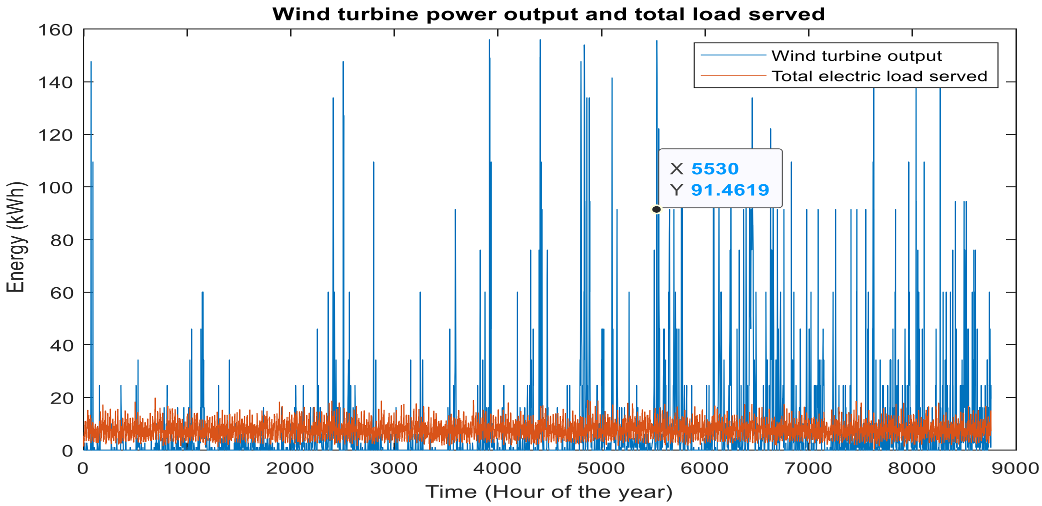


Figure 4.21: Wind turbine power output and total load served under Case 2

The wind turbine provided a complementary power supply to the load when the solar PV system was unable to generate power. Since there was no battery storage system, the excess power would have been wasted.

4.3.2.3 Case 3: PV-biomass-battery

Case 3 comprises of PV system, biomass gasifier and battery storage. Under this case scenario there were no consideration for wind turbines. Hence, the PV system is the primary source of energy, The battery storage system and biomass gasifier were utilized as and when needed according to the operational strategy. Table 4.7 depicts the optimal solution for the hybrid system configuration which was considered in Case 3.

Table 4.7: Comparative results of the proposed HRES sizing with various optimization techniques for Case 3

Algorithm	PV	Wind Turbine	Number Batteries	Gasifier Rating (KW)	Biomass Running (h)	LPSP (%)	NPV (R)	ASC (R/yr)	COE (R/kWh)
SSP	51	0	209	1	1011	0.00021	7637578.71	1638628.82	2.4727
SSA	48	0	211	1	1317	0.00019	7801524.43	1673803.08	2.5257
PSO	45	0	204	2	972	0.00023	8006981.62	1717883.55	2.5922
TLBO	49	0	207	2	968	0.00014	8189661.65	1757077.23	2.6514

The result obtained by the different optimization techniques in the third case is presented in Table 4.7 and the minimum energy cost is estimated by the SSP algorithm to be 2.4727 R per kWh. The respective estimates for SSA, PSO and TLBO are 2.5257, 2.5922 and 2.6514. The number of solar PV, batteries and the rating of the biomass gasifier as obtained by the different techniques are given in Table 4.3. The SSP algorithm found the best result in terms of cost and together with SSA both estimated a reliability index of 0 for this hybrid system configuration. The convergence curve of the comparison algorithms in relation to the COE is shown in Fig. 4.15.

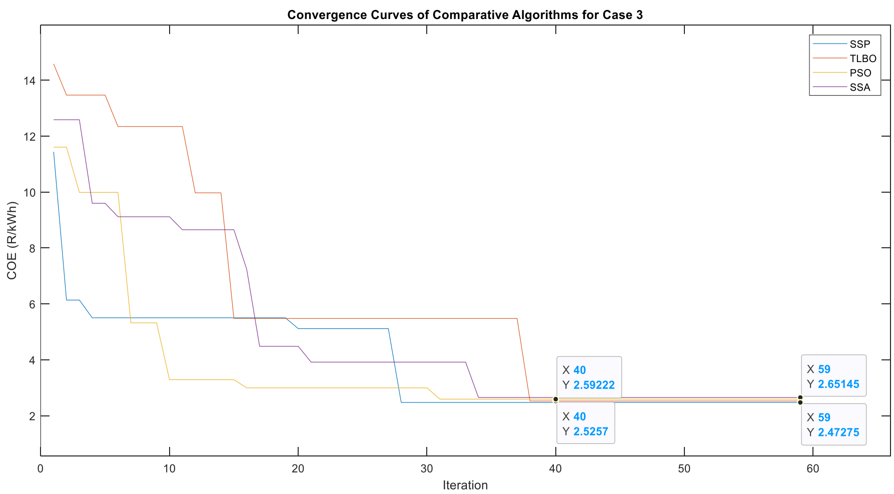


Figure 4.22 Convergence curves of comparative algorithms for Case 3

Table 4.8: Breakdown of NPC and ASC obtained by SSP algorithm for the proposed hybrid system under Case 3

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	Gasifier Running Hours	NPC	ASC
PV	892500.00	0.00	500725.52	0.00	0.00	0	1393225.52	298914.04
WT	0.00	0.00	0.00	0.00	0.00	0	0.00	0.00
BG	25200.00	30501.40	435122.99	-6505.64	218742.94	1011	703061.70	150840.63
Battey	731500.00	975791.50	3762000.00	0.00	0.00	0	5469291.50	1173426.69
Inverter	72000.00	0.00	0.00	0.00	0.00	0	72000.00	15447.47
Total	1721200.00	1006292.90	4697848.51	-6505.64	218742.94	1011	7637578.71	1638628.82

As in the two previous cases presented earlier in this section, the cost component of the optimal hybrid system configuration achieved by SSP is presented in Table 4.8. It was estimated that an amount of R7,637,578.71 would be required to set up a hybrid PV-biomass battery system for the study area. This amount, if spread over the life of the hybrid system, would amount to an annual system cost of R1,638,628.82, which includes all cost components of the power sources and the fuel cost minus the recycling cost.

Components contribution to total power supply for Case 3

The different components and their contribution to the total power delivered to the electrical load connected to the hybrid system for Case 3 are shown in Figure 4.23 through Figure 4.26.

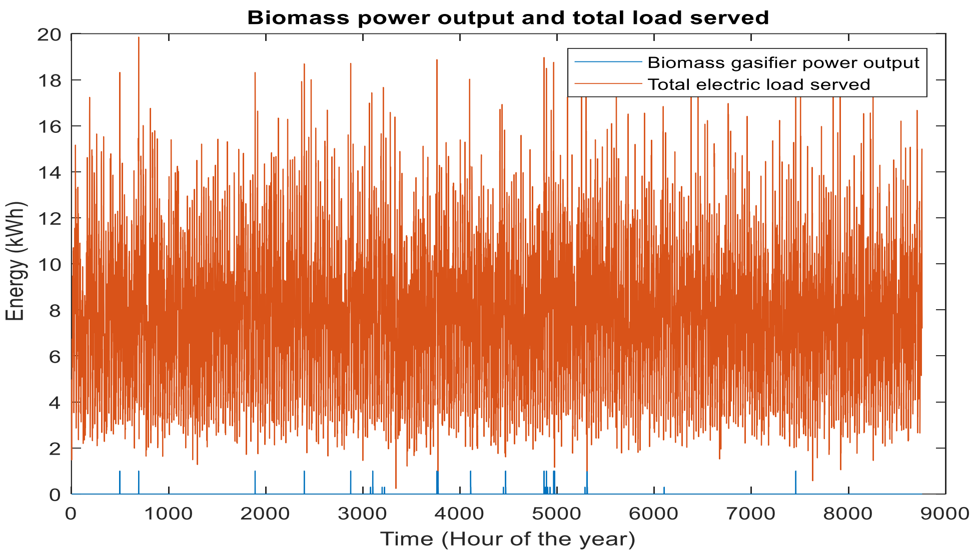


Figure 4.23: Biomass power output and total load served under Case 3

It was observed that the biomass gasifier contributed to the overall performance of the hybrid system, but in a small amount as shown in Figure 4.23. The biomass gasifier as a power saving unit provided electricity to consumers when the primary power source (solar PV array) and storage system (battery) could not meet demand.

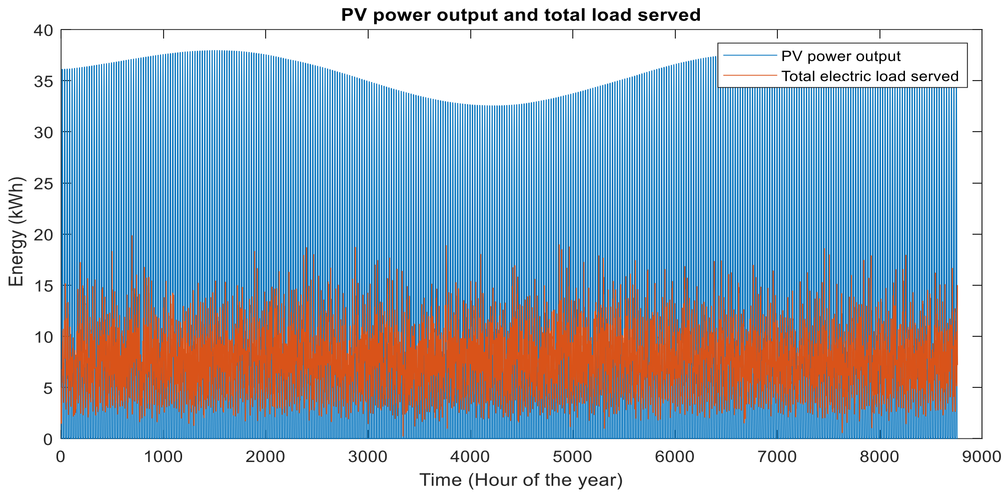


Figure 4.24: Solar PV power output and total load served under Case 3

Figure 4.24 shows the contribution of the solar PV system output power to the total load served under Case 3. It is observed that in the third scenario, the solar PV system produces a significant amount of solar energy when the sun is available.

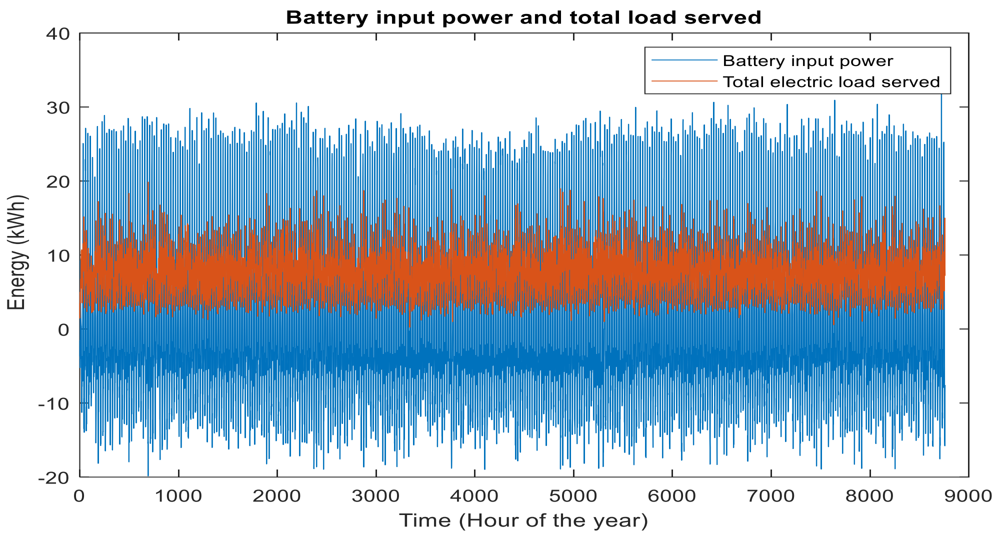


Figure 4.25: Battery input power and total load served under Case 3

The distribution of the battery input power, as shown in Figure 4.25, shows that the battery storage system was heavily used to meet the load demand for most of the year as a lot of current was drawn from it. On the other hand, we see that the hybrid system could charge the battery any time it approaches the 40% threshold (Figure 4.26).

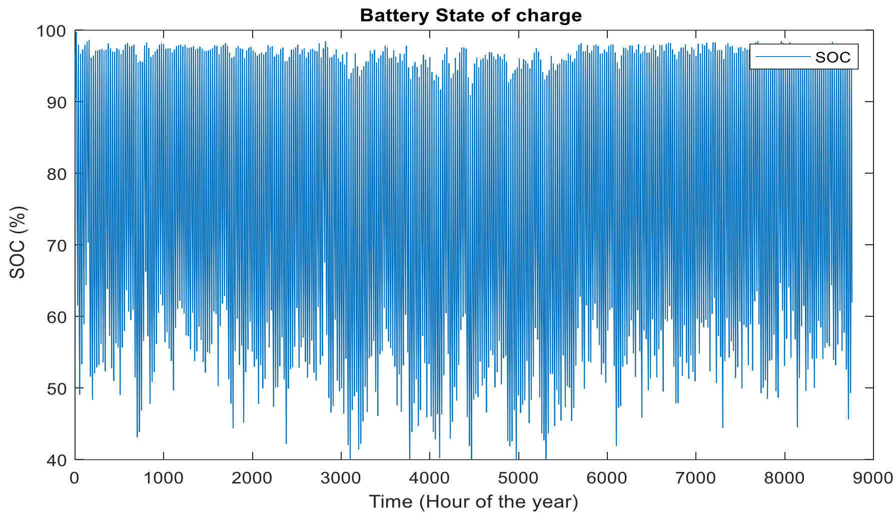


Figure 4.26: Battery state of charge for Case 3 scenario

4.3.2.4 Case 4: PV-wind-biomass-battery

The last case scenario of the hybrid system configuration saw all the four energy sources namely solar PV, wind turbine, battery and biomass gasifier featuring in the setup.

Table 4.9: Comparative results of the proposed HRES sizing with various optimization techniques for Case 4

Algorithm	PV	WT	Gasifier Rating	Number of Battery	Biomass running (h)	LPSP	NPV (R)	ASC (R/yr)	COE (R/kWh)
SSP	42	1	2	201	132	0.0141	6581936.45	1412142.80	2.1309
TLBO	43	2	1	201	141	0.0121	6613630.98	1418942.87	2.1412
PSO	44	2	1	202	142	0.0133	6655880.64	1428007.43	2.1633
SSA	45	1	1	203	139	0.0212	6721081.31	1441996.17	2.1634

The results presented In Table 4.9 show a cheaper cost in all aspects compered to all the previous cases for the hybrid system configuration. At a glance of Table 4.9, the levelized cost of energy recorded by SSP for Case 4 as compared to Case 1 is reduced by more than 50%. The sizing of the system components, reliability index and the economic evaluation are shown in the table. Again, in this case, SSP showed superiority over all the comparative algorithms in terms of cost as it recorded the least value for the levelized cost of energy of R2.1309 per kWh. SSP however had the worst LPSP value with 0.0141 but it was within the constraint boundaries. Figure 4.27 shows the convergence curves of applied optimization techniques used to study the hybrid system performance.

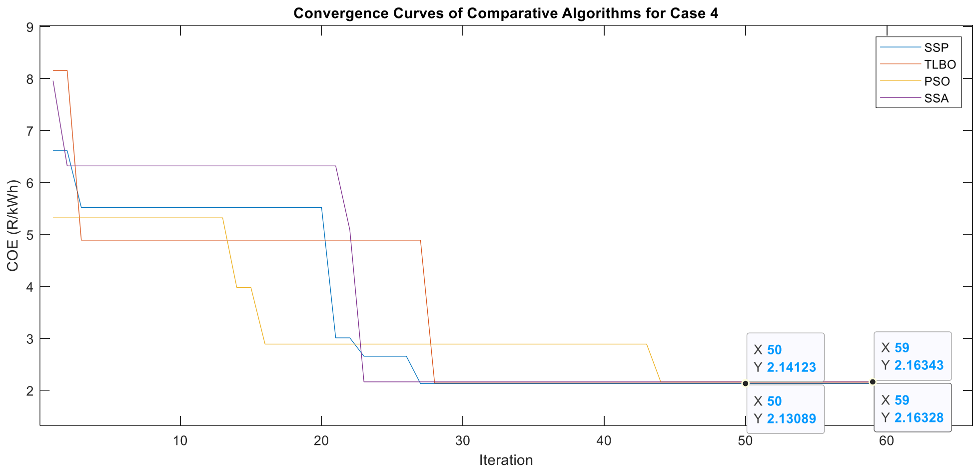


Figure 4.27: Convergence curves of comparative algorithms for Case 4

Table 4.10: Breakdown of NPC and ASC obtained by SSP algorithm for the proposed hybrid system under Case 4

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC
PV	735000.00	0.00	412362.20	0.00	0.00	0	1147362.00	246164.50
WT	25500.00	0.00	9818.14	0.00	0.00	0	35318.15	7577.45
BG	50400.00	0.00	27490.81	-28350.00	13847.23	32	67315.30	14442.38
Battey	703500.00	938440.60	3618000.00	0.00	0.00	0	5259941.00	1128511.00
Inverter	72000.00	0.00	0.00	0.00	0.00	0	72000.00	15447.47
Total	1586400.00	938440.60	4067671.15	-28350.00	13847.23	32	6581936.45	1412142.80

The cost component of the optimal hybrid system configuration achieved by SSP is presented in Table 4.10. It was estimated that an amount of R6,581,936.45 would be required to set up a hybrid PV-wind-biomass-battery system. This amount, if spread over the life of the hybrid system, would amount to an annual system cost of R1,412,142.80, which includes the sum of all cost components of the power sources thus capital, replacement, operation, and maintenance, minus the salvage cost.

The graphical representations of the different components and their contribution to the total power delivered to the electrical load connected to the hybrid system for Case 4 are shown in Figures (4.28 to 4.32). The battery storge system performance and the SOC for the complete year period is also shown in Figure 4.28.

Components contribution to total power supply for Case 4

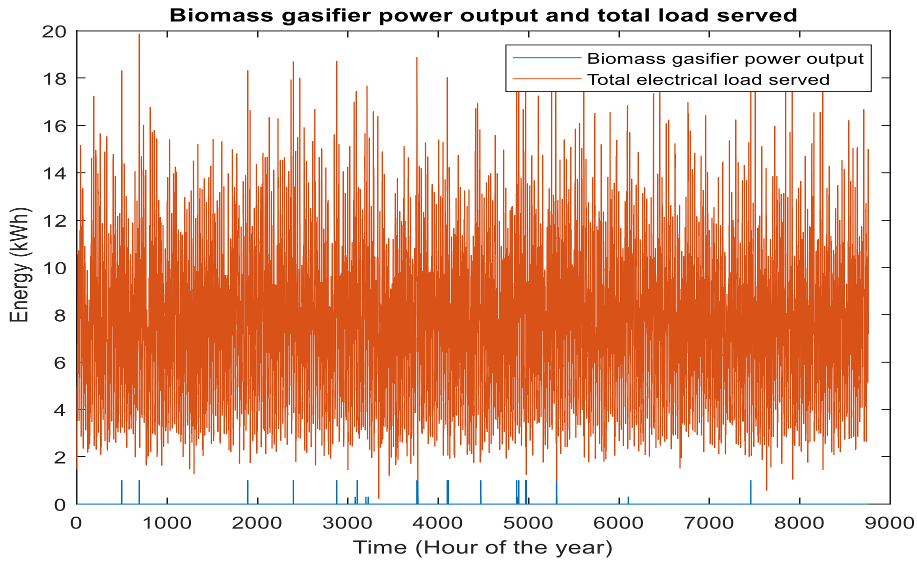


Figure 4.28: Biomass power output and total load served under Case 4

The biomass gasifier power output regarding the total electric load served for the entire year was marginal as can be seen on Figure 4.28. Perhaps the alternative power sources were often available to supply power to the attached load, hence relieving the gasifier to eject power only at crucial times.

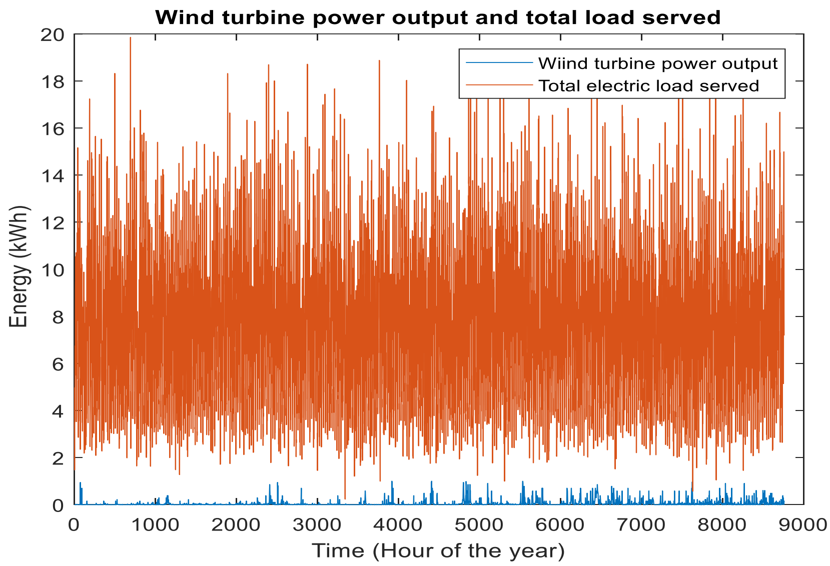


Figure 4.29: Wind turbine power output and total load served under Case 4

From Figure 4.29 the wind power output as compared to the biomass gasifier output was substantial however, the wind resource alone could not meet the load demand as there was always supply deficit. The need for additional power supply in this situation is seen in Figure 4.29 as the demand was always above supply.

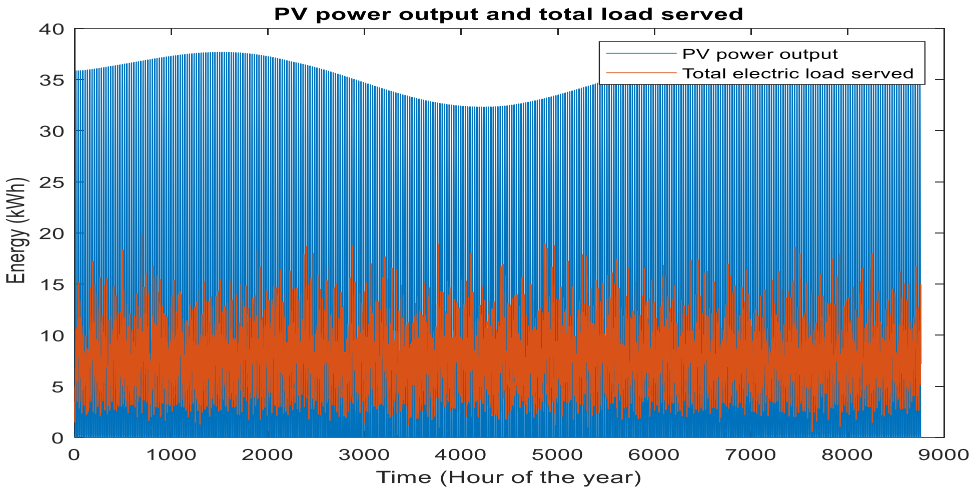


Figure 4.30: Solar PV power output and total load served under Case 4

In Figure 4.30, we see a high output power of the solar PV array that meets the load demand. Perhaps due to the rich PV resources, the solar PV system could produce enough electricity to meet the load whenever the climatic conditions are favorable. However, there have been instances when solar resources have not been available. The battery storage system was necessary to absorb the excess electricity and store it for future use. The battery input power for the total electrical load supplied is shown in Figure 4.31; The battery storage system was used to cover the deficit load when the primary sources could not provide all the required power supply to the load. In addition, the battery state of charge for Case 4 is shown in Figure 4.32.

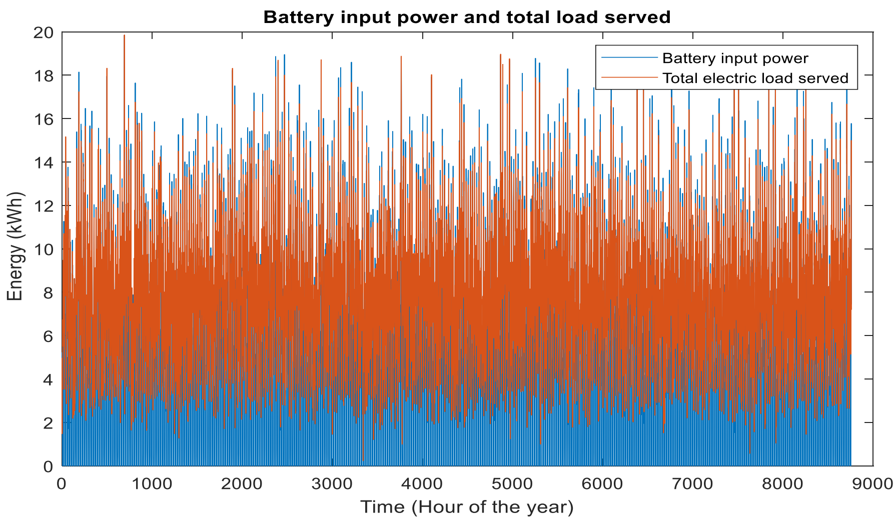


Figure 4.31: Battery input power and total load served under Case 4

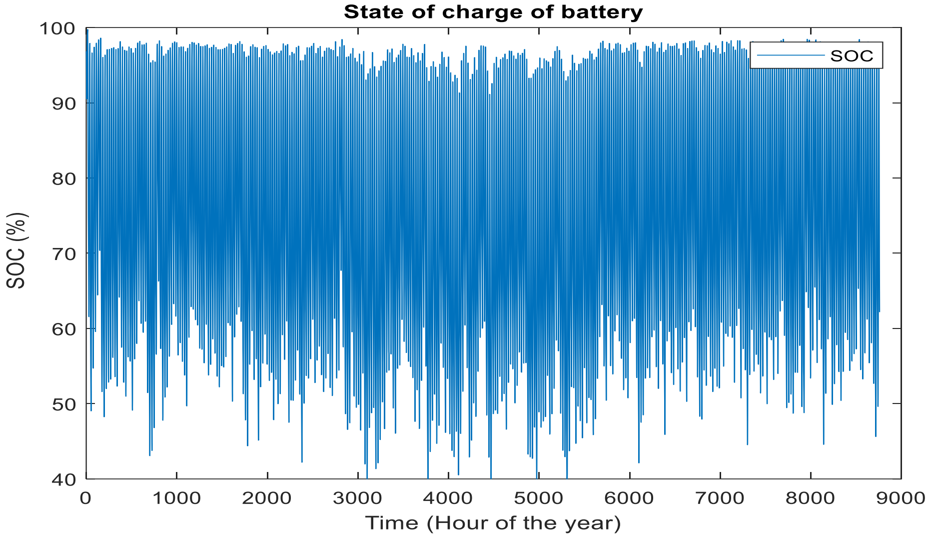


Figure 4.32: Battery state of charge for Case 4 scenario

Among the 4 cases elaborated in this section, thus using the historical data the fourth case study consisting of solar PV module, wind turbine, biomass gasifier and battery storage system revealed the best solution in terms of economic value for the hybrid system configuration. The optimal solution also has a high level of reliability for a year-round power supply. The LPSP value of 0.0142 indicates that the optimal solution would allow a maximum of 6 days in the entire year when the power system may not be able to meet the connected load. It was shown that the combination of PV solar modules, wind turbines, biomass gasifiers and battery storage systems into a hybrid energy system and the correct dimensioning of the system components have both economic and reliable advantages in achieving a sustainable power supply.

4.3.3 HRES Optimization using extrapolated sensor data

Real-time environment data namely temperature and wind speed was collected with the help of the IoT devices (sensors) discussed in chapter three. Due to time constraints for the research a complete year-round data could not be collected. Therefore, the two-month period (April and May 2022) data collected was used to extrapolate for the missing months of the year with supplementary historical data. the supplementary data was gathered from multiple sources. The monthly averages of secondary data were used to fill the missing months for the real-time sensor data. thereafter the extrapolation of the daily and hourly data was carried out. The extrapolation was necessary because sufficient data representing the varying climatic weather conditions for any give location is crucial in determining the proper sizing of a PV-wind based hybrid system. Each algorithm was run 10 times with an iteration of 60 per each run to determine the near optimal solution for the hybrid system. The average results are computed and presented under each case scenario.

The data used to estimate the average monthly readings for solar and wind resources are listed and referenced in Table 4.11. From Table 4.11, under each column namely wind speed and solar irradiance the measured or calculated IoT data is recorded.

Data

Table 4.11: Monthly averages of secondary data and IoT sensor data used for hybrid system optimization

Month	Wind speed (m/s)			Solar irradiance (kWh/m2/day)				Biomass resource	Electric load
	NREL	NASA	IoT/calc.	NASA	Ntlela	Govindas	IoT/calc.		
Jan	1.71	5.19	3.45	6.26	5.67	4.18	5.37	2.50	5121.98
Feb	2.96	4.99	3.98	5.58	5.51	4.00	5.03	2.40	8576.98
Mar	2.64	4.74	3.69	4.88	5.03	4.10	4.67	2.50	7984.87
Apr	3.57	4.91	3.44	3.67	4.40	4.08	3.94	2.70	8992.78
May	1.61	4.44	2.11	2.72	3.81	4.51	3.12	1.80	9848.13
Jun	2.92	4.41	3.67	2.21	3.40	4.37	3.33	2.60	11154.00
Jul	3.25	4.91	4.08	2.47	3.65	5.04	3.72	2.60	9832.46
Aug	4.37	5.75	5.06	3.39	4.25	4.75	4.13	2.50	9985.43
Sep	3.70	6.18	4.94	4.45	4.84	5.15	4.81	1.90	10481.80
Oct	4.06	6.16	5.11	5.43	4.93	4.19	4.85	2.50	10975.60
Nov	3.78	5.84	4.81	5.94	5.30	3.83	5.02	2.70	10825.70
Dec	3.98	5.29	4.63	6.55	5.69	4.15	5.46	2.40	10254.70

It should be noted that both biomass resources and electric load data remained constant during the two scenarios namely, using historical dataset and sensor extrapolated dataset.

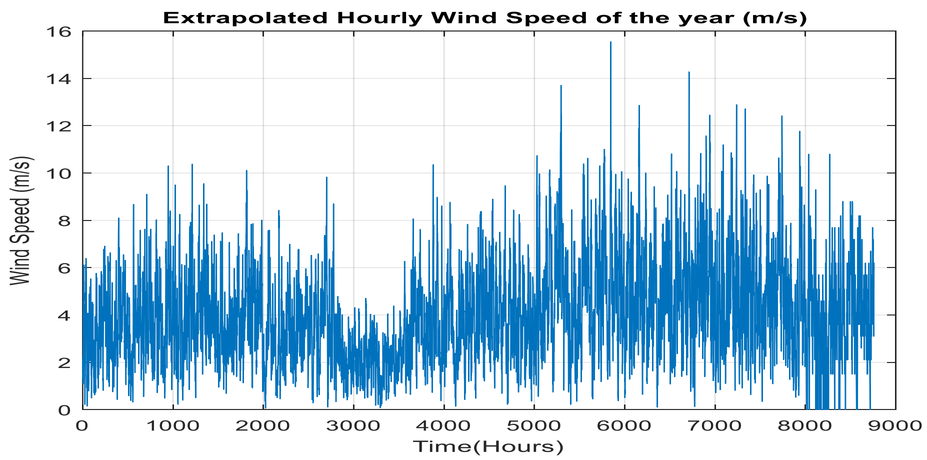


Figure 4.33: Extrapolated hourly wind speed (m/s)

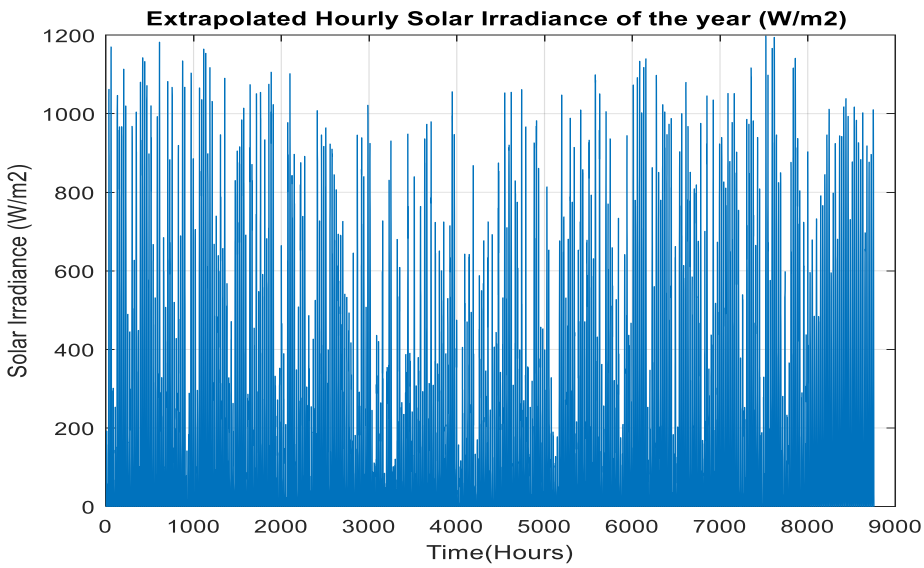


Figure 4.34: Extrapolated hourly solar irradiance (W/m^2)

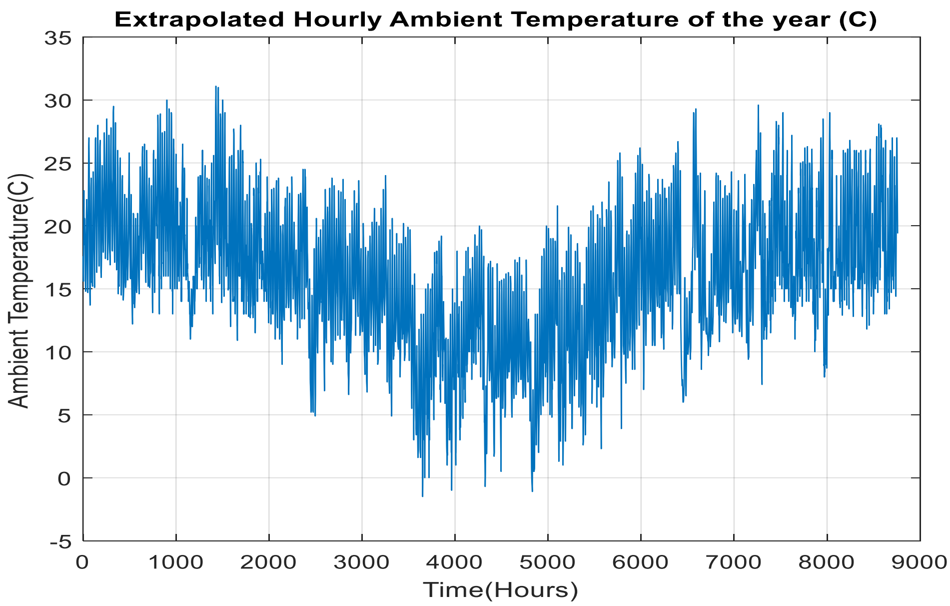


Figure 4.35: Extrapolated hourly temperature (°C)

4.3.3.1 Case 1: Wind-biomass-battery HRES optimization using extrapolated dataset

Similar to Case 1 of the simulation with the historical data as discussed in the previous section, there was no PV subsystem for this case either. The battery storage acts as a backup for the hybrid system. Table 4.12 shows the result obtained for Case 1 using the extrapolated data set.

Table 4.12: Comparative results of the proposed HRES sizing with various optimization techniques for Case 1

Algorithm	No. PV	No. Wind Turbine	Biomass Gasifier Rating	No. Batteries	Gasifier Running Hrs	NPV (R)	ASC (R/yr)	LPSP	COE (R/kWh)
SSP	0	110	10	320	638	16993544.50	3645934.51	0.0341	5.5016
TLBO	0	109	9	331	678	17008837.72	3649215.64	0.0337	5.5066
SSA	0	110	11	319	642	17463977.11	3746864.98	0.0319	5.6539
PSO	0	112	10	410	681	19695610.79	4225657.99	0.0301	6.3764

It can be observed from Table 4.12 that the minimum cost of energy is estimated as R5.5016 per kWh using the SSP algorithm, whereas PSO, TLBO, and SSA output R5.5066, R5.6539, and R6.3764 respectively. The number of wind turbines, number of batteries, and rating of the biomass gasifier as obtained by the various techniques are shown under their respective columns. SSP algorithm found the best result in terms of cost but relatively a high LPSP index of 0.0341. PSO solution produced a reliability index of 0.0301 which was the least however it gave the highest cost of energy of 6.3464 R/kWh. The convergence curve of the comparative algorithms with respect to the levelized cost of energy is shown in Figure 4.36.

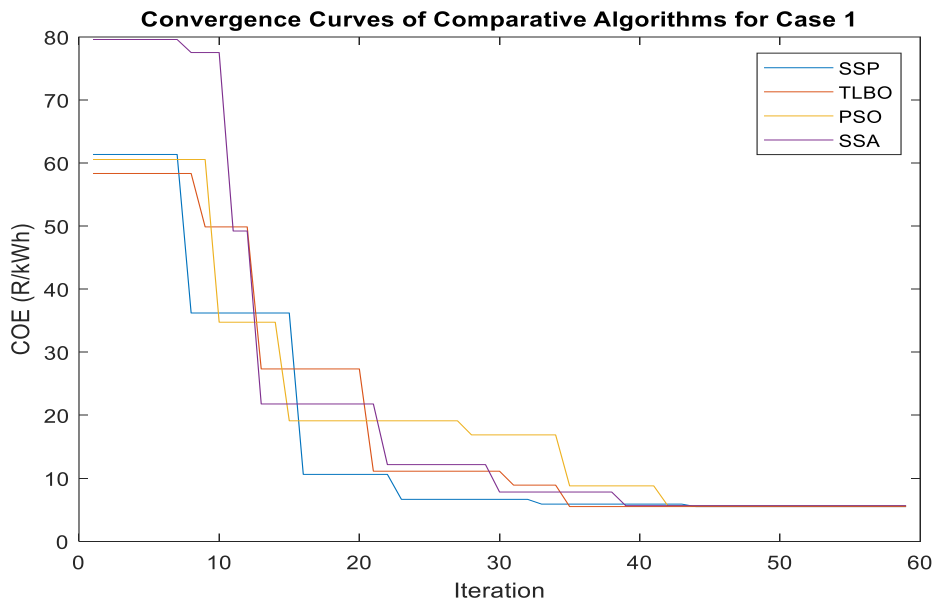


Figure 4.36: Convergence curves of comparative algorithms using extrapolated data for Case 1

Table 4.13: Breakdown of NPC and ASC obtained by SSP algorithm for the proposed hybrid system under Case 1

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC (R)	ASC (R)
PV	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WT	2805000.00	0.00	1079996.21	0.00	0.00	0.00	3884996.21	833518.97
BG	252000.00	305014.02	2745880.00	-20776.18	1380395.61	638.00	4662513.46	1000333.90
Battey	1120000.00	1494034.83	5760000.00	0.00	0.00	0.00	8374034.83	1796634.16
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47
Total	4249000.00	1799048.86	9585876.22	-20776.18	1380395.61	638.00	16993544.50	3645934.51

Table 4.13 shows the breakdown of the cost of the renewable energy technologies for the hybrid system. The Wind/biomass/battery hybrid system will cost an estimated R4 249 000.00 to set up. In addition, the NPC of the system is estimated to be R16 993 544.50 for the entire system lifetime.

The various components and their contribution to the total power supplied to the electrical load under Case 1 are presented in Figures (4.37 – 4.41).

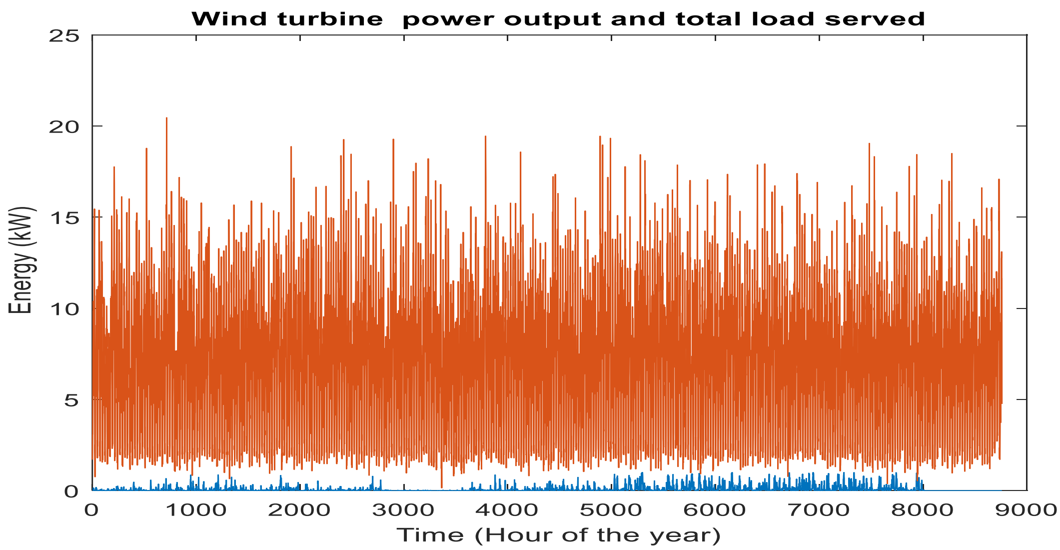


Figure 4.37: Wind turbine power output and total load served using extrapolated data for Case 1

The output power of the wind turbine was insufficient to power the connected load as shown in Figure 4.37. It can be observed that the load demand was always higher than what the wind turbine could supply. Figure 4.38 shows a segment of the annual distribution of wind energy power to the total load served, and it is evident that the power from the wind system could not always meet the load demand.

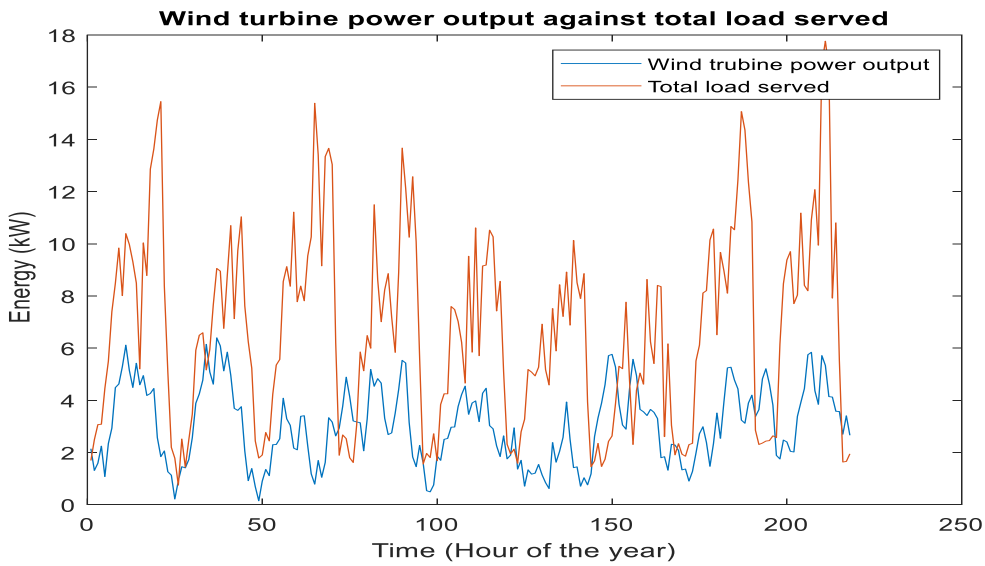


Figure 4.38: Wind turbine power output and total load served using extrapolated data for Case 1

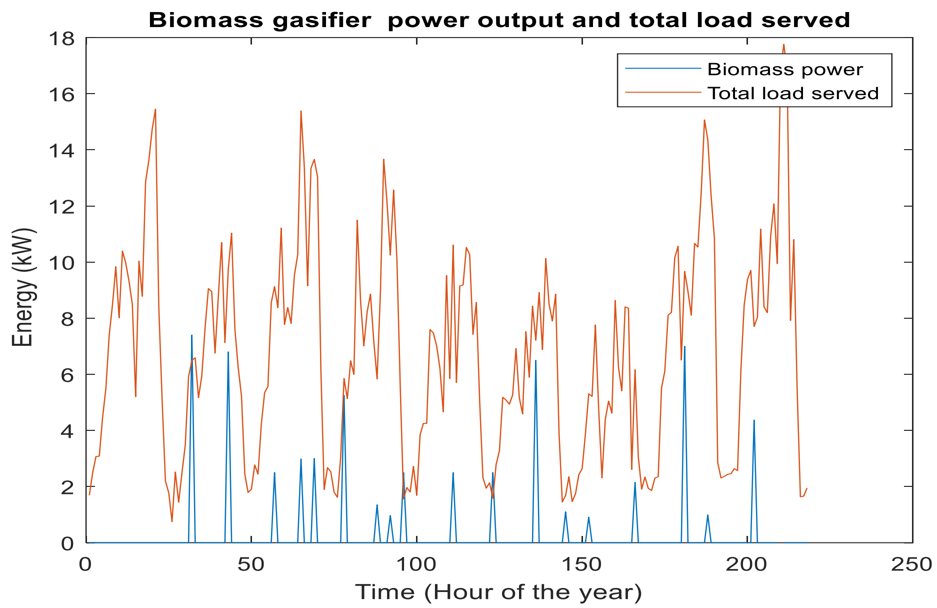


Figure 4.39: Biomass gasifier power output and total load served with extrapolated data for Case 1

It could be observed that the gasifier was utilized to supply power to the load, but it output could not satisfy the demand. Figure 4.39 is a segment of biomass gasifier power distribution graph showing the proportion of the total load it served for certain time of the year as shown on the horizontal axis.

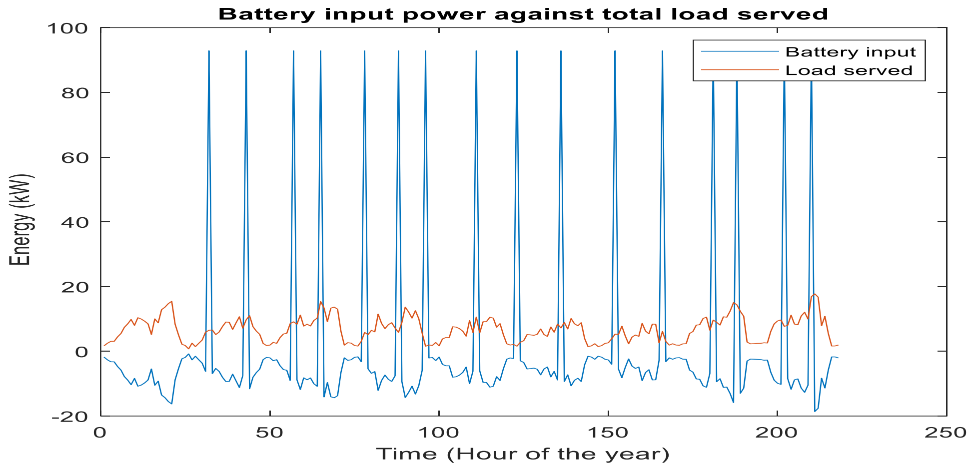


Figure 4.40: Battery input power and total load served with extrapolated data for Case 1

The input power from the battery was used to mitigate the demand deficit when the battery has sufficient storage capacity otherwise it will take power from the system as observed from Figure 4.40. In Figure 4.41 the state of charge of the battery is shown. It could be observed that the battery was extensively used to supply power to the load. It was discharging quite often when it has charged to 60%

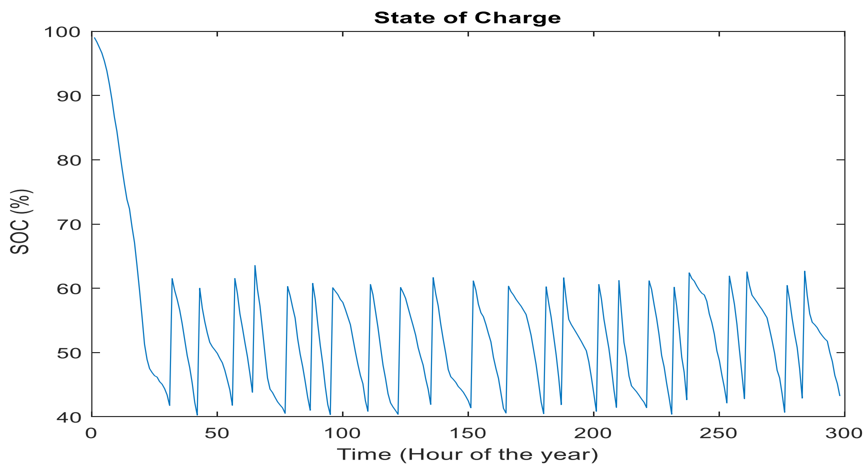


Figure 4.41: Battery state of charge for case1 with extrapolated data

4.3.3.2 Case 2: PV-wind-biomass

In Case 2, there was no battery storage system attached to the hybrid power sources. Hence, the renewable energy power source namely solar PV, wind turbine and biomass gasifier were the only power sources. Table 4.14 depicts the optimal solution for the hybrid system configuration according to the various optimization algorithms for Case 2 using the extrapolated sensor dataset.

Table 4.14: Comparative results of the proposed HRES sizing with various optimization techniques for Case 2

Algorithm	No. PV	No. Wind Turbine	Biomass Gasifier Rating	No. Batteries	Gasifier Running Hrs	NPV (R)	ASC (R/yr)	LPSP	COE (R/kWh
SSP	215	98	14	0	572	15348229.05	3292935.03	0.0614	4.9690
TLBO	217	101	17	0	613	17234325.77	3697593.70	0.0532	5.5795
SSA	217	98	15	0	587	15973183.48	3427017.88	0.0619	5.1713
PSO	215	105	15	0	569	15992169.82	3431091.37	0.0542	5.1774

From Table 4.14, and the minimum cost of energy is estimated as R4.9690 per kWh by SSP algorithm. The respective estimates for TLBO, SSA, and PSO are 5.5795, 5.1713, and 5.1774. Unlike the scenario for Case 1, the hybrid system configuration in this instance accounted for all the three renewable power sources but not battery storage system. After the simulation of the optimization problem the results for the optimal sizing of the hybrid system component to supply reliable power according to the various techniques are presented in Table 4.14. The number of solar PV, wind turbines, and rating of the biomass gasifier as obtained by the various techniques show that SSP algorithm found the best result in terms of cost with R3292935.03 as the annualized system cost of. SSP and SSA estimated the LPSP indices little higher than PSO and TLBO.

Figure 4.42 shows the convergence curves of the cost of energy as estimated by the comparative algorithms.

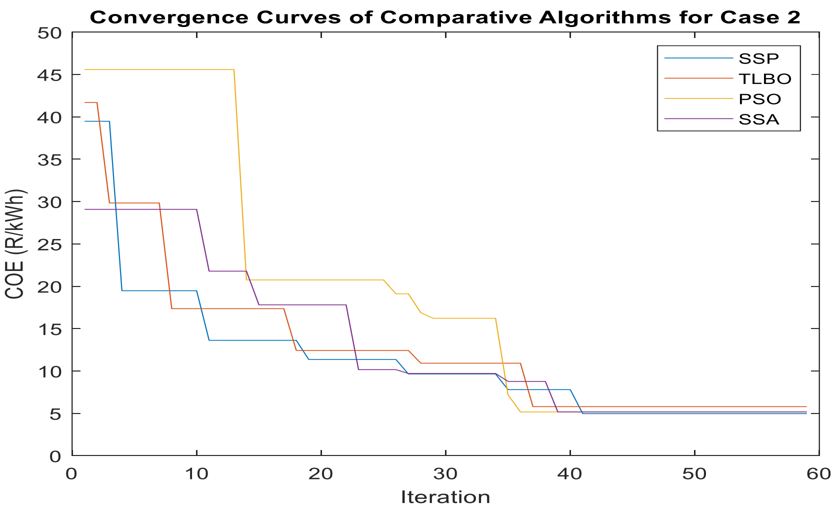


Figure 4.42: Convergence curves of comparative algorithms for Case 2 with extrapolated data

Table 4.15: Breakdown of NPC and ASC obtained by SSP algorithm for the proposed hybrid system under Case 2

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC
PV	3762500.00	0.00	2110901.69	0.00	0.00	0.00	5873401.69	1260127.80
WT	2499000.00	0.00	962178.45	0.00	0.00	0.00	3461178.45	742589.63
BG	352800.00	427019.63	3446552.83	-17358.04	1732634.49	572.00	5941648.91	1274770.12
Battey	0	0	0	0	0	0	0	0.00
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47
Total	6686300.00	427019.63	6519632.97	-17358.04	1732634.49	572.00	15348229.05	3292935.03

Table 4.15 presents the cost of components for configuring the hybrid system. Each renewable energy technology has capital cost, replacement cost, operation and maintenance cost, as well as salvage cost. The salvage cost would be zero once the component out live the lifetime. It was estimated that an amount of R6 686 300 would be needed to set up the PV/Wind/Biomass hybrid system. Additionally, the NPC of the system for the entire system life time is estimated R15 348 229.05 as shown in Table 4.15.

The various components of the hybrid PV/Wind/Biomass system and their contribution to the total power supplied to the electrical load under Case 2 are presented in Figures (4.43 – 4.45).

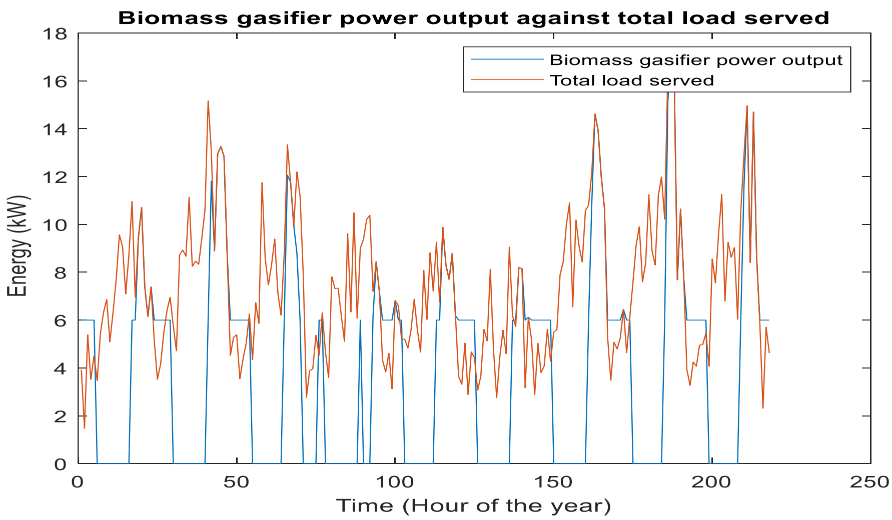


Figure 4.43:Biomass gasifier power output during peak for Case 2 using extrapolated data

Figure 4.43 shows the power distribution of the biomass gasifier and the total load supplied. As shown in the graph, the biomass gasifier alone was not capable of handling the entire load.

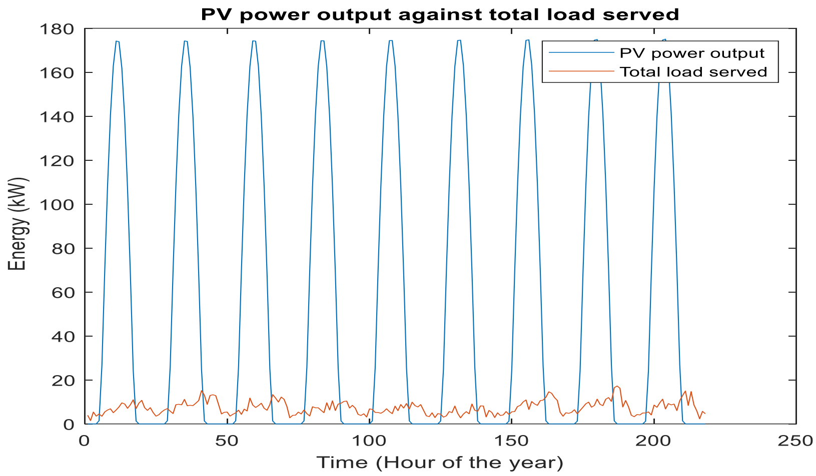


Figure 4.44: Solar PV power output and total load served for Case 2 using extrapolated data

Figure 4.44 shows the PV output power and the total load supplied for Case 2. It can be observed that when there is solar radiation, the electricity is produced in excess of the load requirement, but the load is never covered by the PV system at all times.

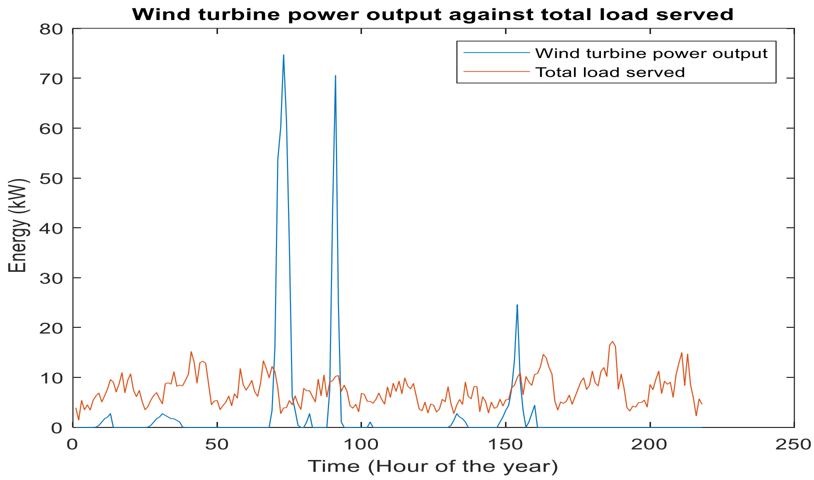


Figure 4.45: Wind turbine power output and total load served for Case 2 using extrapolated data

Figure 4.45 shows the distribution of wind power output and the total load served by the hybrid system described in Case 2. The wind system can produce power in excess of load demand but on rare occasions as shown in Figure 4.45. In most cases, the load demand exceeds the wind system power output.

4.3.3.3 Case 3: PV-biomass-battery

Case 3 comprises of PV system, biomass gasifier and battery storage. Under this case scenario there was no consideration for wind turbines. Hence, the PV system is the primary source of energy, The battery storage system and biomass gasifier were utilized as and when needed according to the operational strategy. Table 4.16 depicts the optimal solution for the hybrid system configuration which was considered in Case 3 using the extrapolated sensor dataset.

Table 4.16: Comparative results of the proposed HRES sizing with various optimization techniques for Case 3

Algorithm	No. PV	No. Wind Turbine	Biomass Gasifier Rating	No. Batteries	Gasifier Running Hrs	NPV (R)	ASC (R/yr)	LPSP	COE (R/kWh)
SSP	167	0	2	211	981	11504955.46	2468367.57	0.0041	3.7247
TLBO	166	0	3	215	972	12255193.62	2629329.82	0.0039	3.9676
SSA	167	0	3	212	978	12215527.43	2620819.51	0.0039	3.9548
PSO	167	0	2	211	984	11508777.23	2469187.52	0.0041	3.7259

The result obtained by the different optimization techniques in the third case is presented in Table 4.16 and the least cost of energy is estimated by the SSP algorithm to be 3.7247 R/kWh. The respective estimates for TLBO, SSA, and PSO are 3.9676, 3.9548 and 3.7259. The number of solar PV, batteries, and the rating of the biomass gasifier for the case under review as obtained by the different techniques are given in Table 4.3. Figure 4.46 shows the convergence curves of the comparative algorithms in achieving the near optimal solution (in terms of COE).

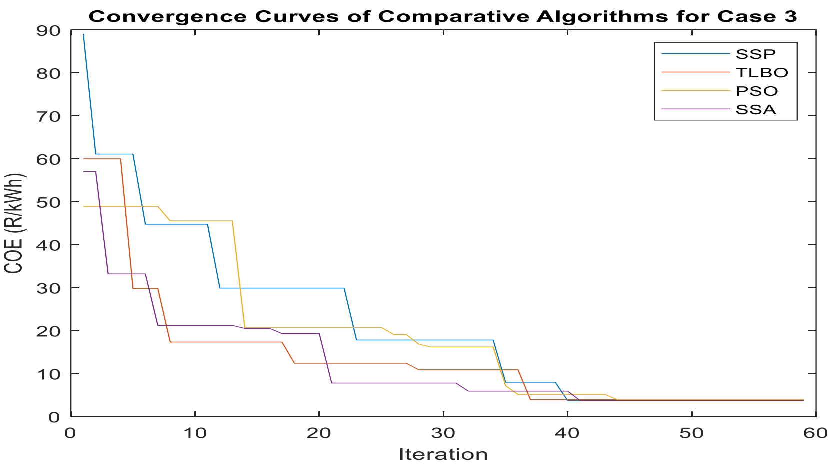


Figure 4.46: Convergence curves of comparative algorithms for Case 3 using extrapolated data

After simulating the third case, all four algorithms appeared to have converged at some point, but the details are revealed in Table 4.16. The breakdown of NPC and ASC costs obtained from the SSP algorithm is shown in Table 4.17.

Table 4.17: Breakdown of NPC and ASC obtained by SSP algorithm for the proposed hybrid system under Case 3

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC
PV	2922500.00	0.00	1639630.62	0.00	0.00	0.00	4562130.62	978796.95
WT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BG	50400.00	61002.80	844422.66	-31133.94	424504.10	981.00	1349195.62	289467.50
Battey	738500	985129.217	3798000	0	0	0	5521629.22	1184655.65
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47
Total	3783400.00	1046132.02	6282053.28	-31133.94	424504.10	981.00	11504955.46	2468367.57

From Table 4.17 it was estimated that an initial capital of R3 783 400.00 would be required to set up a PV/biomass/battery hybrid system for the study area. Meanwhile the entire system cost is estimated at R11 504 955.46, if spread over the life of the hybrid system, it would amount to an annual system cost of R2 468 367.57, which includes the total cost of the hybrid system components and the fuel cost minus the recycling cost.

Components contribution to total power supply for Case 3

The different components and their contribution to the total power delivered to the electrical load connected to the hybrid system for Case 3 are shown in Figure 4.47 to Figure 4.51.

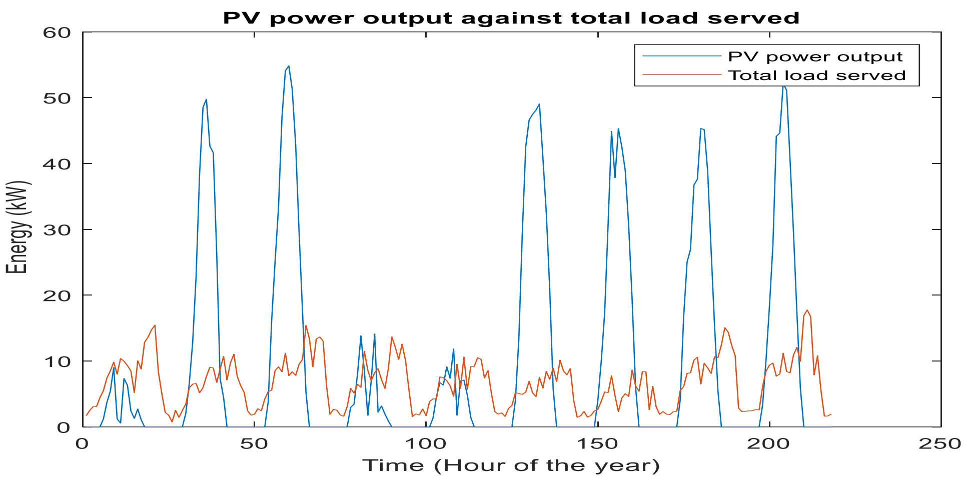


Figure 4.47: Solar PV power output and total load served for Case 3 using extrapolated data

From Figure 4.47 it can be seen that the PV array could produce electricity beyond the load if the sun is available. However, there were days when the sun was not reliable enough to provide energy supplies. In such a situation, the alternative power systems were necessary.

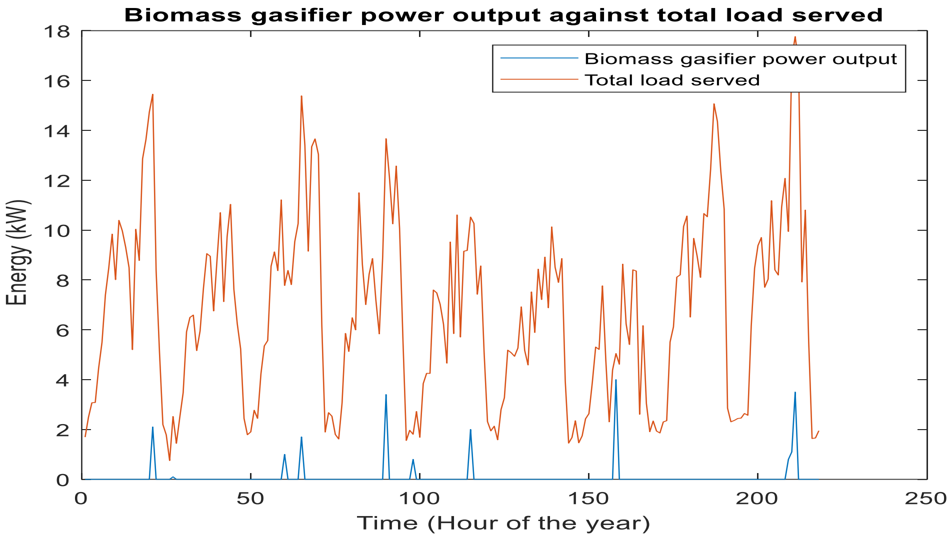


Figure 4.48: Biomass gasifier power output and total load served for Case 3 using extrapolated data

The capacity of the biomass gasifier alone was not sufficient to cover the total load as shown in Figure 4.48. The blue peaks in the graph, representing biomass gasifier performance, were mostly below the total load provided at any given time. This required the use of the battery storage system to provide the necessary power supply when the renewable sources were unable to meet the load demand. Figure 4.49 shows the distribution of battery input power versus total load supplied.

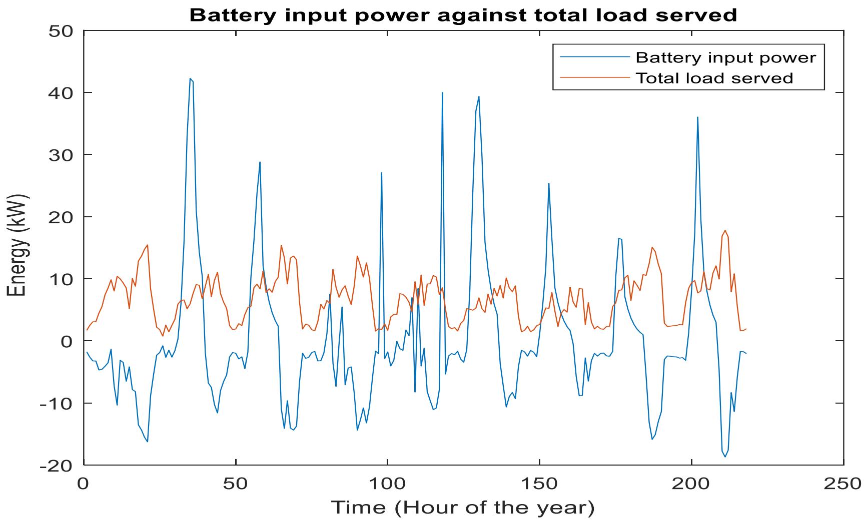


Figure 4.49: Battery input power and total load served for Case 3 using extrapolated data

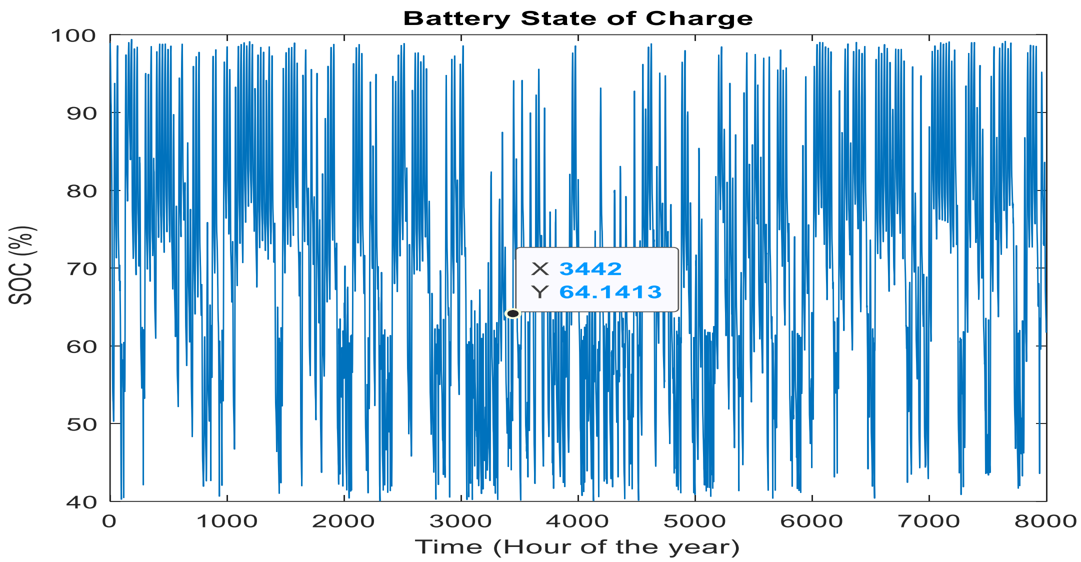


Figure 4.50: Battery state of charge for Case 3 using extrapolated data

Figure 4.50 shows the state of charge of the battery for the case scenario under discussion. The battery storage system was observed to complement the PV and biomass subsystem to power the connected load. In contrast to Case 1, where the battery was discharged frequently and often when charged to about 60%, in Case 3 it is observed that the battery bank could be charged to almost 100% for most of the year. Thus, the PV/biomass/battery hybrid system could satisfactorily meet the connected load as shown in Figure 4.51, where the unmet load is barely noticeable at the bottom of the graph.

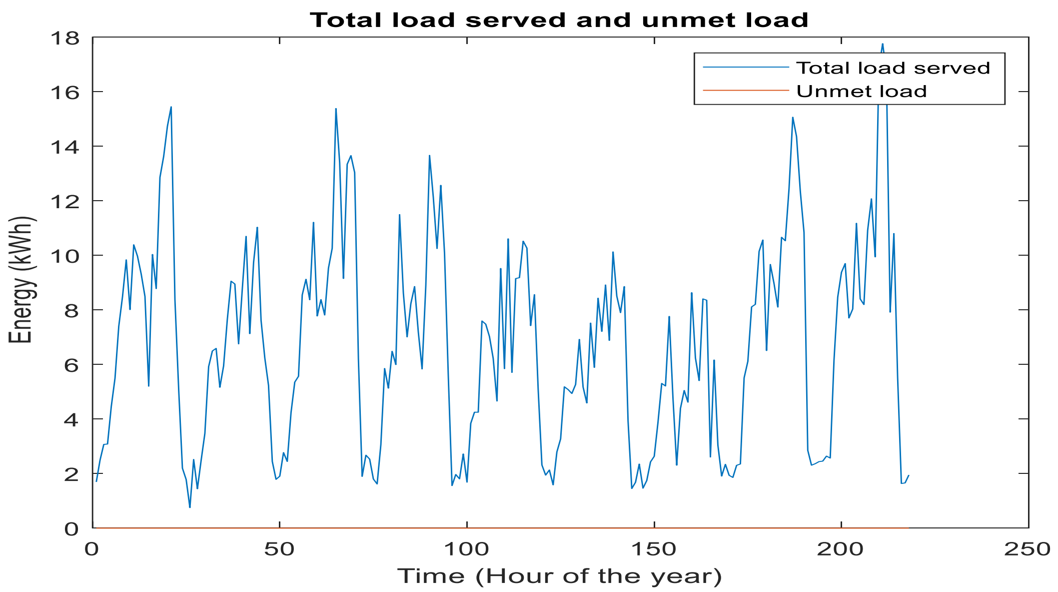


Figure 4.51:Total load served and unmet load for Case 3 using extrapolated data

4.3.3.4 Case 4: PV-wind-biomass-battery

In this hybrid system configuration case example, all four energy sources named solar PV, wind turbine, battery and biomass gasifier were included in the setup and the result of the optimization is discussed below.

Table 4.18: Comparative results of the proposed HRES sizing with various optimization techniques for Case 4

Algorithm	No. PV	No. Wind Turbine	Biomass Gasifier Rating	No. Batteries	Gasifier Running Hrs	NPV (R)	ASC (R)	LPSP	COE (R/kWh
SSP	55	2	2	198	458	7521262.16	1613673.31	0.0157	2.4350
TLBO	53	3	2	201	462	7585267.32	1627405.50	0.0153	2.4557
SSA	55	2	2	199	471	7563107.57	1622651.17	0.0155	2.4485
PSO	54	2	2	199	483	7550314.51	1619906.44	0.0156	2.4444

In Table 4.18, the result obtained by the different optimization algorithms shows that with a minimum amount of R7521 262.31 a hybrid PV/wind/biomass/battery system could be configured to reliably provide power to the electrical load. SSP achieved the lowest energy cost at R2.4350 per kWh, while TLBO estimated the highest energy cost at R2.4557 per kWh. The reliability indices after the comparison algorithms ranged from 0.0153 to 0.0157. TLBO estimated the lowest LPSP while SSP derived the highest LPSP. Figure 4.52 shows the convergence curves of the various optimization methods for the PV/wind/biomass/battery hybrid system using the extrapolated sensor data.

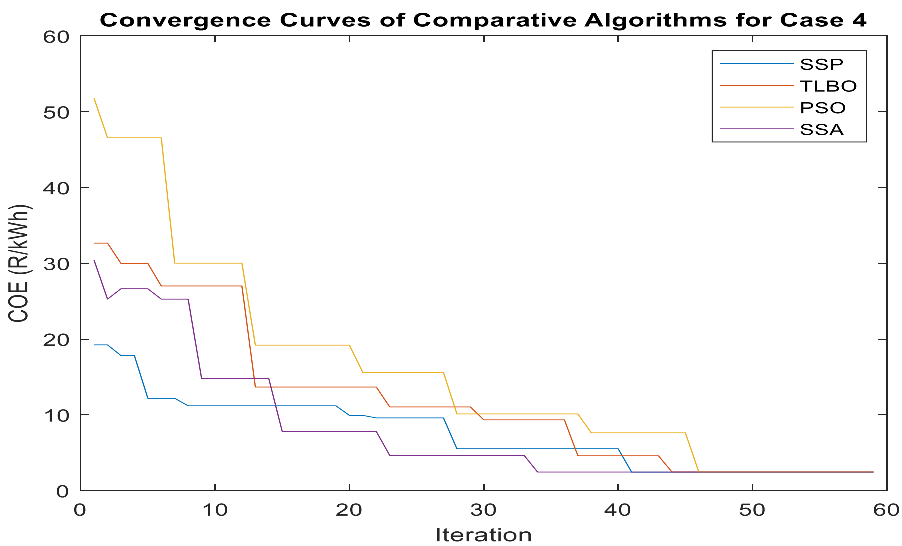


Figure 4.52: Convergence curves of comparative algorithms for Case 4 using extrapolated data

Table 4.19: Breakdown of NPC and ASC obtained by SSP algorithm for the proposed hybrid system under Case 4

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC
WT	51000.00	0.00	19636.29	0.00	0.00	0.00	70636.29	15154.89
BG	50400.00	61002.80	394236.06	-9133.62	198188.46	458.00	694693.70	149045.29
Battey	693000	924434.052	3564000	0	0	0	5181434.05	1111667.388
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47
Total	1828900.00	985436.86	4517870.47	-9133.62	198188.46	458.00	7521262.16	1613673.31

The cost component of the optimal hybrid system configuration achieved by SSP is shown in Table 4.19. An amount of R1 828 900.00 would be required to set up the hybrid system under Case 3. This amount is the capital cost for the hybrid system components. However, for the lifetime of the system, the NPC was estimated at R7 521 262.16; if the NPC is spread over the life of the hybrid system, it would amount to an annual system cost of R1 613 673.31 per year to operate the hybrid wind/biomass/battery system.

The graphs for Case 4 showing the different renewable technologies and their distribution to the total electrical load served are shown in Figure 4.53 through Figure 4.57.

Components contribution to total power supply for Case 4

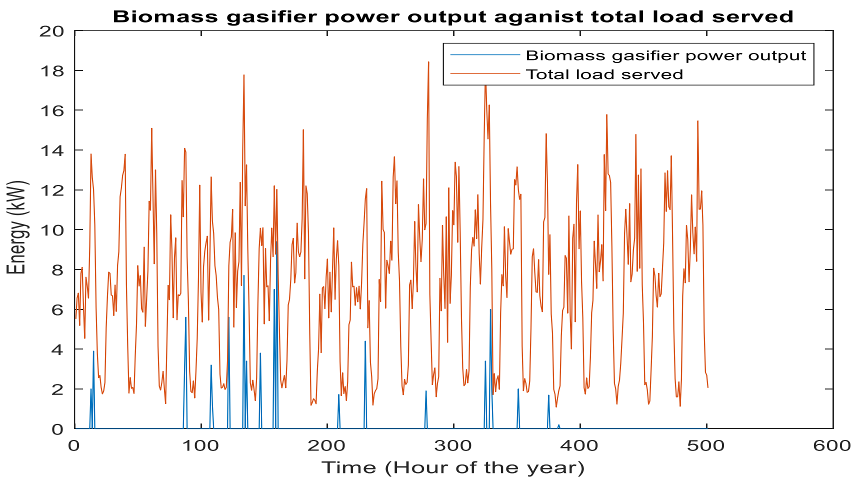


Figure 4.53: Biomass gasifier power output and total load served for Case 4 using extrapolated data

As can be seen from Figure 4.53, the power output of the biomass gasifier was marginal in relation to the total electrical load provided for the entire year. Perhaps the other energy sources were often available to power the connected load, relieving the biomass gasifier to eject power only at crucial times.

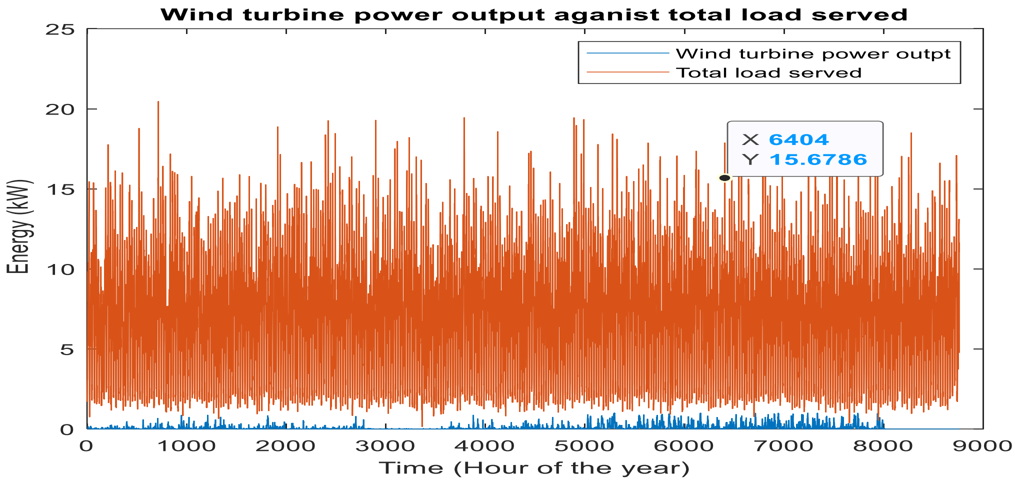


Figure 4.54: Wind turbine power output and total load served for Case 4 using extrapolated data

It can be seen from Figure 4.54 that the wind power output was significant compared to the biomass gasifier output, but the wind resource alone could not meet the load demand as there was always a supply deficit. The need for additional power supply in this situation can be seen in Figure 4.54 as demand has always exceeded supply.

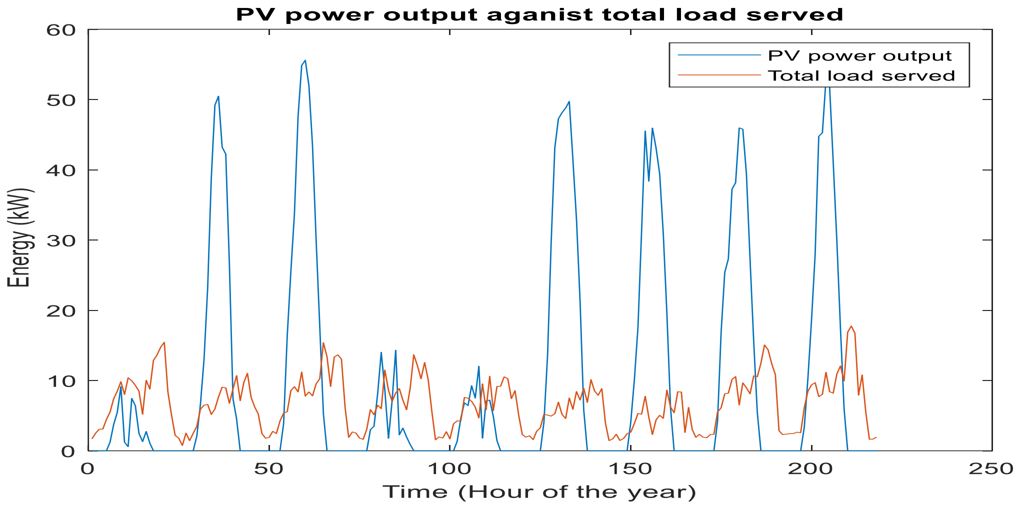


Figure 4.55: Solar PV power output and total load served for Case 4 using extrapolated data

From Figure 4.55, we can see high output power of the solar PV array that meets the load demand. Perhaps due to the rich PV resources, the solar PV system could produce enough electricity to meet the load whenever the climatic conditions are favorable. However, there have been instances when solar resources have not been available. The battery storage system was necessary to absorb the excess electricity and store it for future use. The battery input power for the total electrical load supplied is shown in Figure 4.56. In addition, the battery state of charge for case 4 is shown in Figure 4.57.

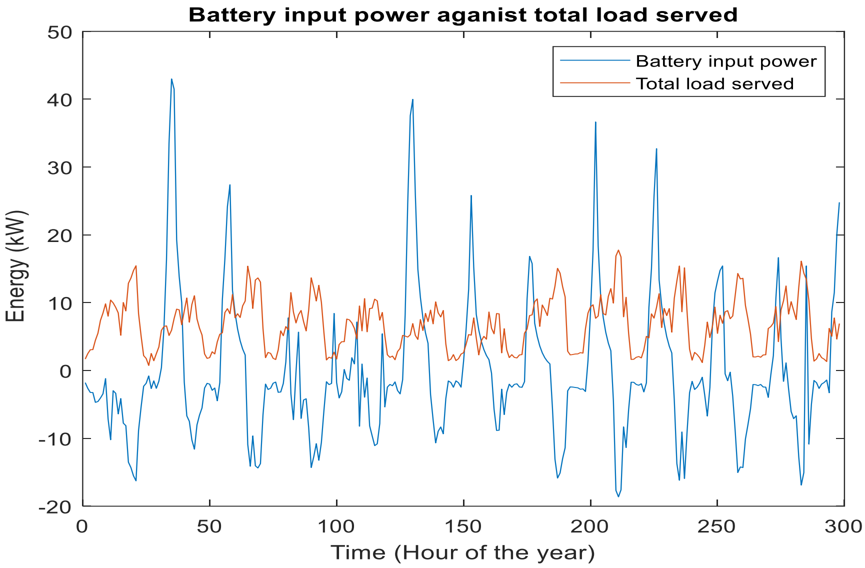


Figure 4.56: Battery input power and total load served for Case 4 using extrapolated data

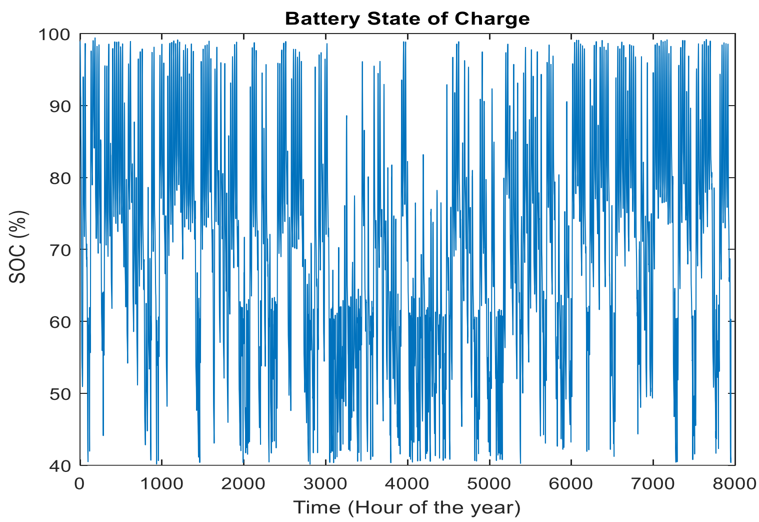


Figure 4.57: Battery state of charge for Case 4 using extrapolated data

4.4 Chapter summary

By using hourly climate and load data that accounts for a year's energy demand, the newly developed meta-heuristic algorithm, dubbed Social Spider Prey (SSP), could find a near-optimal hybrid system dimension that can supply reliable power to the attached load. With the help of two different datasets, the near optimal solution for the case study area consists of 42 solar PV panels, each PV panel rated at 1kW, 1 wind turbine also rated at 1kW, 1kW biomass gasifier, and 201 units of the specified batteries using the historical dataset. On the other hand, the extrapolated sensor data set provided a similar result for the various cases as with the historical data except for some marginal differences in values. For example, in Case 4 which is proven to be the optimal hybrid system configuration, the component sizing according to SSP algorithm is PV (55), Wind turbine (2), number of rated biomass gasifier (2), and number of batteries (198). This means that the optimal hybrid system can ideally generate 44 kW of electrical power from renewable resources when all components participate in the generation of electricity. In addition to the renewable energy sources, there is a storage capacity of more than 21000 Ah to mitigate the power supply deficit in a worst-case scenario when the electricity generated by the hybrid system cannot meet the connected load. The optimization technique used to solve the problem also estimated the economic value and reliability of the energy delivered by the system.

In total, the PV-wind-biomass-battery hybrid system will require a total of R1,586,400.00 as initial capital cost for setup using the historical data. Whereas the same configuration will require annualized amount of R1613673.31 amounting to NPV of R7521262.16 for the entire system lifetime for the sensor extrapolated data. Details of other cost factors are given in Tables 4.10 and 4.28. In addition, the present value of the optimal system is estimated at R6,581,936.45 and the annualized cost of the system is also estimated at R1,412,142.80. The reliability index is also estimated at 0.0142, giving a 98.58% assurance of powering the connected load over a one-year period. This level of reliability is achieved with high penetration of battery storage systems. During the simulation, the battery state of charge remained between 100% and at least 40% to ensure that battery life is prolonged or at least reached the expected 5-year lifespan before they are replaced.

The outcome of this case study can be used to set up an HRES in an area with similar climatic conditions and load patterns. Ideally, the weather data for the area for which the HRES is designed would be used in these calculations, but in situations where such data is not available, IoT sensors could be used to collect enough weather data to predict the weather trend in the area and then the data could be used to simulate a hybrid system. In the next chapter a thorough discussion of the experimental results obtained in this chapter is presented.

CHAPTER 5: DISCUSSION OF RESULTS

5.1 Introduction

In the previous chapter, a series of experiments were performed to validate the performance of the SSP algorithm as a global optimization technique compared to some modern techniques. In this chapter, the results obtained from the experiments of SSP and the comparison algorithms, namely PSO, TLBO and SSA, are discussed on a case basis. These comparative algorithms were selected because of their wide use in literature for related work, simplicity, ease to understand the codes, and good convergence characteristics. Ten (10) independent runs were executed in each comparative algorithm during the experiments as it guaranteed optimality, where each run consists of 60 iterations. Solar irradiance, ambient temperature, wind speed, biomass volume, and load data were the input to the hybrid system models to determine the economic and reliability of the power supply. As stated in the previous chapters 3 and 4 there were 2 different datasets used in this study namely historical and real-time extrapolated sensor data. Therefore, where necessary the emphasis on the data set used in the discussion would be outlined.

5.2 Results and analyses

This section presents the results and analyses of each hybrid renewable energy mix in terms of their economic and reliability criteria, and convergence curves of the feasible solutions. The economic criteria are measured in South African currency, which is ZAR or Rand (R). The USD currency conversion is also provided as the unit of measure of economic criteria.

5.2.1 Analysis of result for the renewable energy mix

Scenarios 1: Wind-biomass-battery hybrid system

Scenario 1 considered the Wind-biomass-battery combination. The sizing optimization of the multi-source renewable system was considered using the comparative algorithms. Whereas the optimal configuration of wind-biomass-battery and its energy analysis were provided, in this experiment, the objective function was considered in terms of minimum levelized cost of energy (LCE) and loss of power supply probability (LPSP). Thus, the objective is to minimize economic expenditure while maintaining a maximum of 1% LPSP. In case one, the hybrid system configuration did not consider solar PV system, thus assuming that the solar resources are completely unreliable. The result of this scenario depicts high numbers of wind turbines and batteries. SSP, TLBO, SSA, and PSO output 107, 118, 115, and 118 numbers of the rated wind turbines respectively. In the same order the number of batteries obtained accordingly are 315,311,321, and 317. The high penetration of the battery storage system for this scenario eventually improved the hybrid system reliability thus loss of power supply probability (LPSP) despite a relatively fewer running hours of the biomass gasifier. The least LPSP index of 0.004 representing 0.0146 day per year was estimated for the hybrid system by SSA. SSP however had the worse reliability index of 0.011 representing 0.0402 day per year. Even with this SSP estimated value for the LPSP index, the hybrid system reliability is considered very high, because there is more than 99% probability the attached load would be met throughout the year over the system lifetime. Table 4.9 and Table 4.18 present the average results of each algorithm after the 10 runs using the historical and extrapolated sensor datasets respectively.

From Table 4.3 the result obtained by the comparative algorithms indicates that the SSP algorithm produced the LPSP value of 0.011, whereas SSA produced the LPSP value of 0.004. The LPSP value is expressed as 0 and 1, where the LPSP value of 1 signifies that the load will never be satisfied, whereas the LPSP of 0 value means that the load will always be satisfied. A lower LPSP ratio corresponds to a higher Levelized Cost of Energy (LCOE). Thus, the optimal reliable solution of 0.004 corresponding to the Wind-biomass-battery configuration is 0 for PV panels (0), number of wind turbines (115), number of batteries (321), gasifier rating (11), and biomass (592). Economically, this translates to a higher cost of 5.6137 (ZAR/kWh) approximately 0.31 USD $/kWh. Thus, higher reliability incurs a higher cost for the wind-biomass-battery HRES.

SSA used a higher number of batteries (321) and gasifier ratings (11) thus leading to higher reliability (0.004) which should be approximately Zero (0). Though the SSA performs well in terms of reliability, the SSP was most optimal as it satisfies all the constraints set in this experiment. Annualized System Cost (ASC in ZAR) of the comparative algorithms of SSP, TLBO, SSA, PSO are 3,431,512.26; 3,718,603.24; 3,720,196.95, and 3,540,940.75 respectively. The Net Present Values (NPVs) of the system as derived from the various optimization algorithms utilized are SSP (ZAR15,994,131.58), TLBO (ZAR17,332,250.36), SSA (ZAR17,339,678.57), PSO (ZAR16,504,173.07) respectively with the proposed SSP algorithm having the least estimated cost. Accordingly, an unit cost of energy in ZAR/kWh is estimated as 5.1781, 5.6113, 5.6137 and 5.3432 with the comparative algorithms SSP, TLBO, SSA and PSO respectively. The SSP produced the optimal cost of energy as 5.1781 (ZAR/kWh) approximately 0.29 USD $/kWh or ZAR5.1781 $/kWh. The SSP optimal solution offers a better economic value for the hybrid system and satisfies the reliability criteria adequately. Thus, suggesting an initial capital cost of ZAR4,129,800.00 is required to set up the hybrid Wind-biomass-battery system.

Having identified SSP as the algorithm that meets the reliability and economic criteria for the hybrid Wind-biomass-battery, further analysis shown in Table 4.3 was conducted to understand how much investment can be committed to running a wind-biomass-battery system for a year and how much initial capital is required to start its deployment. Table 4.4 details the cost constituents in terms of the Net Present Value of the hybrid system. For each component, the SSP estimated the total capital cost (ZAR4,129,800.00), replacement cost (ZAR 1,745,203.16), operation and maintenance cost (ZAR8,994,285.35), and the salvage cost (ZAR18,202.39), and the ASC (ZAR3,431,512.26). In addition to the four cost factors of the hybrid system, fuel cost is also considered for the biomass gasifier which depends on the number of hours it runs yearly. Thus, the results demonstrate that the combination of only wind and battery could not meet the load demand especially when battery state-of-charge is at its minimum then biomass gasifier kick starts.

Meanwhile, the economic indicators of the wind-biomass-battery hybrid system are very high as compared to the other system configurations. The Net Present Values (NPVs) of the system as derived from the various optimization algorithms are SSP (R15 994 131.58), TLBO (R17 332 250.36), SSA (R17 339 678.57), PSO (R16 504 173.07) with SSP having the least estimated cost. Accordingly, the unit cost of energy in R/kWh is estimated as 5.1781, 5.6113, 5.6137 and 5.3432 with the comparative algorithms SSP, TLBO, SSA and PSO respectively. Because SSP solution offers a better economic value for the hybrid system and also satisfies the reliability criteria adequately a thorough analysis of cost components of the hybrid solution is provided in Table 4.4. It is estimated that an initial capital cost of R4 129 800.00 would be needed to set up the hybrid Wind-biomass-battery considered in this study.

Scenarios 2: Solar PV-wind-biomass without battery storage

Scenario 2 considered solar PV-wind-biomass without battery storage system. Table 4.5 depicts the optimal solution for the solar PV-wind-biomass system configuration with the comparative algorithms for Scenario 2. Table 4.6 shows the results, and it is observed that the estimated minimum cost of energy is R3.8476 per kWh for the SSP algorithm. The estimates for the TLBO, SSA, and PSO are 3.9296, 3.96296, and 3.9801. This suggests that the SSP algorithm guarantees the optimal number of solar PV (189), wind turbines (101), and rating of the biomass gasifier (9) and the cost of energy is 3.8476 ZAR/kWh. Additionally, both SSP and TLBO estimated LPSP as 0.0011. It is observed that both SSP and TLBO evaluated LPSP as 0.0011 whereas SSA and PSO estimated 0.01 and 0.0012 respectively. All the estimated LPSP values are within the system constraints, and they all show a very highly reliable system that can supply power almost all year round. Thus, per the results obtained by SSA and TLBO in terms of LPSP index, the PV-wind-biomass hybrid system has more than 99.99% chance of meeting the attached load throughout the year except for only 0.004015 days per year where the hybrid system could not meet the load attached to the system.

It is also observed that the Net Present Values (NPVs) are SSP (ZAR11, 884, 474.55), TLBO (ZAR12, 137, 761.92), SSA (ZAR12, 246, 260.68), and PSO (ZAR12, 293, 751.00). The SSP algorithm guaranteed the least estimated net present cost for the system. Moreover, the unit cost of energy in ZAR/kWh is estimated as 3.8476, 3.9296, 3.9647, and 3.9801 with the comparative algorithms SSP, TLBO, SSA, and PSO respectively. Having identified that the SSP algorithm satisfies the reliability and economic criteria for the hybrid PV-wind-biomass system, further analysis to understand the yearly economic commitment was conducted using the SSP as shown in Table 4.6. The costing constituents in terms of capital cost, replacement cost, operation, and maintenance cost, recycling cost, and the optimal cost are presented for the Case 2 using the historical data are presented in Table 4.6. For each component, SSP estimated the total capital cost (ZAR6,181,800.00), replacement cost (ZAR0.00), operation and maintenance cost (ZAR 4,888,455.59), salvage cost (ZAR-85,418.18), and the ASC (ZAR2,549,792.71). In addition to the four cost factors of the hybrid system, the fuel costs are also considered with the biomass gasifier, which depends on the operating hours in a year. The result of this experiment using solar PV-wind-biomass, suggests that the lesser the gasifier for producing power, the lower its operation and maintenance cost, and the greater its salvage cost. Eventually, the PV-wind-biomass system is far cheaper and more reliable compared to the wind-biomass-battery hybrid system. Thus, though the solar PV-wind-biomass was without a battery storage system, it is reliable and economically viable as compared to the system configuration of Scenario 1.

Considering the configuration of Scenario 2, the gasifier retained energy and supplied it to the system when both solar PV and wind turbine systems could not supply power to the load. It was observed that there were no significant changes in the biomass gasifier rating between Case 1 where no PV system was incorporated in the configuration and in Case 2 where no battery storage system was considered. For instance, SSP estimated 9 kWh biomass gasifier for Case 1 which would run for 587 hours in a year, but for Case 2 the same estimated 9 kWh biomass gasifier would be run for 462 hours per year. The operation time of the gasifier has an impactful contribution in the estimation of the NPV of the system as well as the cost per unit energy that the system will generate. The lesser the gasifier is used in producing power, the lower its operation and maintenance cost, and the greater its salvage cost. Eventually, the PV-wind-biomass system is far cheaper and more reliable as compared to the Wind-biomass-battery hybrid system.

Even though, battery storage system was absented from this hybrid system configuration, yet the PV-wind-biomass system is highly reliable and economically viable as compared to the system configuration of Case 1 where there was no PV module. Here, the solar resources have introduced certain dynamics into the hybrid system. The PV system together with the biomass gasifier system has mitigated the battery storage system. The result of this scenario depicts an evenly distributed wind turbines and solar PV modules as presented in Table 4.6 in chapter 4. For the wind turbine distribution, the various optimization techniques namely, SSP, TLBO, SSA, and PSO output 101, 99, 100, and 98 respectively. In the same vein the number of solar PV obtained by the corresponding optimization algorithms are 189, 189, 191, and 187 respectively. The introduction of PV system coupled with the wind turbines resulted in higher reliable system whose loss of power supply probability (LPSP) estimated value is nearly 0. The high reliability index obtained for the PV-wind-biomass hybrid system could be attributed to the reach solar resources available in the study area. Moreover, the solar and wind system served as the primary energy provider for the hybrid system according to the operational strategy designed for the study as presented in Chapter 4 Figure 4.18.

Scenarios 3: Solar PV-biomass-battery

Scenario 3 considered a solar PV-biomass-battery combination. Table 4.7

Table 3.7 depicts the case of solar PV biomass-battery system configuration. From the results in Table 4.7 it is observed that the SSP guaranteed a minimum energy cost of 2.4727 ZAR per kWh, whereas the SSA (2.5257 ZAR per kWh), PSO (2.5922 ZAR per kWh), and TLBO (2.6514 ZAR per kWh). This suggests that the SSP guaranteed the best result followed by SSA. Again, the SSP and SSA estimated an LPSP index of 0, suggesting that the combination of solar PV and battery storage systems minimizes the biomass gasifier rating. Meanwhile, for the hybrid system reliability index, LPSP per the calculation shows a highly reliable system that can provide almost all year-round power supply. The estimated LPSP values according to the various optimization techniques SSP, SSA, PSO and TLBO are 0.00021 (approximately 99.98%), 0.00019 (approximately 99.98), 0.00023 (approximately 99.98%), and 0.00014 (approximately 99.98%) respectively. These results suggest that there is a high probability approximately 99.98% that the hybrid PV-biomass-battery hybrid system would meet the load demand throughout the year. It is also observed that SSP and SSA estimated one unit of the rated gasifier, PSO (2 units), and TLBO (2 units).

The Net Present Values (NPVs) of the respective algorithms are SSP (ZAR7,637,578.71), TLBO (ZAR8,189,661.65), SSA (ZAR7,801,524.43), and PSO (ZARR8,006,981.62). Also, the ASC of the respective algorithms are TLBO (ZAR1,757,077.23), PSO (ZAR 1,717,883.55), SSP (ZAR 1,638,628.82) and SSA (ZAR1,673,803.08). Having identified that the SSP algorithm can satisfy the reliability and economic criteria for the solar PV-biomass-battery system, further analysis of the yearly economic feasibility shown in

Table 4.8 can provide a better understanding of how to run the solar PV-biomass-battery. The

Table 4.8 shows the results, and it is observed that the SSP estimated costs are capital cost (ZAR 1,721,200.00), replacement cost (ZAR 1,006,292.90), operation and maintenance cost (ZAR 4,697,848.51), recycling cost (ZAR -6,505.64) and ASC (ZAR1,638,628.82).

With this hybrid system configuration, the study assumed that wind energy resources and for that matter wind turbines were completely unavailable. Therefore, solar PV system served as the primary power source. As it can be observed from

Table 4.8 there is a drastic decrease in the number of PV modules in case three compared to case two even though wind resources are absent. However, reasonable amount of battery storage has been injected into the proposed hybrid system to stabilized power supply and to avert the effect of the nonavailability of wind turbines. Accordingly, the results obtained by the various optimization techniques thus, SSP, TLBO, SSA, and PSO in terms of numbers for solar PV are 51, 48, 45, and 49 respectively and for batteries 209, 211, 204, 207 respectively.

The combination of PV subsystem and battery storage system significantly minimized the biomass gasifier rating as compared to the 2 previous cases. Whereas SSP and SSA estimated one unit of the rated gasifier, PSO and TLBO calculated two units of the rated gasifier for the PV/biomass/battery system. Meanwhile the hybrid system reliability index, LPSP per the calculation was very good. The estimated LPSP values according to the various optimization techniques SSP, SSA, PSO and TLBO are 0.00021, 0.00019, 0.00023, and 0.00014 respectively. These results indicate that there is a high probability approximately 99.98% that the hybrid PV-biomass-battery hybrid system would meet the load demand throughout the year. Therefore, the proposed hybrid system considered under this case scenario satisfies the maximum 1% LPSP index earmarked for choosing feasible solution for the optimization problem.

Scenarios 4: Solar PV-wind-biomass-battery

Scenario 4 consists of a solar PV-wind-biomass-battery system. The reliability and economic feasibility of the comparative algorithm results are shown in Table 4.9. From the result, it is observed that SSP (ZAR2.1309 per kWh) guaranteed optimal cost of energy among the comparative algorithms. It is observed that the comparative algorithms produced LPSP values that are within the boundary constraints, where SSP output LPSP value of 0.0141, TLBO (0.0121), PSO (0.0133), and SSA (0.0212). The SSP algorithm estimated solar PV (42), wind turbine (1), biomass gasifiers (2), and batteries (201) respectively. Also, TLBO estimated solar PV (43), wind turbine (2), biomass gasifiers (1), and batteries (201) respectively; the PSO estimated solar PV (44), wind turbine (2), biomass gasifiers (1), and batteries (202) respectively; and the SSA also output solar PV (45), wind turbine (1), biomass gasifiers (1), batteries (203) respectively. This suggests a relatively low number for solar PV, wind turbines, and biomass gasifiers. Further analysis of reliability and economic constraints are presented in Table 4.10 for the hybrid PV-wind-biomass-battery configuration.

From Table 4.10, it is estimated that an amount of ZAR6,581,936.45 is required to set up a hybrid PV-wind-biomass-battery system. Whereas the capital cost (ZAR1,586,400.00), replacement cost (ZAR 938,440.60), operation and maintenance (ZAR4,067,671.15), and salvage cost (ZAR-28,350.00). This suggests that solar PV, wind turbines, biomass gasifier, and battery storage system complements one another to the optimum and provides a sustainable power supply that meets load demand.

It can be observed that the proposed hybrid system under scenario 4 has a fair representation of battery storage system in the configuration but relatively low numbers for solar PV, wind turbines, and biomass gasifier as compared to all the other case scenarios. However, the estimation for the rating of biomass gasifier and the number of rated wind turbine are in the range of 1 and 2 for all the algorithms. The involvement of all the renewable resources considered in this case scenario provides a good reason to believe that the power production units, solar PV, wind turbines, biomass gasifier and the battery storage system complemented one another in providing sustainable power supply to the attached load. Therefore, the spread of the energy production capacity across the individual system components significantly imparted the sizing of the renewable technologies which in effect accrued economic benefits for the PV-wind-biomass-battery HRES.

5.2.2 Discussion of results on economic and reliability criteria

When making investment decisions, the economic performance of the hybrid system is evaluated using the present value method, as future costs are discounted to present value. The initial capital expenditure is a one-time payment upon system installation. They are calculated based on component cost per unit and total component capacity. The comparative algorithms estimated different sizing and varying cost for each scenario. In Scenario 1, thus in reference to the historical dataset the NPV estimates given by the SSP, TLBO, PSO and SSA are ZAR15, 994,131.58; ZAR17, 332, 250.36; ZAR16, 504,173.07; and ZAR16,504,173.07 respectively with the SSP and TLBO having the least and maximum values respectively. Scenario 1 was the most unattractive because it resulted in the highest cost per unit of electric power produced. Scenario 4 had the best NPV and ASC

(ZAR1,412,142.80) from the SSP algorithm, whereas the ASC values for other algorithms are TLBO (ZAR1,418,942.87), PSO (ZAR 1,428,007.43) and SSA (ZAR1,441,996.17) respectively. Scenario 4 provided the most suitable cost benefits considering the amount for the unit cost of energy produced by the proposed hybrid system.

The optimal COE solutions per each algorithm are SSP (2.13ZAR/kWh), TLBO (2.14 ZAR/kWh), PSO (2.16 ZAR/kWh) and SSA (2.16 ZAR/kWh). The SSP outperformed the comparative algorithms from the economic perspective. The COE obtained by the SSP algorithm shows that the proposed PV-wind-biomass-battery system (Scenario 4) can provide a reliable energy supply to the study area at an acceptable cost. The results provide good reason to consider the output of the proposed SSP algorithm that yielded the least COE. Therefore, for detailed economic and reliability discussion, results obtained by the SSP algorithm may be chosen as the optimal combination.

Similar studies on the economic aspect of energy optimization by Sandeep and Nandihalli (Sandeep & Nandihalli 2020), incorporated solar PV and wind and applied Opposition-based Social Spider Optimization (OSSO) for hybrid solar PV-wind power system configuration. The outcome of the study suggested that OSSO generated a minimum cost of "$7040.642" which was lesser than the comparative algorithms namely AGACauchy, PSO, AFSO and SSO. Meanwhile, the OSSO estimated the number of solar PV (81), the number of wind (1) and the number of batteries (12). Unfortunately, none of the scenarios considered in our study is similar to the hybridization approach adopted by Sandeep and Nandihalli. Singh, Singh & Kaushik (Singh, Singh & Kaushik 2016c), hybridized solar PV-wind-biomass-storage and applied an Artificial bee colony (ABC) algorithm for size optimization of their hybrid system. Their findings were compared with HOMER and PSO which indicated that the ABC algorithm has good convergence properties and produced good quality results in terms of optimal configuration. Scenario 2 of our experiment is the same hybridization approach adopted by Singh, Singh, & Kaushik. Comparatively, the ASC values obtained by ABC algorithm are capital cost (55,108$/yr), replacement cost (5,111$/yr), maintenance cost (3,571$/yr), salvage cost (-1071$/yr) and total energy cost (63,006$/yr). Our proposed SSP cost (USD 141,461.43) is higher than the ABC algorithm by Singh, Singh, & Kaushik. The differences in cost are due to the different technical and economical parameters considered for each component (that is, solar PV, wind turbine, and biomass storage).

Abd El-Shafy A. Nafeh (Nafeh 2011), hybridized solar PV-wind incorporating storage battery and applied GA as the optimization approach to determine the total cost and reliability (LPSP technique) constraint. The finding suggests the total cost of solar PV-wind ($57,744) hybrid systems was lower compared to standalone either solar PV ($78,543) or wind ($85,450) systems. Furthermore, the LPSP value is solar PV-wind system (0.0199), standalone solar PV (0.02), and standalone wind (0.02), thus, suggesting that the solar PV-wind hybrid system was the cheapest and most reliable. Alternatively, HOMER estimated the cost at $58,027 which was higher than the GA. The Loss of Power Supply Probability (LPSP) was used to evaluate the reliability of each hybrid system. Reliability is the probability of energy supply failure at a certain hour owing to a decrease in renewable output or unintended technical problems. Thus, a lower LPSP value guarantees a greater possibility of fulfilling load demand. LPSP values vary between 0 and 1. For instance, in Scenario 2, a high-reliability index was obtained which is attributed to the abundant solar energy. This notwithstanding, the economic indicators of the PV-wind-biomass system show a better prospect compared with scenario 1.

Meanwhile, scenario 3 had the least LPSP value (0.00021) suggesting a high likelihood of continuous power supply all year round for the entire system lifespan. However, the analysis reveals that Scenarios 3 as well as scenario 1, have high proportions of battery storage systems that eventually increase the economic cost. On the other hand, Scenario 2 resulted in very high numbers of PV panels and wind turbines in the absence of a battery storage system. There was comparatively higher initial capital than all other scenarios. The experiment results in scenario 2 suggest that biomass gasifiers run fewer hours to only meet load demand at peak hours.

Similar studies on energy optimization by Kaabeche, Diaf and Ibtiouen (Kaabeche, Diaf & Ibtiouen 2017), hybridized solar PV-wind with a storage system and applied firefly algorithm (FA) for size optimization. The Load Dissatisfaction Rate and electricity cost are the reliability constraints for the hybrid system. The findings suggest that FA was effective in solving the hybrid system design as compared with Accelerated Particle Swarm Optimization (APSO) algorithm, Generalized Evolutionary Walk Algorithm (GEWA) and Bat algorithm (BA). Further, the sizing of their hybrid system provided 99% and 100% electrical requirements for the users. Unfortunately, Kaabeche, Diaf and Ibtiouen focused on solar PV-wind and storage which are different from the scenarios considered in our experiment. Torres-Madroñero, Nieto-Londoño and Sierra-Pérez (Torres-madroñero et al. 2020), hybridized solar PV-wind and storage and applied Genetic algorithm (GA) and PSO to optimize the hybrid system. The LPSP and Levelized Cost of Energy (LCOE) are applied as the objective function. The findings suggest that PSO achieves the best technical or economic indicators, depending on the objective function used and the design criteria; however, the GA is suitable to find outlier solutions that meet the reliability and cost values.

5.3 Characteristics of the convergence curves for the comparative algorithms

The convergence curve of the comparative algorithms concerning the levelized cost of energy are depicted under each case. The y-axis shows the levelized cost of energy (COE), whereas the x-axis is the number of iterations. For scenario one using the historical data, it is observed that PSO starts iterating at a lower average COE but converges at 5.3432 (ZAR/kWh). Whereas SSA starts with the highest average COE and converges at 5.6137 (R/kWh). Though the SSP algorithm starts iteration with a COE above 25R/kWh, it has the best convergence (5.1781 ZAR/kWh) among the comparative algorithms. The ability of SSP to explore a wider range of values and still find the best result is an indication that SSP has a very good exploration and exploitation mechanism. Similarly, in Cases 3 and 4, TLBO started with larger values than any of the other algorithms however, it did not find the best COE in any scenario, but it was second only to SSP. The second scenario saw SSA exhibiting similar property for good exploration and exploitation tactics also to converge at 3.9647 ZAR/kWh which was better than only PSO with 3.9801 ZAR/kWh.

5.4 HRES components contribution to total load served

The individual system components and their contributions to the total power supplied to the electrical load attached to the hybrid power system are showcased graphically under each case scenario. Depending on the combination of renewable energy technologies specifically, solar PV system, wind turbine and biomass gasifier, the strain on the battery storage system as well as the sizing of the components varied significantly. For instance, under case one by using the extrapolated dataset it was estimated that a total of 110 rated wind turbines would be required to generate enough power to supply the attached load while ensuring a minimal LPSP. Even with that number of wind turbines larger size of batter storage facility is required. The total number of batteries estimated to for this case is 320. For the same scenario, a relatively high number of rated biomass gasifier were injected to the hybrid system to stabilize energy balance between demand and supply. Whereas Case 1 recorded 10 of the rated gasifiers, cases 2, 3, and 4 output 14, 2 and 2 respectively according to SSP algorithm.

Alternatively, by using both PV and wind turbine systems without battery storage systems as scenario 2 depicted also introduced several PVs, wind turbines, and biomass gasifiers into the hybrid system configuration. Under this case, the biomass was extensively utilized to stabilize the power supply in the absence of favourable conditions. It can be observed that by aggregating the number of gasifiers used in each case, then Case 2 runs the gasifiers much more frequently than any other case, if only for the reason that no other storage system was available to augment the hybrid system's lack of production. However, the number of rated gasifiers was reduced drastically to 2 units in cases 3 and 4 when solar resources and battery storage systems were both introduced, as extra productive capacity and augmented storage respectively, to the hybrid system configuration.

Cases 3 and 4 revealed the economic significance of hybridizing the rightful renewable resource to provide reliable power. This indication is based on comparing the reliability indices for all cases, the apparent value of the economic variables, and on preliminary reasoning that the integration of solar PV and battery storage system for the community under study would improve the hybrid system performance significantly. For example, in Case 3 there were no wind turbine but with 167 PVs and 211 batteries, the hybrid system could reliably meet the load according to the criteria set for the system. Even a better output of PV and battery storage combination is seen under scenario 4, where a combination of only 55 PVs, 198 batteries, two wind turbines, and two biomass gasifiers was able to meet the load demand satisfactorily.

5.5 Statistical analysis of results based on historical dataset

The techniques described in the previous part have been implemented to find the near-optimal solution to the objective function given in equation (3.16). All algorithms have similar initialization settings (i.e., number of search agents 30 and maximum iteration of 60). Using the historical data set, Figures 4.1, Figure 4.2, Figure 4.3, and Figure 4.4 of the previous chapter illustrate the convergence of the constructed algorithms. According to the data, the convergence produced by applying SSP and TBLO approaches converged with a more significant number of iterations. The objective function has a converged value and gives superior results in terms of COE and limitations related to LPSP. All four algorithms were used throughout the simulation of sizing the hybrid system for optimal power generation. The SSP approach determines the minimum fitness function value under all case scenarios. To determine the statistical significance of the implemented algorithms, the Kruskal-Wallis test was performed on the convergence values of the comparison algorithms.

The Kruskal–Wallis analysis is a statistical analysis tool of variance that is frequently utilized instead of a typical one-way ANOVA when data are from a suspected non-normal population (Vargha & Delaney 1998). The approach seeks to identify several group disparities. Typically, a parametric analysis of variance (ANOVA) approach is utilized when comparing means across three or more groups. When data do not fulfil the normality requirements of ANOVA but are continuous, independent, and have homogeneous variances, a nonparametric test can run an omnibus test to determine whether the group distributions are distinct. The Kruskal-Wallis test does not presume normally distributed data because it primarily examines whether or not the groups have the same median. A multiple comparison test is often conducted using a method that adjusts for the overall (experiment-wide) significance level to determine the effective combination of means or pairwise differences. These results are then used to interpret the statistically significant difference. As opposed to a hypothesis based on means, the null hypothesis for Kruskal-Wallis is that the data come from populations with the exact location. The evaluation is based on an examination of mean rankings. To execute a Kruskal-Wallis test, the ranks of the data values are allocated to produce the test statistic, H, provided by the formula (Hecke 2012; Elliott & Hynan 2011):

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1) \tag{5.1}$$

where N denotes the total sample size, k is the number of groups that have been compared, R_i is the sum of ranks for group i, and n_i is the sample size of group i.

The chi-square distribution finds the H to be a crucial cut-off point (chi-square is chosen since it is a decent estimate of H, mainly if the sample size of each group is more than five). If the H statistic is significant (H is more than the cut-off), the null hypothesis is rejected; if the H statistic is not significant (H is less than the cut-off), the null hypothesis is not rejected. In this position, the null hypothesis is that the medians of each group are identical for each algorithm's convergence data point since they were all created with identical parameter values. This indicates that all groups share the same distribution. The alternative hypothesis states that at least one of the groups has a different median, indicating that at least one derives from a different distribution than the others.

Table 5.1: Hypothesis test summary and asymptotic significance

Hypothesis Test Summary				
	Null Hypothesis	Test	Sig.[a,b]	Decision
1	Iteration categories have similar arithmetic mean for objective values.	Independent-Samples Median Test	<.001	Reject the null hypothesis.
2	The range of objective values is identical across iteration types.	Independent-Samples Kruskal-Wallis Test	<.001	Reject the null hypothesis.
a. The significance level is .050.				
b. Asymptotic significance is displayed.				

To assess how the comparable algorithms (SSP, TBLO, SSA, and PSO) perform relative to one another, this may be measured by evaluating whether each algorithm produces the same fitness values by confirming that the methods presented the same data distribution. Less than 0.05 for p shows statistical significance among the algorithms. The outcomes are shown in Table 5.1. For the analysed fitness value distribution, the mean, standard deviation (SD), median, and other statistical characteristics were determined and tabulated in Table 5.2.

Table 5.2: Statistical parameters of comparative algorithms

Algorithm	Count	Mean	SD	Median	Percentile 25	Percentile 75
SSP	60	0.003436	0.001685	0.002131	0.002131	0.00552
TLBO	60	0.003587	0.001707	0.002141	0.002141	0.00489
SSA	60	0.003312	0.001214	0.00289	0.002163	0.00398
PSO	60	0.003791	0.002109	0.002163	0.002163	0.00632

Each row in Table 5.3 tests the null hypothesis that the Algorithm 1 and Algorithm 2 distributions are identical. The significance values have been corrected using the Bonferroni adjustment for multiple tests. Table 5.3 displays the pairwise comparisons of test results for comparative algorithms.

Table 5.3: Pairwise comparisons of objective values

Algorithm 1-Algorithm 2	Test Statistic	Sig.	Adj. Sig.[a]
SSP-TBLO	0.034	0.855	1.000
SSP-PSO	0.549	0.459	1.000
SSP-SSA	1.861	0.172	1.000
TBLO-PSO	0.853	0.356	1.000
TBLO-SSA	5.167	0.023	0.138
SSA-PSO	1.861	0.172	1.000

The adjusted significance of the critical alpha value for all the pairs is >=0.05. Figure 5.1 shows the pairwise comparison of the algorithms; nodes a, b, c, and d represent SSP, TLBO, SSA and PSO respectively.

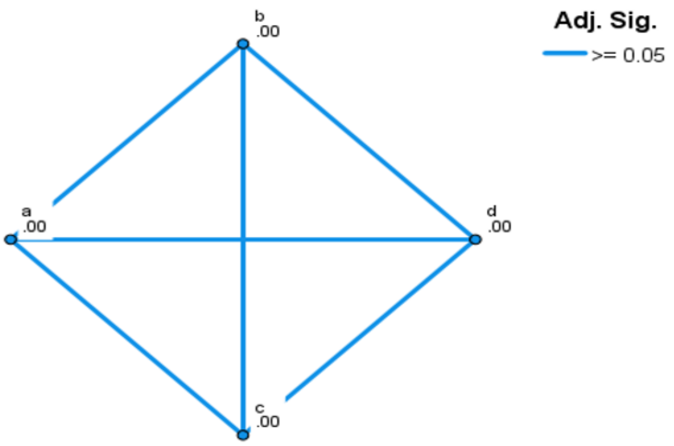


Figure 5.1: Pairwise comparison of algorithm showing the sample average rank

The independent samples Kruskal-Wallis test reveals different means among the comparative algorithms. In figure 5.4 a, b, c, and d represent SSP, TLBO, SSA and PSO respectively

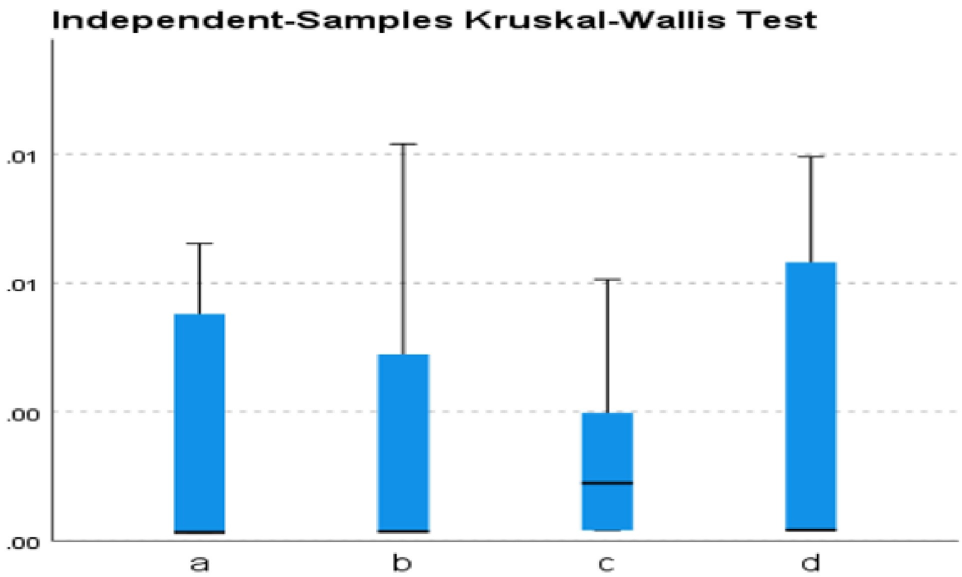


Figure 5.2: Independent samples Kruskal-Wallis test showing different means among algorithms

The pairwise comparison of the algorithms along with their significance levels is presented in Table 5.4 and Figure 5.3

Table 5.4: Pairwise comparisons of algorithms statistics

Algorithm 1-Algorithm 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
SSP-TLBO	-13.050	12.594	-1.036	.300	1.000
SSP-SSA	-37.583	12.594	-2.984	.003	.017
SSP-PSO	-51.833	12.594	-4.116	<.001	.000
TLBO-SSA	-24.533	12.594	-1.948	.051	.308
TLBO-PSO	-38.783	12.594	-3.079	.002	.012
SSA-PSO	-14.250	12.594	-1.131	.258	1.000

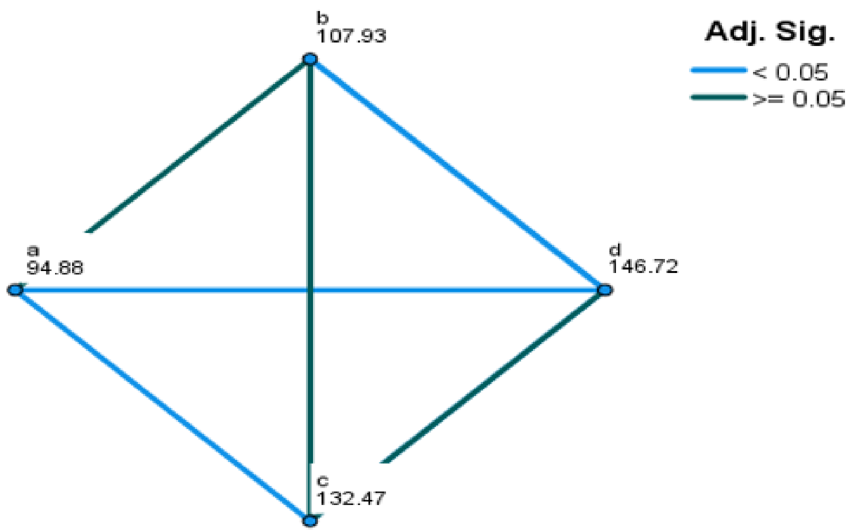


Figure 5.3: Pairwise comparison of algorithm showing the sample average rank and significance

Finally, from the results obtained from Kruskal-Wallis Test, it is observed that H is larger than the critical cut-off for SSP-TLBO, SSP-SSA, TLBO-SSA, T LBO-PSO, and SSA-PSO hence we reject the null hypothesis; thus, the medians are not the same across all four groups, at least one of them has a different median than the others. However, it is interesting to note that SSP-PSO turned out to have same distribution from the statistical result as the significance value and the adjusted significance are <0.001 and 0 respectively. This means that all 4 algorithms do not perform equally, hence there is significant difference among the algorithm performance in identifying the global optimum.

5.6 Chapter summary

A hybrid energy system provides more stable, cost-effective, and appropriate sources of electricity, especially for off-grid regions. Using a newly developed SSP algorithm, a mathematical model has been built to determine the best size of components of a hybrid PV-wind battery with biomass. Along with the operational strategy and implementation processes of the SSP algorithm, the mathematical modelling of the study's many components is initially reviewed and given in Chapter 4. Finally, the SSP algorithm's findings were compared with those of three other meta-heuristic algorithms: TBLO, PSO, and SSA. The proposed algorithm provided better results in terms of economic value in all the case scenarios as compared to comparative algorithms. The performance of the proposed hybrid system is analysed by considering cost components and reliability criteria. Moreover, a statistical test is carried out on the convergence results obtained by the various algorithms to assert their significant differences. It can be gleaned from the chapter that the proposed optimal hybrid system designed in Case 4 satisfactorily meets the load demand. Therefore, for a profitable and reliable hybrid system setup for the study area, a good combination of the available renewable resources, namely solar, wind and biomass, coupled with a battery storage system, will be ideal.

CHAPTER 6: CONCLUSION, RECOMMENDATIONS, AND FUTURE WORK

6.1 Introduction

This chapter concludes the study by summarizing the processes used by the researcher to achieve the research goals mentioned in Chapter 1. It provides a concise summary of the experimental results, leading to highlighting the challenges of the proposed framework for optimizing hybrid renewable energy systems. Furthermore, recommendations for future work and the concluding remarks at the end of the study are presented.

6.2 Research objectives

This section offers an outline of the research goals aligned with the questions asked in perspective to analyse how the responses to these research questions achieved the study's objectives.

6.2.1 Research objective 1:

Deploy IoT devices (sensors) to collect real-time environmental data, and after extrapolating this data for an entire year along with the use of supplementary historical data, to determine the optimal configuration of a hybrid renewable energy system based on the availability of the renewable resources on site.

The aim of study objective 1 is to use current low-cost technologies, namely sensors, to record and transmit significant environmental weather data such as temperature, wind speed, and humidity. After collecting a reasonable amount of real-time data from the environment spanning a period of two months and using data analysis processes, the sensor data, supplemented with historical datasets, are extrapolated to create a time-series dataset detailing seasonal fluctuations throughout the year. The resulting dataset is believed to provide a more accurate dataset of the renewable resources (solar and wind) at the selected site, useful for optimal HRES design and configuration.

The research question asked to examine Objective 1 and the related research responses are presented below.

Research question 1:

Can real-time sensor data collected from the environment over a period of time and supplemented with historical environmental data be extrapolated to present a time series of climatic weather data showing a whole year's variation for effective optimization of a hybrid renewable energy system?

In response to this research question, the researcher deployed temperature and wind speed sensors to collect relevant wind and solar energy data from the environment. After data collection, the researcher used data pre-processing to refine the data for further analysis. And using historical (secondary) data, the sensor data was extrapolated to map a complete annual record suitable for the HRES optimization problem. The year-round record represents the time series data from which hourly load demand and available renewable resources are provided. The general outline of the procedures in Section 3.22 was followed throughout the experiment to refine the dataset for study purposes.

6.2.2 Research objective 2:

Modelling and mathematical formulation of selected aspects of social spider and prey behaviour, which are then transformed into a global optimization algorithm to determine optimal hybrid power generation.

Research objective 2 aims to find interesting behavioural traits of animals (social spider and prey) that are in congruence with the dynamics of hybrid renewable energy production operations. Once these features are identified, they are mathematically modelled and converted into a global optimization algorithm. Consequently, the developed algorithm is used to solve the HRES optimization problem posed in Section 3.2.3.7 with the aim of minimizing the objective function in Equation (3.16).

The research question posed in relation to Objective 2 and the researcher's answer are given below.

Research Question 2:

After modelling the social characteristics of spider-prey interaction in the social web, would the representation adequately represent a global optimization algorithm that can solve the optimal power generation from the proposed hybrid renewable energy system?

To answer Question 2, mathematical models based on social spiders identified interesting foraging behaviour and prey traits mapped on the social web were formulated and translated into a global optimization algorithm in Section 3.3.1. The newly developed global optimization algorithm, SSP, was tested on five benchmark functions. The test result is promising and shows the algorithm's prospects of solving complex optimization problems. The general overview of the procedure in Section 4.2 was followed to test the algorithm on benchmark functions. Furthermore, Section 4.3 used the SSP algorithm to find the near-optimal solution to the HRES optimization problem posed in this research. Chapter 5 presents the results of the optimization problem.

6.2.3 Research objective 3:

Develop a hybrid renewable energy generation scenario into an optimization problem and determine the near-optimal power generation from the PV-wind- based hybrid system using the newly developed metaheuristic algorithm.

Four case scenarios were developed using different combinations of renewable energy sources and the battery storage system. Because biomass was critical to providing reliable power to the connected load in the absence of sun and wind and in situations where the battery bank is insufficient, all four scenarios included a biomass gasifier engine. The four cases of wind/biomass/battery, PV/wind/biomass, PV/battery/biomass, and PV/wind/biomass/battery were investigated. Sections 4.3.2 and 4.3.3 present the results of the different hybrid system designs based on historical data and extrapolated real-time sensor data, respectively.

The newly developed tool, SSP, was used to solve a complex optimization problem such as the optimal power generation of HRES. Different HRES configurations were investigated to inform the design of the optimal HRES system. The optimization objective and constraints are discussed in Section 3.2. Therefore, the research question posed for the 3rd research objective and the answer are presented below.

Research Question 3:

Could the stochastic but dynamic climatic weather conditions that solar and wind energy rely on be modelled into an optimization problem and further explored to determine a near-optimal hybrid renewable energy system using a meta-heuristic algorithm?

Two different datasets, including the NREL dataset, a benchmark dataset for hybrid renewable energy system optimization or design, and the real-time extrapolated sensor dataset, were used in this research as inputs to the optimisation problem under investigation. Section 3.2.3 outlines the general procedures taken to model the HRES configuration. Thereafter, the SSP algorithm (a novel meta-heuristic optimization algorithm) was the tool used to solve the optimization problem for the best solution. The general procedures in Section 3.3 were followed to run SSP on the datasets to design a near-optimal hybrid renewable energy system. Amidst the different data inputs of the optimization problem, the SSP performance is satisfactory as reported in Chapter 5.

6.2.4 Research objective 4:

Carrying out a comparative evaluation on the performance of the social spider prey algorithm against selected comparable optimization techniques using the benchmark dataset.

With this goal in mind, the researcher tries to empirically validate the performance of SSP compared with other metaheuristic algorithms that have performed very well in similar optimisation problems. Both the benchmark dataset (NREL) and the extrapolated sensor data- set and appropriate metrics were used in the performance validation process. The research question supporting objective 4 of the study and the answers from the study are presented below.

Research Question 4:

Can the evaluation of the model and the algorithmic structure be empirically validated against corresponding meta-heuristic algorithms using a benchmark dataset?

The model and the algorithmic structure can be empirically validated using a benchmark data set and evaluated using comparative meta-heuristic algorithms using appropriate metrics (refer to Section 5.2). The decision variables of the near-optimal hybrid system, namely the number of solar PV, number of wind turbines, nominal capacity of the biomass gasifier, and number of batteries, were included in the evaluation of the system's costs and reliability. Therefore, the system cost and the reliability index formed the matrix on which the decision for the optimal system design was based. The detailed validation and evaluation were performed experimentally in this work, and the results are presented and discussed in Chapters 4 and 5, respectively.

6.3 Overview of HRES optimization

Renewable energy sources are usually seen as an answer to current ecological, social, and economic problems. However, the random nature of these sources requires the development of appropriate tools and rules for their use and exploitation to be beneficial. This work investigated the result of a simulated PV/wind/biomass/battery hybrid system. The hybrid system considers the combination of intermittent energy resources (solar and wind), the capacities of the biomass gasifier and the battery storage system, and the load profile, among other things. The storage facilities retain excess production energy and release energy when the load exceeds the renewable power supply. The optimization method is based on a novel metaheuristic technique (SSP) inspired by nature and developed to solve complex optimization problems.

It is possible to design different hybrid systems for the study area, considering the range of renewable resources available to Durban, namely solar, wind, biomass, ocean, and hydroelectric power. Also, there are several renewable technologies on the market today with different operating capacities, costs, lifetimes, etc. This makes the development of an inexpensive but reliable HRES system a complex problem. For example, for the study area, a hybrid system consisting of PV/wind, PV/battery, PV/biomass, PV/biomass/battery, PV/wind/biomass, wind/battery, wind/biomass, and many others could be studied since studies indicate efficient use of PV/wind and battery in South Africa can be accomplished. In this study, the consideration of biomass resources as an alternative renewable energy source enabled a more stable HRES system design, particularly when other selected renewable resources’ production is insufficient. For this reason, the inclusion of biomass in the system configuration was considered in all investigated cases. Interestingly, the optimal result of the HRES includes solar PV, wind turbine, biomass gasifier along with the battery storage system.

Solar and wind energy share a common disadvantage: they are unpredictable and subject to weather and climate changes, and the fluctuations of solar and wind energy may not match the time distribution of the load demand. This unpredictable effect on the hybrid system's performance causes the batteries to discharge prematurely. Due to these uncertainties, the recommended best arrangement included a biomass gasification generator set. Consequently, the operation of this model yields a Reliability Index (LPSP) for the ideal system that is significantly higher.

Since the optimal solutions are highly dependent on the actual load demand curve and the input data from the power sources, data collection is paramount when designing an optimal PV/wind hybrid system. In areas lacking radiometric (weather) data, inexpensive sensors could be deployed to collect the necessary data for system configuration. To this end, a methodology was proposed in this study that develops a framework that uses low-cost IoT devices to collect a reasonable amount of climatic weather data and further augment the dataset with historical data for the extrapolation of a full year's time-series dataset. The extrapolated data can be used in the absence of appropriate environmental data to design reliable and cost-effective HRES. Thus, the usage of sensors and advanced IoT analytics could serve as tools to assess the renewable energy potential of a site and to further estimate the hybrid system components dimension. This process is beneficial in the development of hybrid renewable systems that can reliably meet load demands. As such, the general methodological framework of the thesis could mitigate the unavailability of radiometric data for system measurement. Although numerous studies use readily available datasets for similar projects to assess energy investments and power reliability, this research added an alternative validated data resource collection system with advanced analytics to provide alternative means of collecting environmental data.

Using an algorithm inspired by nature, it can automatically adjust to hyperparameters in cost and size models. These updated models may determine the most cost-effective and dependable design of hybrid renewable energy system components. Utilizing historical data and sensor extrapolated data, four alternative scenario studies were examined using these improved models. One of the analysed scenarios, the PV-wind-biomass-battery hybrid system, was determined to be the best-suited design for the study's primary objective.

6.4 Contributions of the study

Practical implications

- Inform other researchers and practitioners that bio-inspired algorithms can produce a very good design for HRES systems.
- Inform energy system policymakers and stakeholders: that they can adopt bioinspired HRES systems for reliable/sustainable renewable energy projects.

Theoretical implications

- The randomization used in nature-inspired algorithms such as SSP allows the search strategy to search stepwise for a global optimal solution for multiple objectives (cost, size, reliability).
- Nature offers solutions to difficult and/or complex problems. The solution can be based on the interactions of organisms or natural phenomena. Both the scientific and engineering community can explore alternative nature-inspired approaches to solving or even better attempts at some of the very difficult real-world problems.

6.5 Challenges of the proposed methodological framework

Based on the proposed methodological framework, observed, or anticipated challenges of this thesis are discussed as follows:

Challenges in feasibility analysis phase:

These challenges shed light on the issues encountered in the preliminary assessment of available renewable energy resources at the site and data quality concerns to better assess the proposed HRES.

- Data issues: although it is strongly recommended to use a full year's time series data to design an optimal hybrid power system, sensor data collection only lasted a limited period of 2 months due to a delay in acquiring the equipment (sensors). This ultimately limited the period of data collection. As a result, historical data values were used to augment the real-time sensor data to extrapolate the full year's records. While extrapolation can serve a purpose, it can compromise data quality due to the large missing gap in a full annual dataset.

Challenges in the optimization process of the HRES design phase

- Techno-economic issues: Even though the study could identified the near optimal design for the HRES among the possible case scenarios with reasonable cost and high reliability using specific renewable energy components, it was found that due to the variety of resources available, not all potential renewable energy components with different specifications could be included in to be examined in a study. As a result, few components are specific to the system models (lead-acid battery, fixed rated biomass gasifier, and rated wind turbine and solar PV panel, etc.). One can hypothesize that perhaps other combinations of renewable technologies would provide an even a better solution to the optimization problem. In addition, the optimal power generation model used in the research is based on the cost, size, and reliability of the hybrid system.
- The electrical and electronic details of the system were intentionally discarded as being highly technical and beyond the researcher's area of expertise hence, in this research, simplifying assumptions were made when developing the model, which led to limitations in the analyses. For example, the total power generated does not take into account the power loss and the efficiency of the connecting and transmission cables from the substation (generating units) to the consumer.
- The near-optimal performance measure of HRES power generation is indirectly derived using cost and size models. The study is based on certain assumptions about the capacity/size of the components (PV, wind turbine and batteries) and operating hours of the biomass gasifier and parameters such as interest rates, component lifespans, etc. could be used to determine the optimal system configuration. This hypothetical system is then used to estimate how much electricity could be obtained from the assembled components using the data provided. The relationships between the models and the conversion factors used empirical data, which need not necessarily be the same when implementing the hybrid system.

6.6 Conclusions and future work

This section provides the conclusion regarding the benefits of the proposed model, a summary of the contributions, the success of the study, and future work.

6.6.1 Conclusion

The thesis proposed a metaheuristic algorithm which is used to find a near optimal solution for a complex problem like HRES optimal power production. The random nature of the input variables coupled with the multiple factors that ought to be considered for the hybrid system configuration required a robust tool to find a good result. The newly developed global optimization algorithm, SSP has reasonably handled the dynamics of the hybrid system input data with intelligence inspired by nature. This development of SSP marks one core aspect of the thesis from which different scenarios of hybrid system configurations were evaluated. The experimental test results show that for the considered study area, a combination of solar PV panels, wind turbines, biomass gasifier and a battery storage system would provide the most economical power supply to the load with satisfactory reliability. Interestingly both the benchmark dataset and the real-time sensor data which was extrapolated confirm the mixture of those components as the best option in the study.

The data collection method, which used IoT devices (sensors) to collect environmental data and further analysed this data to optimize HRES, tries to solve the problem of data scarcity. Therefore, areas without radiometric or weather data can use the proposed framework to build a collection of relevant environmental data for the intended application. Additionally, where there is an adequate and high-quality renewable energy data set, the combination of the real-time sensor data and the secondary data can facilitate the HRES design as much as it results in high-quality output for the system.

It was observed that the optimization technique used to examine the HRES optimization problem presented in this study showed satisfactory success with the output. The good results of the newly developed meta-heuristic algorithm, SSP, could be attributed to the intelligent mechanism that controls the cooperation of the search agents (social spiders) when hunting their prey. Given the largely bio-inspired nature of this thesis, the proposed model considered the advantages of similar or different bio-inspired algorithms in structure (see Section 3.30) to arrive at the following conclusions on the advantages of the proposed model in SSP as a global optimization algorithm:

- the ability to self-adjust parameter values during the iteration of the input variable using a penalty random value in the frequency function (see equation 3.31). The randomness of the frequency variable can help the algorithm to escape a local optimum.
- The two-phase model (spider phase and prey phase) of search agent refinement was adopted from TLBO (teacher phase and learner phase) to improve the mobility of weaker solutions or move the global average in the search space from exploration to exploitation within the right parameters of supply while ensuring that it does not remain in local optimum.
- the ability of SSP to identify local and global optima based on spider and prey exploration and exploitation behaviour.
- The SSP algorithm is very simple and easy to implement in mathematical models. It has no complex equations or derivative functions, and there are few input parameters to be set.

These advantages somehow distinguish the proposed algorithm from other meta-heuristic algorithms as evident from the statistical test result (see section 5.5). In addition, the mathematical formulation of the concept of intensity, frequency, and attenuation contributes to the effectiveness of SSP in finding the near-optimal solution. The near-optimal solution provides the following importance over the other cases considered:

1. Due to the potential of the energy sources to mutually compensate for changes in output, the daily production of the system remains constant over the long term. Because wind power is not limited by sunlight, the system will generate electricity both day and night, even if the amount changes. While performance does not increase at night, it will no doubt be higher during the non-cloudy day. Therefore, biomass could serve as electricity storage to supplement the power supply in cases where wind and solar PV are ineffective.
2. The hybrid system is resistant to seasonal weather changes. The seasonal changes in output are evened out each year as solar systems are more productive in summer and wind turbines are more productive in winter. However, the solar

energy system had a larger part of the ideal system because of this distribution, suggesting that the research region has significant solar energy potential.

3. Energy storage capacity can be reduced to the bare minimum to reduce replacement costs by running one of the primary sources during the day and the other at night as a battery bank is required in an off-grid mode. Batteries may also be subjected to a smoother charge/discharge cycle because of this incident, extending their useful life.
4. The renewable energy PV-wind-biomass-battery hybrid systems, where the biomass gasifier acts as a power retention facility, can be scaled-down because there is less uncertainty about the combined wind and solar power supply, bringing more economic benefits to the system.

6.6.2 Recommendations and future work

Based on the research findings and conclusion presented, the following recommendations are suggested:

1. Because HRES can provide reliable and cost-effective power supply, governments of developing countries facing power crises should consider HRES options to stabilize the power supply.
2. HRES can operate in standalone mode or be connected to the grid, so it is highly recommended for rural electrification projects or communities where national grid expansion is not feasible.
3. Individuals or institutions that rely heavily on electricity for their routine operations should consider the HRES option as it brings long-term economic benefits.

Practical considerations and potential avenues for future research are discussed in line with the proposed methodological framework, which brought forth a new approach to solving the HRES optimization problem using the newly developed global optimization algorithm SSP.

The potential applications of nature-inspired algorithms and IoT analytics in science and engineering have been extensively described in the literature, and this research has proposed a method that uses a concept observed in nature, particularly among animals, advanced IoT analytics, and mathematical models to make an informed decision (near optimal) when designing HRES. In the initial stages of designing an HRES, on-site quality data is required for proper system component sizing. Therefore, future work requires an increase in the duration of real-time sensor data collection and the investigation of more accurate predictive models to improve the quality of the input data. In addition, the integration of more optimized data pre-processing platforms to manage real-time sensor data requires further studies.

Future work also requires simplified energy models that can accurately estimate energy production based on environmental data and technical specifications of components. Therefore, renewable energy models that have parameterized variables to estimate power generation components need to be studied with a developed framework. The proposed framework, which is broadly a data-driven architecture, requires high-quality environmental data in the proof-of-concept, either streamed in real-time from sensors or retrieved from the data centre. The next phase of the framework uses SSP to manipulate the data for an optimal solution based on the specified optimization problem and the models provided in the problem definition. Therefore, a simplified model for renewable energy would be studied. In order to finally make an informed decision, several alternatives could be considered. An educational decision would be based on empirical evidence and be able to make such a choice. Therefore, a hybrid system with different storage devices and a wider range of components needs further investigation to measure system performance with others, and finally, a comprehensive statistical analysis of SSP performance on multiple benchmark functions is required to evaluate the effectiveness and efficiency from SSP for the many unknown optimization problems it can solve.

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Other websites

https://www.adafruit.com/product/1733\

https://pvwatts.nrel.gov/pvwatts.php

Historical data downloaded from: https://pvwatts.nrel.gov/pvwatts.php

070715

Product data sheet

130 Watt Foldable Solar Panel

Specifications

Mechanical	Snow loads up to 5400Pa; Wind loads up to 2400Pa
Low Light Performance	Excellent low light performance (morning, evening and cloudy days)
Durable	Independently tested for harsh environmental conditions (salt mist, ammonia and known PID risk factors)
Module Type	130W_Foldable
Maximum Power (Pmax / W)	130 (65*2) 17.9
Power Tolerance	+-3%
Maximum Power Voltage (Vm / V)	17.9
Maximum Power Current (Im / A)	6.71
Open Circuit Voltage (Voc / V)	21.5
Short Circuit Current (Isc / A)	7.25
Module Efficiency (%)	14.48
Electrical Performance	STC:AM 1.5, 1000W/m2, 25°C

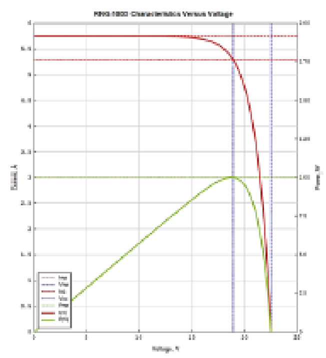
Mechanical Properties

Dimensions (LxWxH/mm/inches)	824 x 503 x 80/33" x 20" x 3"
Weight (kg)	12.8 kg/28 lbs
Solar Cells	Monocrystalline
# of Cells	72 (2 x 3 x 12)

Temperature Properties

Normal Operating Cell Temperature	45±2°C
Temperature Coefficient of Pm	-0.4 %/°C
Temperature Coefficient of Voc	-0.346 %/°C
Temperature Coefficient of Isc	+0.046 %/°C
Maximum System Voltage (VDC)	1000 (IEC)
Maximum Series Fuse Rating (A)	10
Operating Module Temperature (°C)	-40 to +85

IV-Curve



Intertek

APPENDIX B: SAMPLE DATASHEETS FOR WIND TURBINE

raum ENERGY
a revolution in wind energy

3.5 kW Wind Turbine System Specification Sheet

Wind is a naturally occurring and abundant resource and is one of the cleanest ways to produce electricity. Very little processing needs to be done to convert it into clean, free energy. Operation of our wind turbines produces no pollution with no emissions, excessive noise or waste heat by-products. Wind can be harvested with minimal impact on the environment, a very important factor in meeting our increasing energy needs.

Synergy

- Solar
- Biomass
- Diesel Generator
- Hydroelectric
- Geothermal

Applications

- Commercial and Industrial
- Residential and Resort
- Agricultural
- Remote Communities
- Off-Grid Power
- Institutional and Public

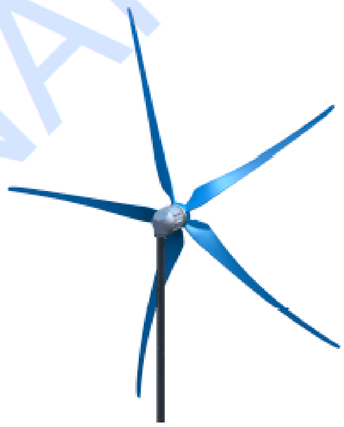
Key Benefits

- Energy cost savings from wind generated power
- No scheduled maintenance
- Designed to reliably operate in harsh cold & hot climates
- Operation creates virtually no environmental impact
- Cost-effective and financially viable
- 5-Year Warranty

Turbine

Rated Power Output	3.5 kW
Energy Production*	500 kWh/month
Type	5 blades, downwind
Generator	Gearless, brushless, permanent magnet
Swept Area	12.6 m²
Blade Diameter	4 m
Blade Material	Fibreglass reinforced plastic
Total Turbine Mass	68 kg
Voltage/Phase @ Rated Power	150 Vac peak
Current/Phase @ Rated Power	8 Aac peak
Generator NEMA Rating	Class B, 5 HP
Life Expectancy	> 20 years

*5.0 m/s (18 km/h) average wind speed, Rayleigh Distribution, Sea Level elevation



Operational Data

Rated Wind Speed	11 m/s (39 km/h)
Start-up Wind Speed	2.8 m/s (11 km/h)
Braking Wind Speed	22 m/s (80 km/h)
Furling Method	EM Brake
RPM at Rated Power	350 RPM
Survival Wind Speed	50 m/s (180 km/h)
Survival RPM	1,000 RPM

Conversion Table

m/s	km/h	mph
4	14	9
6	22	13
8	29	18
10	36	22
12	43	27
18	65	40
25	90	56
45	162	101

APPENDIX C: SAMPLE DATASHEETS FOR LITHIUM-ION BATTERY SPECIFICATION

victron energy
BLUE POWER

www.victronenergy.com

Lithium-Ion battery specifications

	Lithium-ion 24V 100Ah 2.6kWh battery	Lithium-ion 24V 180Ah 4.75kWh battery
Technology	Lithium iron phosphate (LiFePO4)	Lithium iron phosphate (LiFePO4)
Nominal voltage	25,6V	25,6V
Nominal capacity	100Ah	180Ah
Nominal power	2,6kWh	4,75kWh
Weight	30kg	55kg
Power/Weight ratio	86Wh/kg	86Wh/kg
Dimensions (lxwxh)	592 x 154 x 278 mm	623 x 193 x 351 mm
Charge/Discharge		
Charge cut-off voltage at 0.05C	28,8V	28,8V
Discharge cut-off voltage	20V	20V
Recommended charge/discharge current	30A (0,3C)	54A (0,3C)
Maximum charge current (1C)	100A	180A
Maximum discharge current (1.5C)	150A	270A
Pulse discharge current (10s)	500A	1000A
Cycle Life @80% DOD (0.3C)	3000	3000
Configuration		
Series configuration	Yes, up to 2 (more in series on request)	Yes, up to 2 (more in series on request)
Parallel configuration	Yes, easy up to 10 (more parallel on request)	Yes, easy up to 10 (more parallel on request)
Environmental		
Operating temp. charge	0~45°C	0~45°C
Operating temp. discharge	-20~55°C	-20~55°C
Storage temp.	-20~45°C	-20~45°C
Standards		
EMC: Emission	EN-IEC 61000-6-3:2007/A1:2011/C11:2012	
EMC: Immunity	EN-IEC 61000-6-1:2007	
Low voltage directive	EN 60335-1:2012/AC:2014	

APPENDIX D: APPLICATIONS OF IOT IN THE ENERGY SECTOR

Table 6.1: Applications of IoT in the energy sector

Application		Sector	Description	Benefits
Regulation and Market	Energy democratization	Regulation	Granting many small end users access to the grid so they can freely choose their supplier and engage in peer-to-peer power trading	Eliminating market dominance, hierarchy, and centralized supply in the energy supply chain; deregulating the energy market to lower consumer prices; and raising public awareness of energy use and efficiency
	Aggregation of small prosumers (virtual power plants)	Energy market	Combining the load and production from a number of end customers to provide it to the markets for power, balancing, or reserves.	enabling small loads to take part in competitive markets, assisting the grid by lowering load during peak periods, hedging against the risk of expensive electricity bills during those times, enhancing the grid's flexibility and reducing the need for asset balancing, and providing profitability to consumers
Energy supply	Preventive maintenance	Upstream oil and gas industry/utility companies	Using big data analysis to track faults, leaks, and fatigue using stationary and mobile sensors or cameras	lowering the cost of operation and maintenance, minimizing the danger of failure, output loss, and maintenance downtime, as well as preventing accidents and raising safety
	Fault maintenance	Upstream oil and gas industry/utility companies	Locating and potentially fixing virtual energy network issues and failures.	increasing a service's dependability, repairing district heating leaks or power grid breakdowns more quickly, cutting down on maintenance time and health and safety risks
	Energy storage and analytics	Industrial suppliers or utility companies	Examining market information and potential system flexibility solutions, such as energy storage	lowering the possibility of a supply and demand mismatch, maximizing the use of flexible and storage alternatives to increase energy trade profitability, and assuring the best possible approach for storage assets.

Table 6.1 (continued)

Application		Sector	Description	Benefits
	Digitalized power generation	Utility companies and system operator	Examining large amounts of production unit data and managing them at various time scales	enhancing supply security, optimizing asset use and management, lowering the cost of backup capacity provision, speeding up the response to load loss, and lowering the danger of blackouts.
Transmission and distribution grid	Smart grids	Electric grid management	A grid operation platform that uses big data and ICT technologies rather than conventional grids.	enhancing supply security, increasing energy efficiency, integrating distributed generation and load, and lowering the need for backup supply capacity and prices
	Network management	Electric grid operation and management	Utilizing big data at various grid nodes to operate the grid more effectively	locating weak places in the grid, strengthening it if necessary, and lowering the danger of a blackout
	Integrated control of electric vehicle (EV) fleet	Electric grid operation and management	Examining EV charge/discharge cycle data and data from charging stations.	Improved responsiveness to peak charging demand, analysis and forecasting of the load impact of EVs, and identification of potential locations for future charging station installation and distribution grid reinforcement
	Control and management of vehicle to grid (V2G)	Electric grid operation and management	EV load and charge/discharge pattern analysis for grid support when required	by allowing EVs to start supplying electricity to the grid, the system's flexibility is increased; minimizing the requirement for backup capacity at peak hours Controlling and managing the EV fleet to provide the best possible grid-to-EVS relationship
	Microgrids	Electricity grid	Management tools for grids apart from the main grid	enhancing supply security, fostering flexibility and interoperability between microgrids and the main grid, and providing consumers linked to the microgrid with stable electricity pricing

Table 6.1 (continued)

Application		Sector	Description	Benefits
	Control and management of the District heating (DH) network	DH network	Examining large data sets of consumer connectivity, network temperature, and load	Increasing the grid's capacity to handle demand; lowering the temperature of the hot water supply and conserving energy where possible; and detecting grid sites that require reinforcing.
Demand side	Demand response	Residential/ commercial and industry	Central management (e.g., shedding, shifting, or levelling)	lowering the demand at peak hours, which in turn lowers grid congestion
	Demand response (demand side management)	Residential/ commercial and industry	Central control (i.e., shedding, shifting, or levelling; load of numerous consumers by examining the load and appliance operation)	lowering consumer electricity costs, grid congestion, and the requirement for grid backup capacity investment. Reducing demand during peak hours, which also lowers grid congestion.
	Advanced metering infrastructure	End users	Utilizing sensors and devices to gather and examine temperature and load data at a customer site	having access to comprehensive load changes over a range of timescales; recognizing opportunities to increase energy efficiency (such as by turning off additional lights or unduly air-conditioned rooms); and bringing down the price of energy use
	Battery energy management	End users	Utilizing data analytics to activate batteries at the most appropriate time	enhancing energy efficiency and supporting the grid during times of peak demand, lowering the cost of energy use, and developing the best charging and discharging strategies for batteries on various time scales
	Smart buildings	End users	Appliance and gadget control from a distance and centrally	increasing awareness of energy use and environmental impacts; lowering manual intervention to save time and energy; enhancing readiness for joining a smart grid or virtual power plant; and better integrating distributed generation and storage systems. Improving comfort by controlling appliances and HVAC systems optimally.

APPENDIX E: IOT IN ENERGY MANAGEMENT

Table 6.2: Capacities of IoT for energy management

IoT based applications	Capabilities for energy management	References
Monitoring and resource optimization	IoT-based Energy Management System (EMS) monitors energy use and manages potential for energy savings. Ultimately, integrating IoT increases energy consumption optimization and resource governance efficacy. Using energy efficiently also cuts down on carbon emissions.	Khatua et al. (2020); Shapsough et al. (2020)
Integrating sensor network	In order to collect data and make choices, sensor networks are used in conjunction with smart hardware, such as smart meters, smartphones, electric vehicles, and other smart devices. By automating decision-making, energetic data may be utilized in a best way possible in various seasons and climates. Because of this, IoT-based decision support systems have enormous prospects for implementing more energy-efficient alternatives, providing customer services, and allowing cloud computing applications.	Paiho et al. (2021); Ismagilova et al (2019); Kar et al (2021)
Decentralized data exchange	The data produced is mostly responsible for the impact of IoT adoption. IoT data is frequently more accurate, granular, and of higher quality than data generated through conventional methods. Increased convenience and transparency are two advantages of IoT adoption thanks to data interchange from diverse sources. As a result, it encourages a thorough examination of the distributed energy system as a whole.	Ismagilova et al. (2019); Brous et al. (2020)
Real-time monitoring and control	Strategic dangers and opportunities are presented in real-time by improved forecasting and trend analysis. As a result, IoT enables energy data to be crucial in establishing a real-time trading platform or smart contract for consumers and prosumers. By utilizing RE generated at various sites to its fullest potential, such energy-sharing networks reduce the need for fossil fuels. Sequential, prompt management of local renewable energy resources promotes stability and effectiveness at the city level.	Paiho et al. (2021); Yeh, H. (2017).
Data management system and cost savings	IoT enables advancements in the management and preservation of energy from various sources. Therefore, recognizing operational inefficiencies results in cost reduction and increased service efficiency.	Brous et al. (2020); Vahidinasab et al. (2021).
Flexibility of services	The system's communication with customers is improved by the IoT's capacity to link distributed energy resources. Therefore, it offers insights into local self-production of power and demand-side control, two flexible energy applications.	Vahidinasab et al. (2021); Brous et al. (2020); Kar et al. (2021).

APPENDIX F: COMPLEMENTARY RESULTS

Data

NREL 2007 Data for Durban

Month	Solar Irradiance (W/m2)	Ambient Temperature (*C)	Wind speed (m/s)	Daily Radiation (kWh/m^2/day)
Jan	260.940	19.936	1.712	6.262555
Feb	232.647	19.378	2.964	5.583523
Mar	203.158	18.606	2.637	4.875804
Apr	153.035	15.725	3.569	3.672834
May	113.111	13.630	1.607	2.714674
Jun	92.262	10.133	2.924	2.214284
Jul	102.963	10.002	3.253	2.471109
Aug	141.334	12.703	4.365	3.392026
Sep	185.314	15.993	3.698	4.447545
Oct	226.138	17.157	4.056	5.427314
Nov	247.588	17.828	3.775	5.94211
Dec	273.036	19.299	3.977	6.552875

Durban data sourced from (Ntlela and Davidson, 2022)

Month	Clearness index	Daily Radiation (kWh/m^2/day)	Solar Irradiance (W/m2)
Jan	0.475	5.670	236.25
Feb	0.500	5.510	229.58
Mar	0.531	5.030	209.58
Apr	0.582	4.400	183.33
May	0.639	3.810	158.75
Jun	0.653	3.400	141.67
Jul	0.659	3.650	152.08
Aug	0.620	4.250	177.08
Sep	0.557	4.840	201.67
Oct	0.472	4.930	205.42
Nov	0.455	5.300	220.83
Dec	0.468	5.690	237.08

Extrapolated data

	Wind speed (m/s)			solar irrad (kWh/m2/day)			
Month	NREL Wd	meteoblue	Augmt Wind	NREL Irrd	Ntlela	Govindas	Augme PV
Jan	1.712	5.187	3.450	6.263	5.670	4.175	5.3693416
Feb	2.964	4.989	3.977	5.584	5.510	4.004	5.0326505
Mar	2.637	4.742	3.689	4.876	5.030	4.102	4.6692854
Apr	3.569	4.913	3.444	3.673	4.400	4.075	3.9449336
May	1.607	4.439	2.106	2.715	3.810	4.505	3.1171119
Jun	2.924	4.406	3.665	2.214	3.400	4.374	3.3293789
Jul	3.253	4.906	4.079	2.471	3.650	5.036	3.7190881
Aug	4.365	5.746	5.055	3.392	4.250	4.746	4.129437
Sep	3.698	6.177	4.938	4.448	4.840	5.153	4.8135791
Oct	4.056	6.155	5.106	5.427	4.930	4.189	4.8486764
Nov	3.775	5.841	4.808	5.942	5.300	3.833	5.0249078
Dec	3.977	5.289	4.633	6.553	5.690	4.145	5.4625826

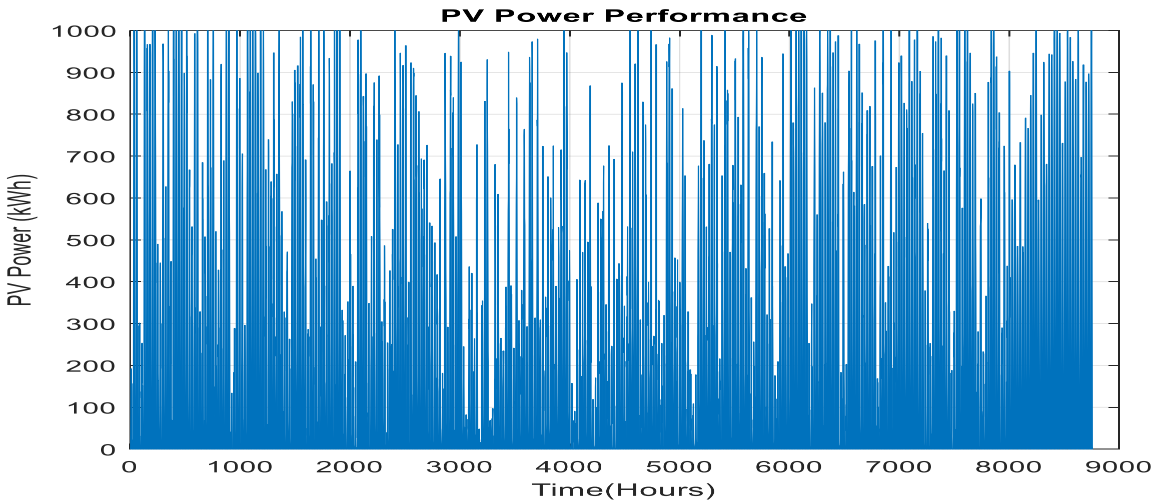
Data used for HRES configuration based on historical record

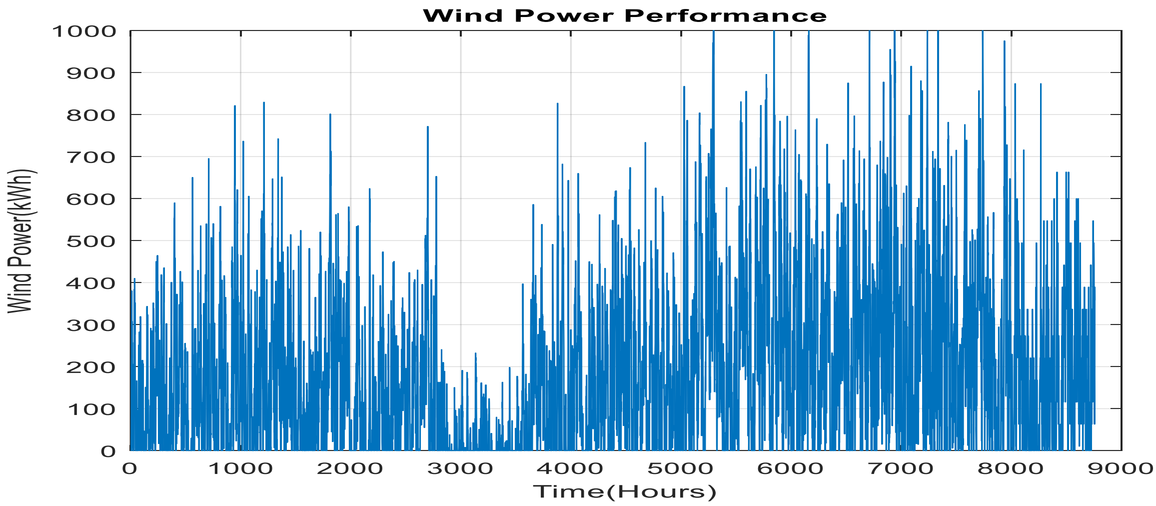
Month	Solar Irradiance (W/m^2)	Wind speed (m/s)	Biomass	Load (W)
January	260.94	1.71	2.5	5121.98
February	232.65	2.96	2.4	8576.98
March	203.16	2.64	2.5	7984.87
April	153.03	3.57	2.7	8992.78
May	113.11	1.61	1.8	9848.13
June	92.26	2.92	2.6	11154
July	102.96	3.25	2.6	9832.46
August	141.33	4.36	2.5	9985.43
September	185.31	3.7	1.9	10481.8
October	226.14	4.06	2.5	10975.6
November	247.59	3.78	2.7	10825.7
December	273.04	3.98	2.4	10254.7

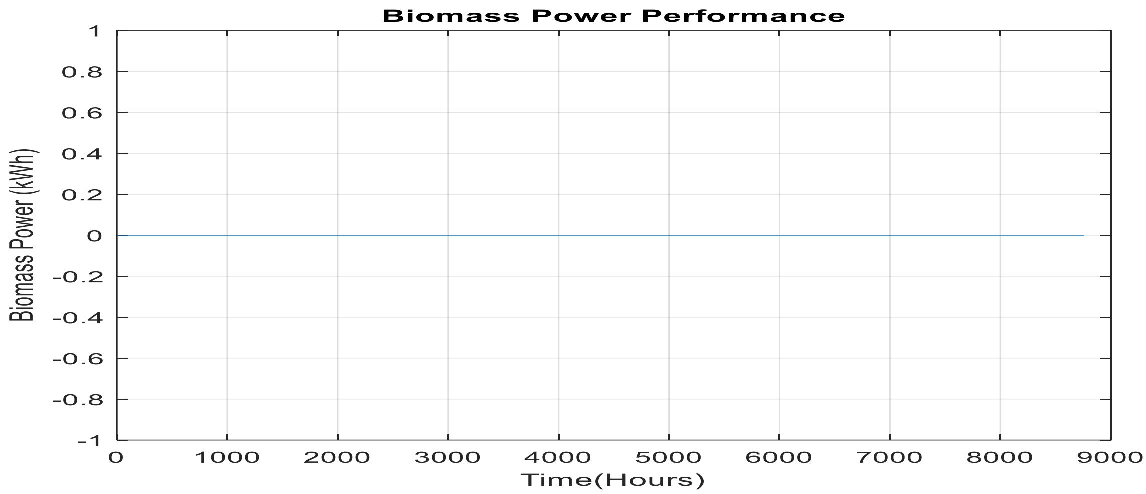
Estimated data for HRES configurations based on historical data

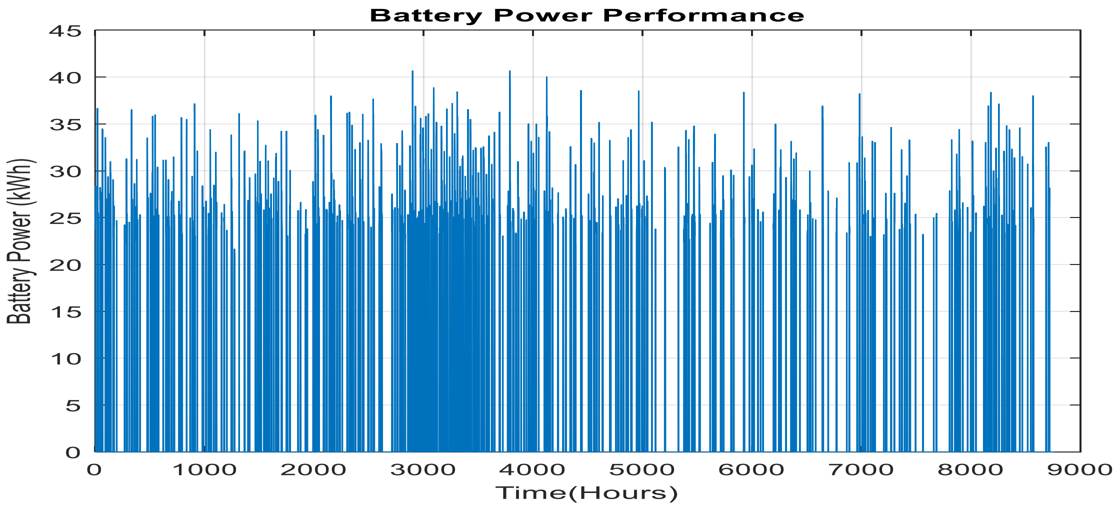
	Avg max Temp	Avg min Temp	max Tem	Min Temp	Calculated (MJ/m2/day)	converted kWh/m2/day	wind speed (km/h)	wind speed (m/s)
Jan	27.516	20.419	31	17	18.301	5.084	18.674	5.187
Feb	27.286	20.857	31	17	18.163	5.045	17.961	4.989
Mar	27.032	19.129	29	16	17.369	4.825	17.071	4.742
Apr	23.900	16.233	28	10	20.282	5.634	17.687	4.913
May	23.355	13.097	27	9	20.126	5.590	15.981	4.439
Jun	22.433	8.667	27	4	22.573	6.270	15.862	4.406
Jul	22.903	10.097	29	3	23.813	6.615	17.661	4.906
Aug	22.516	10.484	33	5	24.518	6.811	20.684	5.746
Sep	23.967	14.800	31	6	22.984	6.385	22.238	6.177
Oct	25.548	19.516	31	17	17.064	4.740	22.160	6.155
Nov	26.333	19.600	28	18	14.306	3.974	21.027	5.841
Dec	27.161	19.871	30	17	16.181	4.495	19.040	5.289

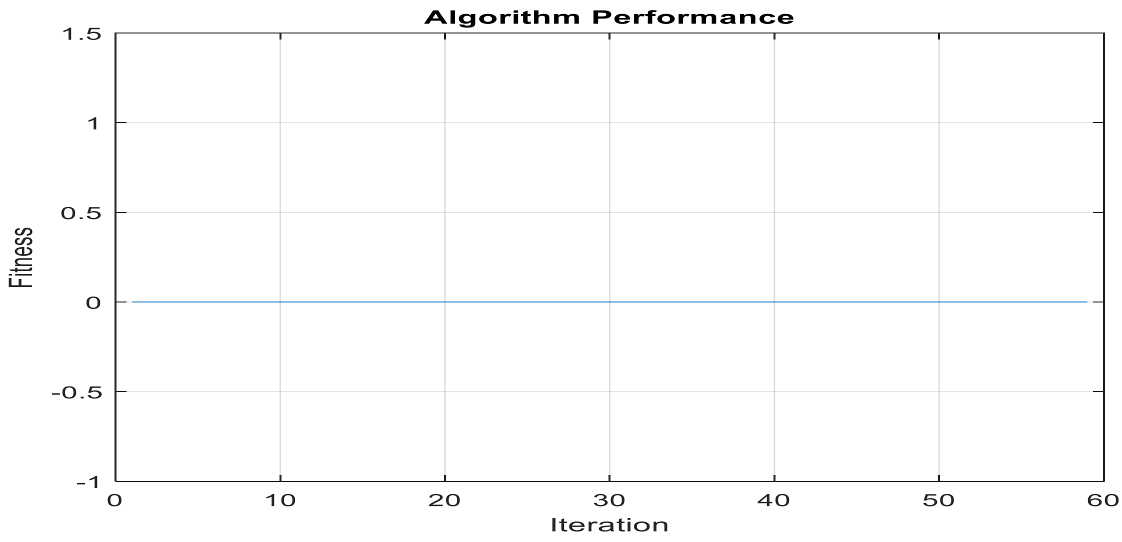
Using MATLAB for hybrid system configuration (Case 4)

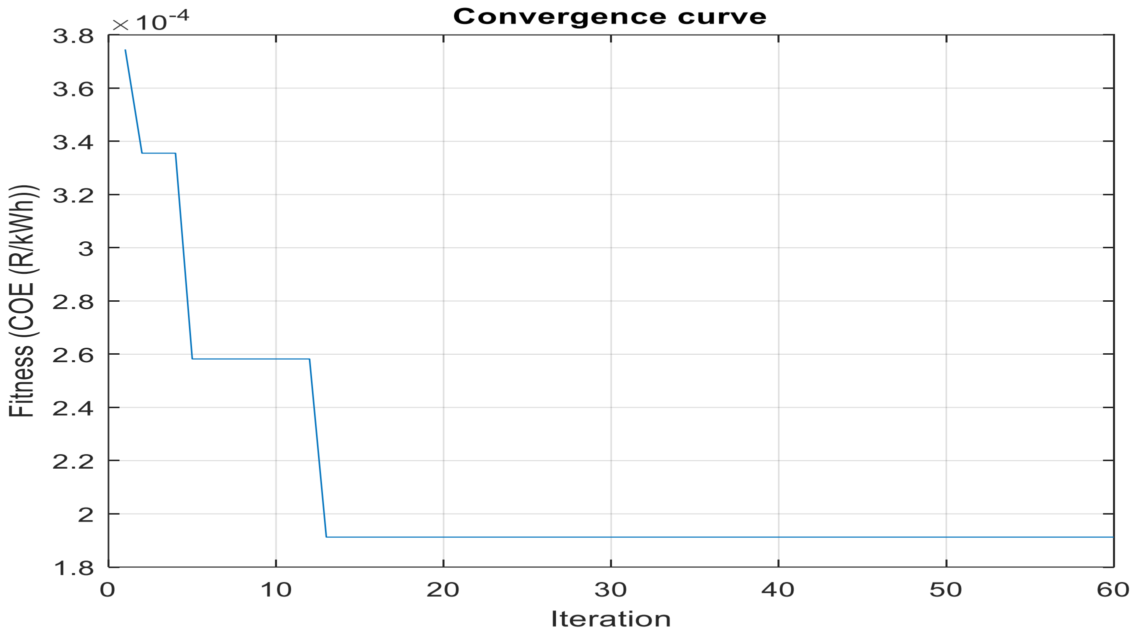



Wind Power Performance
Wind Power(kWh)
Time(Hours)


Biomass Power Performance
Biomass Power (kWh)
Time(Hours)


Battery Power Performance
Battery Power (kWh)
Time(Hours)


Algorithm Performance
1.5
1
0.5
0
-0.5
-1
Fitness
0
10
20
30
40
50
60
Iteration


Convergence curve
×10^-4
3.8
3.6
3.4
3.2
3
2.8
2.6
2.4
2.2
2
1.8
Fitness (COE (R/kWh))
0
10
20
30
40
50
60
Iteration

Components cost on case bases using consolidated sensor data

Case 1: Wind-biomass-battery

SSP

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.501636502
WT	2805000.00	0.00	1079996.21	0.00	0.00	0.00	3884996.21	833518.97	
BG	252000.00	305014.02	2745880.00	-20776.18	1380395.61	638.00	4662513.46	1000333.90	
Battey	1120000.00	1494034.83	5760000.00	0.00	0.00	0.00	8374034.83	1796634.16	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	4249000.00	1799048.86	9585876.22	-20776.18	1380395.61	638.00	16993544.50	3645934.51	

LCOE= 5.5016

TLBO

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.50658766
WT	2779500.00	0.00	1070178.07	0.00	0.00	0.00	3849678.07	825941.53	
BG	226800.00	274512.62	2626231.94	-22523.89	1320246.71	678.00	4425267.38	949433.18	
Battey	1158500	1545392.279	5958000	0	0	0	8661892.28	1858393.46	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	4236800.00	1819904.90	9654410.01	-22523.89	1320246.71	678.00	17008837.72	3649215.64	

LCOE= 5.50658766

SSA

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.653938407
WT	2805000.00	0.00	1079996.21	0.00	0.00	0.00	3884996.21	833518.97	
BG	277200.00	335515.43	3039405.10	-20960.75	1527955.14	642.00	5159114.92	1106878.86	
Battey	1116500.00	1489365.97	5742000.00	0.00	0.00	0.00	8347865.97	1791019.68	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	4270700.00	1824881.40	9861401.32	-20960.75	1527955.14	642.00	17463977.11	3746864.98	

LCOE= 5.65393841

PSO

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	6.376426721
WT	2856000.00	0.00	1099632.51	0.00	0.00	0.00	3955632.51	848673.86	
BG	252000.00	305014.02	2930947.15	-22646.70	1473431.68	681.00	4938746.15	1059599.13	
Battey	1435000.00	1914232.13	7380000.00	0.00	0.00	0.00	10729232.13	2301937.52	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	4615000.00	2219246.15	11410579.66	-22646.70	1473431.68	681.00	19695610.79	4225657.99	

LCOE= 6.37642672

Case 2: PV-wind-biomass

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**3762500.00**	0.00	2110901.69	0.00	0.00	0.00	5873401.69	1260127.80	
WT	2499000.00	0.00	962178.45	0.00	0.00	0.00	3461178.45	742589.63	
BG	352800.00	427019.63	3446552.83	-17358.04	1732634.49	572.00	5941648.91	1274770.12	SSP
Battey	0	0	0	0	0	0	0	0.00	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	6686300.00	427019.63	6519632.97	-17358.04	1732634.49	572.00	15348229.05	3292935.03	

LCOE= 4.9690

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**3797500.00**	0.00	2130537.99	0.00	0.00	0.00	5928037.99	1271849.92	
WT	2575500.00	0.00	991632.89	0.00	0.00	0.00	3567132.89	765321.97	
BG	428400.00	518523.84	4485080.80	-19568.03	2254718.28	613.00	7667154.89	1644974.34	TLBO
Battey	0	0	0	0	0	0	0	0.00	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	6873400.00	518523.84	7607251.67	-19568.03	2254718.28	613.00	17234325.77	3697593.70	

LCOE= 5.5795891

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**3797500.00**	0.00	2130537.99	0.00	0.00	0.00	5928037.99	1271849.92	
WT	2499000.00	0.00	962178.45	0.00	0.00	0.00	3461178.45	742589.63	
BG	378000.00	457521.04	3789572.63	-18202.39	1905075.76	587.00	6511967.04	1397130.86	SSA
Battey	0	0	0	0	0	0	0	0.00	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	6746500.00	457521.04	6882289.07	-18202.39	1905075.76	587.00	15973183.48	3427017.88	

LCOE= 5.17129603

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**3762500.00**	0.00	2110901.69	0.00	0.00		5873401.69	1260127.80	
WT	2677500.00	0.00	1030905.48	0.00	0.00	0.00	3708405.48	795631.75	
BG	378000.00	457521.04	3673367.68	-17183.83	1846657.76	569.00	6338362.65	1359884.34	PSO
Battey	0	0	0	0	0	0	0	0.00	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	6890000.00	457521.04	6815174.85	-17183.83	1846657.76	569.00	15992169.82	3431091.37	

LCOE= 5.17744283

Case 3: PV-biomass-battery

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**2922500.00**	0.00	1639630.62	0.00	0.00	0.00	4562130.62	978796.95	SSP
WT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
BG	50400.00	61002.80	844422.66	-31133.94	424504.10	981.00	1349195.62	289467.50	
Battey	738500	985129.217	3798000	0	0	0	5521629.22	1184655.65	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	3783400.00	1046132.02	6282053.28	-31133.94	424504.10	981.00	11504955.46	2468367.57	
		Total Energy:	662700						

LCOE= 3.7247

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**2905000.00**	0.00	1629812.47	0.00	0.00	0.00	4534812.47	972935.89	TLBO
WT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
BG	75600.00	91504.21	1255013.49	-30955.56	630914.36	972.00	2022076.50	433832.89	
Battey	752500	1003804.652	3870000	0	0	0	5626304.65	1207113.577	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	3805100.00	1095308.86	6754825.96	-30955.56	630914.36	972.00	12255193.62	2629329.82	

LCOE= 3.96760197

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**2922500.00**	0.00	1639630.62	0.00	0.00	0.00	4562130.62	978796.95	
WT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
BG	75600.00	91504.21	1262760.49	-31074.85	634808.89	978.00	2033598.74	436304.96	SSA
Battey	742000	989798.0758	3816000	0	0	0	5547798.08	1190270.132	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	3812100.00	1081302.28	6718391.11	-31074.85	634808.89	978.00	12215527.43	2620819.51	

LCOE= 3.95476009

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**2922500.00**	0.00	1639630.62	0.00	0.00	0.00	4562130.62	978796.95	
WT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
BG	50400.00	61002.80	847004.99	-31192.68	425802.28	984.00	1353017.39	290287.46	PSO
Battey	738500	985129.217	3798000	0	0	0	5521629.22	1184655.65	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	3783400.00	1046132.02	6284635.61	-31192.68	425802.28	984.00	11508777.23	2469187.52	

LCOE= 3.72595069

Case 4: PV-wind-biomass-battery

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**962500.00**	0.00	539998.11	0.00	0.00	0.00	1502498.11	322358.28	SSP
WT	51000.00	0.00	19636.29	0.00	0.00	0.00	70636.29	15154.89	
BG	50400.00	61002.80	394236.06	-9133.62	198188.46	458.00	694693.70	149045.29	
Battey	693000	924434.052	3564000	0	0	0	5181434.05	1111667.388	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	1828900.00	985436.86	4517870.47	-9133.62	198188.46	458.00	7521262.16	1613673.31	
		Total Energy:	662700						

LCOE= 2.4350

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**927500.00**	0.00	520361.81	0.00	0.00	0.00	1447861.81	310636.16	TLBO
WT	76500.00	0.00	29454.44	0.00	0.00	0.00	105954.44	22732.34	
BG	50400.00	61002.80	397679.17	-9490.91	199919.36	462.00	699510.43	150078.71	
Battey	703500	938440.6285	3618000	0	0	0	5259940.63	1128510.833	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	1829900.00	999443.43	4565495.43	-9490.91	199919.36	462.00	7585267.32	1627405.50	

LCOE= 2.45571979

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**962500.00**	0.00	539998.11	0.00	0.00	0.00	1502498.11	322358.28	
WT	51000.00	0.00	19636.29	0.00	0.00	0.00	70636.29	15154.89	
BG	50400.00	61002.80	405426.17	-10272.61	203813.90	471.00	710370.26	152408.67	SSA
Battey	696500	929102.9108	3582000	0	0	0	5207602.91	1117281.869	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	1832400.00	990105.72	4547060.57	-10272.61	203813.90	471.00	7563107.57	1622651.17	

LCOE= 2.4485456

Component	Capital cost	Replacement cost	O&M cost	Salvage cost	Fuel cost	BG Running Hours	NPC	ASC	
PV	**945000.00**	0.00	530179.96	0.00	0.00	0.00	1475179.96	316497.22	
WT	51000.00	0.00	19636.29	0.00	0.00	0.00	70636.29	15154.89	
BG	50400.00	61002.80	415755.50	-11269.57	209006.61	483.00	724895.35	155525.00	PSO
Battey	696500	929102.9108	3582000	0	0	0	5207602.91	1117281.869	
Inverter	72000.00	0.00	0.00	0.00	0.00	0.00	72000.00	15447.47	
Total	1814900.00	990105.72	4547571.75	-11269.57	209006.61	483.00	7550314.51	1619906.44	

LCOE= 2.44440387