Optimization of Hybrid Renewable Energy System (HRES) for a Remote Area in Bangladesh

by

Sk Asad Al Abir (200021331)
Pushpita Khan (200021354)
K.M. Sirazul Monir (200021247)

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Department of Electrical and Electronic Engineering
Islamic University of Technology (IUT)
Gazipur, Bangladesh

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Approved by:

Hasan Jamil Apon

Supervisor and Lecturer,
Department of Electrical and Electronic Engineering,
Islamic University of Technology (IUT),
Board Bazar, Gazipur-1704.

Date:

Table of Contents

List of Tables

List of Figures

List of Acronyms

HRES	Hybrid Renewable Energy System
PV	Photovoltaic
kWh	Kilo-watt hour
HOA	Hippopotamus Optimization Algorithm
$\mathbf{V_{OC}}$	Open Circuit Voltage
$\mathbf{I_{SC}}$	Short Circuit Current
SoC	State of Charge
CoE	Cost of Energy
LPSP	Loss of Power Supply Probability

Abstract

Rapid increase in energy demand and the limited access to the national power grid in remote regions of Bangladesh has prompted the need for a reliable, cost-effective, and sustainable energy system. In this work, a Hybrid Renewable Energy System (HRES) consisting of photovoltaic (PV), wind turbine, and biomass energy sources, coupled with battery storage, has been proposed and optimized for a remote area in Bangladesh. Due to the variable nature of renewable energy sources, an efficient and reliable energy storage system is essential. To achieve this, an optimal system design was sought using the Hippopotamus Optimization Algorithm (HOA) in conjunction with MATLAB simulations. In this study, the optimal configuration of PV modules, wind turbines, biomass consumption, and battery storage was determined to minimize the cost of energy (CoE), excess energy, and loss of power supply probability (LPSP). The HOA algorithm efficiently balances exploration and exploitation of the solution space, inspired by the territorial behaviors of hippopotamuses. The simulation results demonstrated the system's ability to provide reliable power while minimizing costs and environmental impact. A comparative analysis was conducted to assess the economic and performance efficiency of the proposed system, with results indicating a significant reduction in cost compared to traditional energy solutions. The findings emphasize the feasibility of HRES for remote areas in Bangladesh and contribute to the global push for environmentally friendly, renewable energy solutions.

Chapter 1

Introduction

Due to the increasing demand of electricity in all over Bangladesh, the pressure on the national power grid is also increasing. However, the national grid is not very easily accessible in the remote areas of Bangladesh. To address this problem and to minimize the pressure on the national grid to some extent, the development of an optimized Hybrid Renewable Energy System (HRES) has become crucial in today's date. Bangladesh, due to its geographical location, receives 4–6.5 kWh/m^2/day solar radiation, which is ideal for PV systems [1]. April and December are the most and least windiest months of Bangladesh respectively. During this period, the wind speed ranges from 2.6 m/s (Dec) and 5.3 m/s (Apr), which is sufficient for small wind turbines [1]. About 35 million metric tons of rice husk is produced in our country annually [1]. Which is again, another great source of biogas. The main objective of this research work is to enhance energy access and reliability by utilizing these resources and through the integration of renewable and green sources such as solar, wind and biomass, supported by batteries.

1.1 Basic Functionalities of HRES

The Hybrid Renewable Energy System works exactly as its name implies. It links solar panels, wind turbines and a biomass unit so that each one feeds electricity into the same network. A battery stores the surplus power and releases it when the sky is dark, the air is still or the biomass burner rests. Every part is chosen because it runs on fuel that already exists nearby plus the whole setup is sized to match the amount of power the neighborhood habitually uses. Ensuring sustainability and efficiency in the off-grid region is the end goal of our project. Some of the core functionalities of HRES can be mentioned as:

- Resource-Based Load Matching: It does not select one best source while ignoring the less effective sources. Rather, the power of HRES is that it chooses the optimal source by combining multiple renewable sources.
- Peak Load Support: When the demand is very high, the system is capable of supplying energy from stored energy in the battery.
- Grid-Independent Operation: HRES is independent and can operate in off-grid mode, which makes it ideal for rural and remote areas.
- Fuel Saving: HRES minimizes or eliminates the need for costly and environmentally harmful diesel generators.
- CO_2 Reduction: Since HRES works on renewable sources, it can significantly contribute to reducing carbon emission.

1.2 Different Aspects of the Project

The research will work around a certain number of agendas:

1. Assessing whether implementing HRES in geographically remote locations of Bangladesh will be feasible or not.

2. Designing mathematical models for solar, wind, biomass and battery as parts of the system.
3. Developing an optimization algorithm considering the real-world constraints to minimize the cost function.
4. Comparing the performance with respect to cost behind implementing the system.
5. Evaluating socio-economic, environmental and ethical implications of deploying HRES in rural and remote areas.

A well-structured and properly-planned HRES consisting of solar, wind and biomass can produce up to 27.12 kW, which alone is enough to supply 25-30 rural households (based on average rural load of 1 kW per household).

1.3 Background and Motivation

Experiencing the energy crisis in Bangladesh first-hand, every conscious citizen will feel the need of building an all-encompassing system that will cater to the needs of people while protecting the environment. Since renewable energy is a growing sector worldwide, working with it would solve two problems at a time. Firstly, it is environmentally harmless; and secondly it solves the problem of energy crisis without relying much on the national grid. So, after the installment cost and a little maintenance cost, it is economically more viable than the traditional system.

As per our rural demographic, almost 72% of the entire population of Bangladesh live in rural areas. Which is even higher than half of the population. So, making a decentralized energy system such as HRES will ensure seamless electricity to a large population in our country.

The greater picture of this project can be seen as an initiative to improve the lives of the communities that live in rural or remote locations and cannot enjoy uninterrupted electricity.

1.4 Literature Review

Researchers are concentrating on renewable energy sources because of the rising demand for energy and the financial and environmental constraints of traditional fossil fuels. Due to their widespread availability and eco-friendliness, wind and solar power have attracted a lot of attention among the various renewable energy sources. However, for energy systems that depend entirely on these renewable resources, their erratic and intermittent nature has presented serious difficulties. Hybrid renewable energy systems (HRES), which integrate several renewable energy sources like solar, wind, and energy storage, have become a viable substitute for conventional energy systems in order to address these issues[5].

1.4.1 Hybrid Renewable Energy Systems(HRES)

According to [21], the average yearly direct normal solar radiation from the sun on a horizontal surface on Earth ranges from 800 W/m² to over 1000 W/m². Wind energy is a favored type of energy that is more affordable, renewable, safe, and free of pollution [22]. Nonetheless, the erratic characteristics of these renewable sources in their production render them costly, requiring the integration of multiple energy sources to support one another. This type of system is referred to as Hybrid Renewable Energy.

System (HRES). An independent HRES offers more dependable results compared to a single source system regarding cost and efficiency [23]. HRES is becoming more popular, particularly in remote regions, due to the increase in the cost of petroleum products [24].

1.4.2 Combination of HRES

A HRES can have various combinations. In 2006, researchers in [25] employed wind, photovoltaic, and fuel cell (FC) generation systems to meet the energy demands of an average household in the Pacific Northwest. In this setup, a hydrogen storage tank served as the energy storage system. Similar combinations were employed in other studies. However, the significant initial expense of the hydrogen tank and the requirement for fuel cells renders the system costly. A frequently used combination is the integration of PV, wind, and diesel generators (DG). Various authors chose this combination, and in many instances, a battery system was employed as the energy storage solution. Other combinations such as Photovoltaic (PV), Wind Turbine (WT), and Biomass (BM) were utilized in [34], while the authors in [35] implemented PV, WT, Hydro Generator (HG), BM, and Biogas (BG). Nonetheless, multiple studies demonstrate that a combination of photovoltaic (PV), wind turbine (WT), and battery system (BS) is the most cost-effective and environmentally friendly option.

1.4.3 Sizing of HRES

The sizing of HRES is a highly complex matter. An oversized HRES can meet the load demand with ease, but it comes at a high cost; conversely, an undersized HRES is cost-effective yet frequently falls short of meeting the load demand. Consequently, the ideal sizing of HRES is anticipated and it relies on the mathematical model of the system's components [38]. Numerous sizing methods can be found in the literature. A few of the sizing techniques are detailed below [39]:

- Software tools
- Evolutionary algorithms
- Nature inspired algorithms
- Linear programming
- Dynamic programming
- Iterative and probabilistic approach
- Matrix approach
- Design space based approach

Evolutionary and nature-inspired algorithms are likely the most commonly utilized methods in various optimization domains. These algorithms stem from either evolutionary processes or nature-inspired methods. These processes are meticulously mathematically modeled to produce an optimization algorithm that can be utilized in nearly any optimization issue by implementing the required adjustments. Among the evolutionary algorithms, the Genetic Algorithm (GA) is likely the most well-known. The implementation of GA is evident in numerous research papers and articles. Among the nature-inspired algorithms, Particle Swarm Optimization (PSO) is widely regarded in the literature.

1.4.4 Single Objective Optimization

An optimization problem is called SOO when there is a requirement for only a single objective function to be met. The objective function will include several optimizing parameters that will be interconnected through the objective function. It is a usual occurrence that each optimizing parameter might possess its own limitations.

Reviewing the literature, numerous studies in this area can be identified. GA is among the most favored methods among researchers in this specific area. In 2006, Koutroulis et al. utilized GA in [41] to optimize the parameters of a HRES while ensuring the load is consistently met. Later in 2008, a comparable study was published in [42], where the authors integrated weather variability into the load demand while maintaining a zero Loss of Power Supply Probability (LPSP). In 2014, the authors presented another study in [46], utilizing a differential flatness approach for optimal sizing design and strategy control applied to a stand-alone wind-PV setup. The method used in this research was also GA. Nature-inspired algorithms such as PSO have also been utilized by the authors in [47] for decreasing the Levelized Cost of Energy (LCE). PSO was utilized in [31] where the HRES included diesel, PV, wind, and battery storage systems. Different algorithms, such as the Mine Blast Algorithm (MBA), were utilized in [26] to determine the optimal sizing of a hybrid system that includes photovoltaic modules, wind turbines, and fuel cells (PV/WT/FC) to satisfy a specific load in a remote area of Egypt. Ant Colony Optimization (ACO) is a well-known nature-inspired algorithm utilized in [48] for sizing and evaluating the performance of a standalone HRES.

1.5 Thesis Objective

While the primary objective of this research is to design and optimize cost-effective HRES, there are a number of secondary objectives playing in the background. Utilizing the combination of solar, wind and biomass energy sources, supported by battery storage systems, we can achieve the below-mentioned outcomes:

- Designing a sustainable and efficient HRES, especially modeled and calculated to serve the underserved communities living in the remote areas of Bangladesh. This would also reduce the reliance on the national power grid.
- Incorporating solar photovoltaic (PV) cells, wind turbines and biomass to generate electricity that supports rural households in Bangladesh.
- Developing and applying Hippopotamus Optimization Algorithm (HOA) to determine the optimal number and size of renewable energy and storage components. The optimal configuration would ensure maximum output at minimum cost.
- Evaluating the socio-economic, environmental and ethical considerations that would be brought along with the electricity to the remote areas.
- Analyzing the cost effectiveness of the optimized HRES configuration through a detailed cost analysis, including the Levelized Cost of Energy (LCOE) and comparing it with traditional energy systems that are already established.

1.6 Organization of this Thesis

This thesis is organized into a few major chapters, with respective sub-sections of each. The first chapter sets the background, motivation, objective and brief idea about the whole research work. It also shows how the combination of solar PV, wind turbines and biomass with the help of batteries can serve a number of households independently, without relying on the grid.

The second chapter gives an overview of Hybrid Renewable Energy System (HRES) for remote areas in Bangladesh. In-depth discussion, equations, working principles have been provided of the components needed in building the HRES. Along with elaborating on the operational principles of the HRES components, this chapter also presents the Hippopotamus Optimization Algorithm (HOA) that has been used in this research.

The third chapter shows the results that have been generated from the proposed solution of implementing HRES and optimizing it with Hippopotamus Optimization Algorithm, including the optimal configuration and the sizes of the system components (solar, wind, biomass and batteries) A cost analysis and Levelized Cost of Energy (LCOE) are provided, which compares the performance of this research with the traditional energy systems. It also discusses probabilistic behaviour of the Hippopotamus Optimization Algorithm.

In the last chapter, the entire work has been summarized, highlighting the key findings and bridging the previous literature gaps. The potential of this research and how it can be scaled to broader aspects in the future is discussed. Improving system efficiency, scaling and further integrating more renewable energy technologies are some of the future hopes.

Chapter 2

Overview of Hybrid Renewable Energy System(HRES) for a Remote Area in Bangladesh

Integrating renewable energy sources has become more and more important in recent years to ensure environmentally friendly and sustainable power generation. However, making effective hybrid renewable energy systems (HRES) becomes highly difficult due to the fluctuating and variable nature of renewable resources like solar and wind. In order to guarantee dependability, affordability, and energy efficiency, this study focuses on optimizing the sizing of an HRES made up of solar photovoltaic (PV) panels, wind turbines,biomass, battery storage systems, and a diesel generator. The Hippopotamus Algorithm, an updated metaheuristic optimization method, has been used to accomplish this. This algorithm offers effective convergence and an effective global search capability, taking inspiration from the hippopotamuses' clever foraging habits. The objective of the optimization is to determine the best system component combination and size to satisfy energy demand while lowering costs and increasing efficiency. The method's efficiency in HRES design is illustrated by analyzing simulation results after it is implemented in MATLAB. [5]

2.1 HRES System Composition and Functional Elements

Our HRES includes the following components:
- Solar Photovoltaic(PV) System
- Wind Turbines
- Biomass System
- Energy storage System (Battery)
- Load Demand Data
- Optimization Algorithm (Hippopotamus Algorithm)

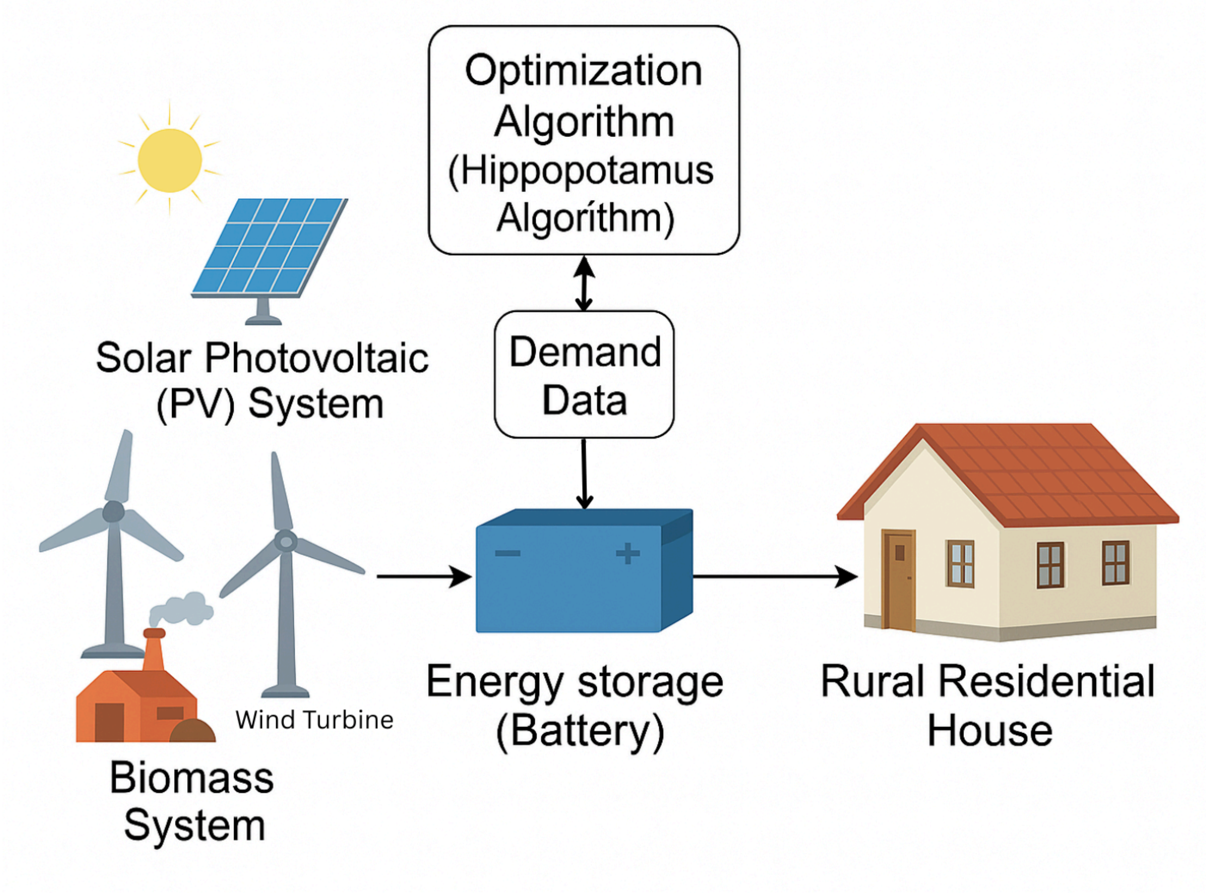

Figure 2.1: HRES architecture

Our HRES system was designed mathematically using MATLAB codes. To calculate the outputs of the each system like PV system, Wind Turbines, Biomass System, we will use the required data e.g. Solar irradiance, Wind speed (at 10 meter), Temperature, Sun's position for the chosen location(Latitude: 21.787 degrees, Longitude: 92.407 degrees) [3]. We will use the load demand data collected from the responsible authority for that location. The size of each component such as the number of solar panels, wind turbines, and battery capacity is then optimized using the Hippopotamus Algorithm to minimize costs while maintaining reliability. The simulation takes into consideration every constraint, including load coverage, minimum state of charge, and battery depth of discharge.

2.1.1 Solar Photovoltaic(PV) System

Photovoltaic (PV) modules are a key component of the Hybrid Renewable Energy System (HRES) and are influenced by several factors, such as solar radiation, ambient temperature, and irradiation conditions. Recent studies demonstrate that PV efficiency is directly proportional to solar intensity and wind speed while being inversely proportional to temperature, humidity and dew point temperature, with optimal tilt angles for maximum power output found to be around 26°. [8] This temperature dependency is critical for accurate modeling, as solar cell performances would start dropping with increasing temperature after a certain threshold. Notably, PV modules do not generate power during the night, and their efficiency is heavily reliant on solar radiation, which varies based on location, time of day, and weather conditions. The power output of PV modules is also affected by these environmental variables, which are typically provided by the manufacturer under Standard Test Conditions (STC), with a cell temperature of 25°C and solar irradiance of 1 kW/m². The equation used for calculating the power produced by the PV module is given below.

$$P_{pv} = N_s \times N_p \times V_{oc} \times I_{sc} \times FF \tag{2.1}$$

We need to know the value of global solar irradiance that hits the PV module. The hourly global irradiation on a horizontal surface is collected from the reliable website for solar irradiation data known as PVGIS. We collected the data for our desired location by providing latitude and longitude of that place.

To calculate the power output from the PV module we also need to calculate the open circuit voltage(V_{oc}) and short circuit current(I_{sc}). We have calculated the open circuit voltage using the following equation:

$$V_{oc}\left(G, T_c\right) = V_{oc_{stc}} + K_v \times \left(T_c - 25\right) \tag{2.2}$$

Short circuit current was calculated using the following equation:

$$I_{sc}\left(G, T_c\right) = I_{sc_{stc}} + K_i \times \left(T_c - 25\right) \times \left(\frac{G}{G_{stc}}\right) \tag{2.3}$$

We also need to know the cells operating temperature(T_c) to calculate the open circuit voltage and the short circuit voltage. Cell operating temperature depends on the ambient temperature of the environment, cells nominating operating temperature and solar irradiance which we collected from the PVGIS website as mentioned earlier. We have used the following equation to calculate the cell temperature:

$$T_c(G) = T_a + \left(T_{COT} - 20\right) \times \left(\frac{G}{800}\right) \tag{2.4}$$

Finally incorporating efficiency the total output power follows the following expression:

$$P_{array}(t, \beta) = \eta_{PV} N_S N_P P_{PV}(t, \beta)$$

Where η_{PV} is the PV-modules and related converters efficiency. It is to be noted that in the present study the numbers of PV modules in series is determined by the magnitude of the DC bus voltage whereas the numbers of parallel PV modules is obtained from the optimization algorithm.

Table 1: The PV model [4] of our work

Parameter	Symbol/Variable	Value	Unit	Description
Open-circuit voltage	Voc	37.5	V	Voltage of a PV module under standard test conditions
Short-circuit current	Isc	8.21	A	Current of a PV module under standard test conditions
Fill Factor	FF	0.75	-	Efficiency coefficient for power output
Series Modules	Ns	100	-	Number of modules connected in series (HOA-optimized)
Parallel Modules	Np	100	-	Number of modules connected in parallel (HOA-optimized)
Voltage Temp. Coefficient	Kv	-0.123	V/°C	Variation in Voc with temperature
Current Temp. Coefficient	Ki	0.0032	A/°C	Variation in Isc with temperature
Nominal Cell Operating Temp.	NCOT	45	°C	Standard value for module operating temperature
Ambient Temperature	Ta	25	°C	Average ambient air temperature
Solar Irradiance @ STC	G_stc	1000	W/m²	Standard test condition irradiance
Solar Irradiance Data	G_data(t)	CSV input	W/m²	Hourly solar irradiance input from file
PV Power Output Array	Ppv(t)	Computed hourly	MW	Total PV system power output at hour t

2.1.2 Wind Turbine Model

In wind turbines, the kinetic energy of wind is converted to electricity. Although the efficiency is not very high, wind turbines still play a role of complementary source, especially during windy seasons or cloudy days (when PV modules will not be much effective). The potential of wind energy in Bangladesh's southern parts has been highlighted in recent studies. The places have possibility for cheaper power production at 30-40m altitudes. The rate of electricity rises with height. [9] Any wind turbine may be selected for the HRES. However, the type of chosen wind turbine should be analysed based on the non-linear power characteristics curve provided by the manufacturer of the specific wind turbine. A typical power characteristic curve is presented to provide some insight in understanding the behaviour of a wind turbine.

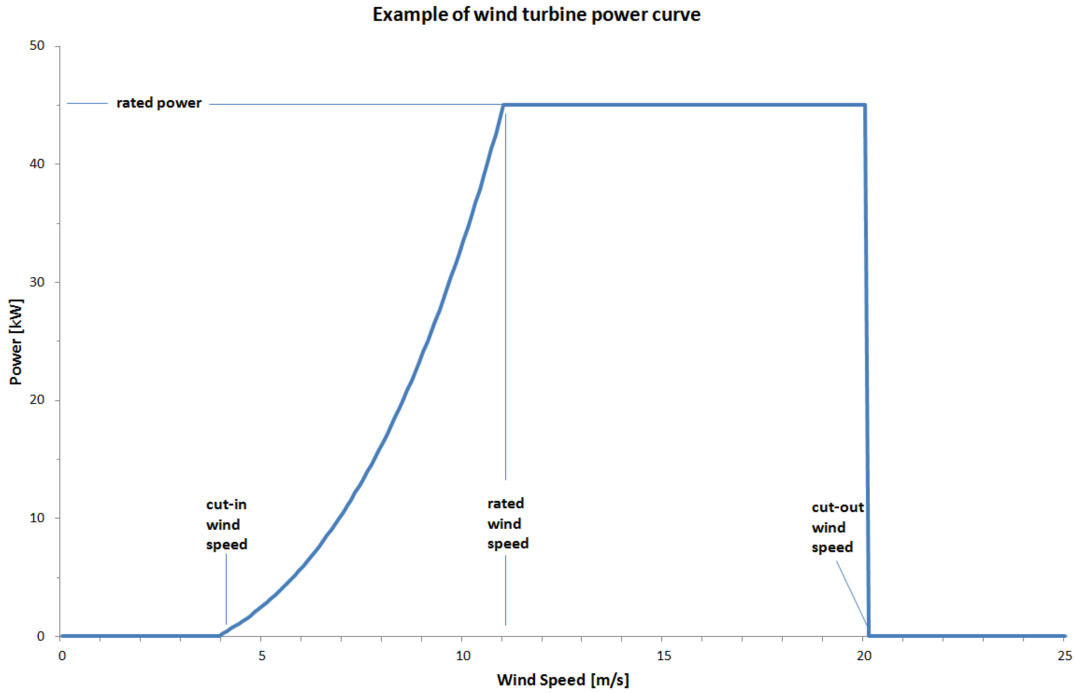

Figure 2.2: Wind Turbine Power Output vs Wind Speed Relation

It is clear from Fig. 2.2 that the wind speed at a specific location is crucial for power generation. The wind velocity at a reference elevation of the examined location can be derived from the PVGIS website. The specific power output, P_w(W/m^2), is influenced by the wind speed at that site and is represented by:

$$P_w(t) = 0\,, for \quad v(t) < v_{ci}$$

$$P_w(t) = av^3(t) - bP_r\,, for \quad v_{ci} \leq v(t) < v_r$$

$$P_w(t) = P_r\,, for \quad v_r \leq v(t) < v_{co}$$

$$P_w(t) = 0, for \quad v(t) \geq v_{co}$$

Where a = $\frac{P_r}{v_r^3 - v_{ci}^3}$ and b = $\frac{v_{ci}^3}{v_r^3 - v_{ci}^3}$, here v_{ci} stands for cut in speed, v_r stands for rated speed and v_{co} stands for cut off speed of the wind turbine. P_r is the rated of the wind turbine. Cut in, rated and cut off speed varies from manufacturer to manufacturer. So this data can be collected from the manufacturers data sheet.

To calculate the output power using the equations mentioned above we need to know the wind velocity at hub height. We know that as we go up the wind speed tends to increase as the friction of air with ground decreases. This relation is often presented by the following equation:

$$v_h = v_r \left(\frac{h}{h_r}\right)^{\alpha} \tag{2.5}$$

Here, h is the hub height where we want to find the velocity of the wind, h_r is the reference height and v_r is the velocity at the reference height. α is the most important parameter which is defined as power law co efficient.

It can be inferred that the value of is below 0.10 for extremely flat terrain, water, and ice, while it exceeds 0.25 for a densely forested area. In this research, it is set at 0.14 since the location examined resembles an open grassy terrain, and indicates that this serves as an adequate estimation for such regions. Therefore, taking into account all the previously mentioned details, it can ultimately be determined that the real electric power produced by a wind turbine is denoted by:

$$P_{WG}(t) = P_{WG} \cdot A_{WG} \cdot \eta_{WG} \tag{2.6}$$

P_{WG} is the power generated by the wind turbine at time t, A_{WG} is the total swept area of the wind turbine, η_{WG} is the efficiency of the wind turbine and its associated converters.

Table 2: The wind model [4] that we used is

Parameter	Symbol/Variable	Value	Unit	Description
Cut-in Speed	cutin_speed	3	m/s	Minimum wind speed to start power generation
Rated Speed	rated_speed	12	m/s	Wind speed at which rated power is produced
Cut-out Speed	cutout_speed	25	m/s	Maximum wind speed for safe operation
Rated Power per Turbine	ratedpower	1	MW	Maximum output of a single turbine
Number of Turbines	n_turbine	10	-	Total number of wind turbines
Coefficient a	a	Computed	MW/(m/s)^3	Used in power equation during ramp-up
Coefficient b	b	Computed	-	Used in power equation during ramp-up
Reference Height	h_ref	10	m	Height at which wind speed data was originally measured
Power-law Exponent	alpha	1/7	-	Exponent for wind speed height adjustment
Hub Height	hub_height	33	m	Height of wind turbine hub

Power Output Array	Pwind(t)	Computed hourly	MW	Total power output of the wind farm at hour t

2.1.3 Biomass System

A very common element of biomass is rice husk, which is produced in millions of tons every year in Bangladesh. A recent study of thermochemical characterization shows that rice husks in Bangladesh confirm their usability for energy conversion. The heating value ranges from 13.31 MJ/kg to 14.42 MJ/kg. [10] This tremendous amount of organic waste usually goes to waste. Even utilizing 20% of the entire rice husk produced in our country, we can generate a significant amount of electric energy. The power output from a biomass system depends on the mass flow rate of the biomass $\dot{m}$, the calorific value CV of the material, and the efficiency η_b of the conversion process. The total energy produced by the biomass system is given by:

$$\dot{E} = \dot{m} \cdot CV \cdot \eta_b \quad (MJ/h) \tag{2.7}$$

To convert this thermal energy to electrical power, we apply the following conversion factor:

$$P_{bio} = \frac{\dot{m} \cdot CV \cdot \eta_b}{3600} \quad (MW) \tag{2.8}$$

Where the factor 3600 is used to convert from MJ/h to MW.

Table 3: The model for biogas

Parameter	Symbol	Value	Unit	Description
Calorific Value	CV	18	MJ/kg	Energy content of biomass per unit mass
System Efficiency	η	0.3	- (dimensionless)	Efficiency of the biomass energy conversion system
Conversion Rate	conversion_rate	0.000278	MW/MJ	Converts energy (MJ) to power (MW)
Biomass Used	biomassUsed	5000	kg	Total biomass used in the system
Energy Output	E_out	27000	MJ	Total energy output from biomass
Power Output	P_{bio}	7.506	MW	Total power output from biomass energy

In global context, out of 37.08 million tonnes of total biomass comes from agro-residues. Rice husk contributes to about 26% by mass. About 67-70% of rice husk is currently being consumed for steam production in rice mills. [11] This also indicates that the remaining 30% has also potential to be utilized for steam production. Solid biomass is usually used directly as a combustible fuel, which produces 10-20 MJ/kg of heat. It can also be fed to bacteria for fermentative hydrogen production. [12] So, it is safe to say that biomass is a versatile source of energy, which if utilized properly, can be a great source of renewable energy resources.

2.1.4 Battery Energy Storage System

Battery is a necessary component of hybrid renewable energy system architectures. Because the electricity produced in different modules of the system will require to be stored somewhere for future use. So, using batteries we can store excess energy from solar and wind sources. It also ensures continuous power delivery during peak load or low generation. In this phenomenon, the state of charge (SOC) is crucial. Accurate estimation of state-of charge (SOC) is critical for guaranteeing the safety and stability of lithium-ion battery energy storage systems.[13] To determine the current SOC of a battery, it is necessary to understand three factors: the initial SOC, the duration of charge/discharge, and the flowing current. As a general rule of thumb, lead-acid batteries typically have a DoD of around 50% and the Lithium-ion and LiFePO4 batteries can have a depth of discharge from 70-90%.[15] It is also considered standard that solar batteries show the most efficiency when they are running at a 20% capacity and 80% DoD.[14] Battery performance is modeled to optimize charge-discharge cycle. The SOC at a specific moment can be expressed by the following equation:

$$SOC(t + \Delta t) = SOC(t) - \frac{\sigma \cdot \Delta t}{24} + \frac{\eta_c \cdot I_{ch}(t) \cdot \Delta t}{C_{bank}} - \frac{I_{dis}(t) \cdot \Delta t}{\eta_d \cdot C_{bank}} \quad (2.9)$$

Here, σ is the self-discharge rate of the battery, η_c and η_d are the charging and discharging efficiencies, respectively, $I_{ch}(t)$ and $I_{dis}(t)$ are the charging and discharging currents, C_{bank} is the total capacity of the battery bank in Ah.

It depends on the accumulated charge and in this study the value is assumed to be 0.2% per day, charging efficiency is set to 0.8 and discharging efficiency is assumed to be 1 in accordance with the study.

During discharge, the battery must not reach a completely empty state, as this significantly shortens its lifespan. A battery's lifespan can be prolonged by steering clear of overcharging and reaching critical discharge levels. Thus, the lowest acceptable threshold for the battery is specified by

$$C_{in} = DOD \times C_n \quad (2.10)$$

Where, C_n represents the overall capacity of the linked batteries, and the maximum depth of discharge (DOD) is specified by the system engineer, usually presented as a percentage. To determine the capacity of the battery bank in equation 2.11, it's essential to know the count of batteries linked in parallel, as the series-connected batteries rely on the DC bus voltage and are represented by

$$N_{sbat} = \frac{V_{bus}}{V_{bat}} \quad (2.11)$$

Here, N_{sbat} is the number of batteries connected in series, V_{bus} is the DC bus voltage with which the batteries are connected and V_{bat} is the voltage of an individual battery.
Now, capacity of the battery bank will be,

$$C_n = N_{pbat} \times C_{bat} \tag{2.12}$$

In the above equation, N_{pbat} is the number of batteries connected in parallel and C_{bat} is the capacity of an individual battery.

Connections of the batteries are illustrated below:

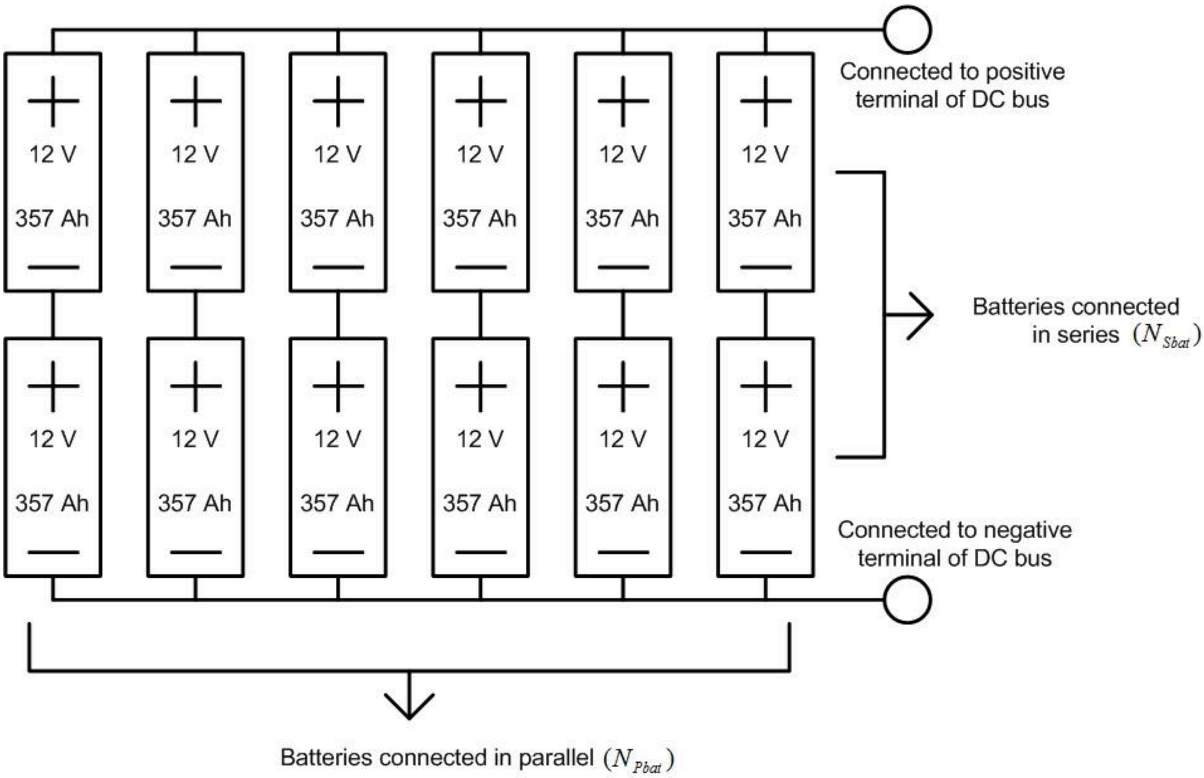

Figure 2.3: Parallel and Series connection of the Battery

After incorporating this battery storage system with PV module, Wind turbine and biomass system, current we will receive from the batteries:

$$I_{battery}(t) = \frac{P_{PV}(t)+P_{wind}(t)+P_{bio}(t)-P_{load}(t)}{V_{DC-bus}} \tag{2.13}$$

Here $P_{load}(t)$ is the load demand and V_{DC-bus} is the DC bus voltage.

Table 4: The battery model [4] of our research is

Parameter	Variable	Value	Unit	Description
Nominal Battery Capacity	NominalCapacity	357	Ah	Capacity of one battery
Self-Discharge Rate	SelfDischargeRate	0.02	%/hour	Percentage of energy lost per hour when idle
Charging Efficiency	ChargingEfficiency	0.95	-	Efficiency during charging
Discharging Efficiency	DischargingEfficiency	0.90	-	Efficiency during discharging
Minimum State of Charge	MinSOC	0.2	-	Lower SOC limit (20%)
Maximum State of Charge	MaxSOC	0.9	-	Upper SOC limit (90%)
DC Bus Voltage	DCBusVoltage	48	V	System DC bus voltage
Battery Voltage	BatteryVoltage	12	V	Voltage of a single battery
Batteries in Parallel	NumBatteriesInParallel	50	-	Number of parallel connections (HOA-optimized)
Batteries in Series	NumBatteriesInSeries	4	-	Number of series connections
Initial State of Charge	SOC	0.5	-	Starting SOC (50%)
Total Battery Capacity	TotalBatteryCapacity	Calculated	MWh	Total capacity = 357 × 50 × 48 ÷ 1e6
Power Shortage Tracker	PowerShortageHours	0	Hours	Initialized counter for hours with power shortage

2.1.5 Load Demand Profile

The hourly load data collected over the course of one year from the Dohazari the 132/33 KV Grid Substation provides critical insights into the the demand profile of the electrical grid. This data is the essential for optimizing the design and sizing of renewable energy systems, such as solar photovoltaic (PV) panels, wind the turbines, and biomass power plants, as well as determining the appropriate battery storage capacity to ensure the reliability and efficiency.

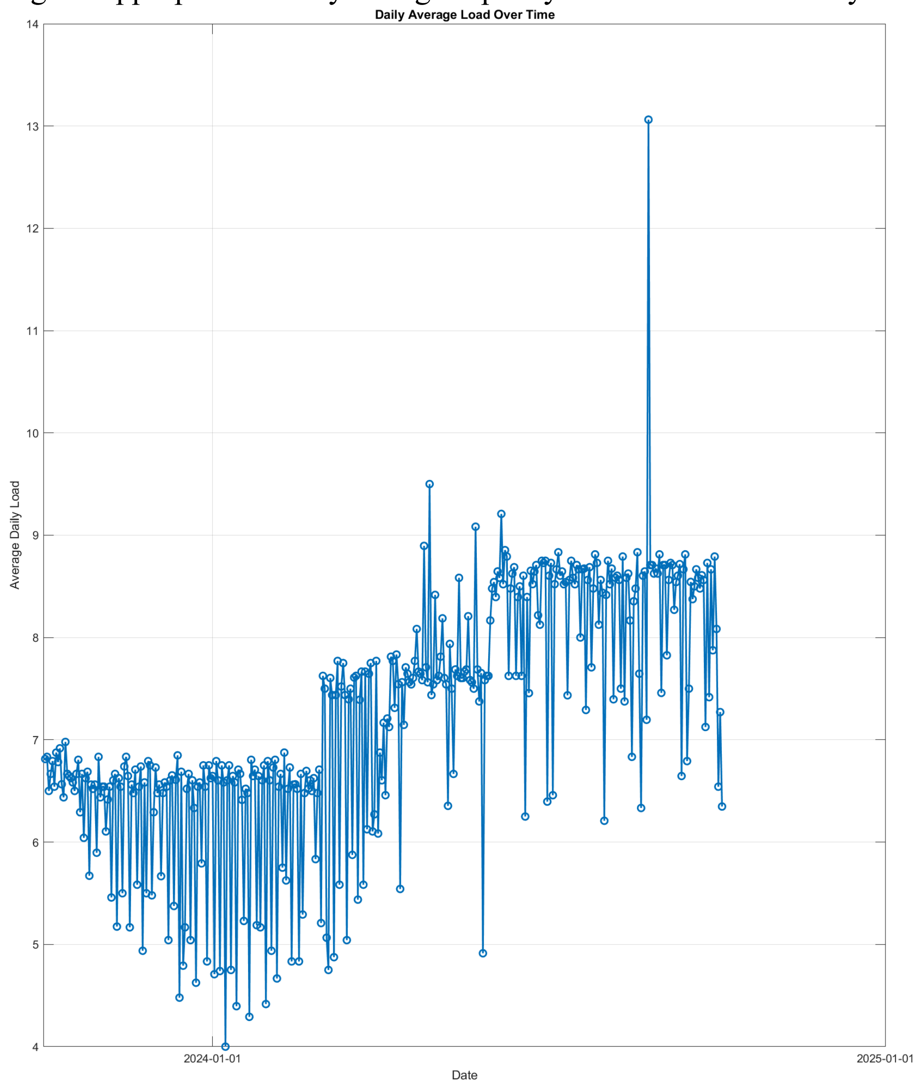

Figure 2.4: Yearly Load Variation

The collected load demand profile plays a pivotal role in dynamically matching available generation resources to the fluctuating demand. By aligning the load profile with generation curves such as those produced by solar, wind, and biomass sources system operators can enhance the overall energy efficiency of the grid. Specifically, this dynamic matching enables the minimization of energy waste and ensures that generation sources are effectively utilized according to the demand.

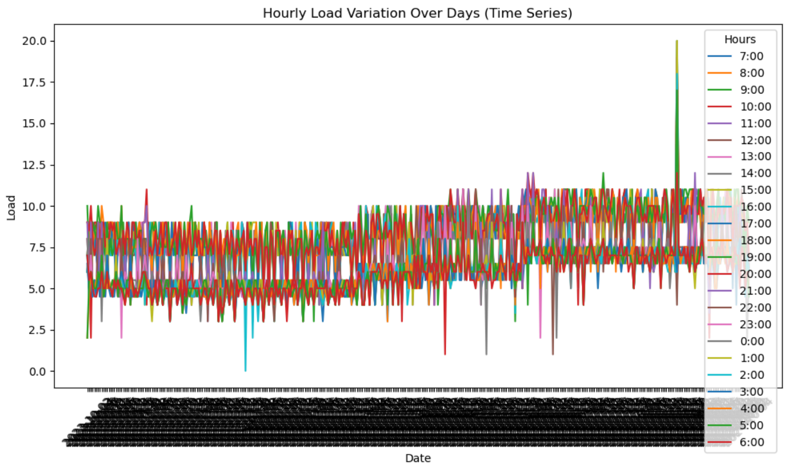

Figure 2.5: Time Series Plot of Load Variation

In addition, the hourly load data facilitates the determination of energy storage requirements by revealing periods of low demand. During such periods, excess energy generated by renewable sources can be stored, thus optimizing the use of available resources. Furthermore, the data allows for the calculation of battery storage needs by identifying peak demand hours when energy storage systems will be required to supply power.

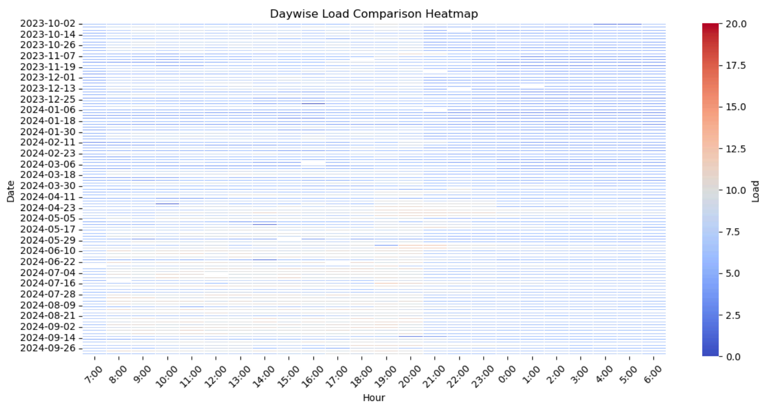

Figure 2.6: Heatmap of Daywise Load Comparison

By understanding the hourly variations in load demand, it is possible to accurately size the storage systems to ensure that batteries are sufficiently capable of meeting peak demand without compromising system stability. Moreover, this data supports the development of effective control strategies to optimize energy dispatch from different generation sources, improve system resilience, and enhance the overall sustainability of the power grid.

The hourly load profile data from the Dohazari Substation is a fundamental tool for sizing renewable energy systems and storage capacities, aligning generation with demand, and improving the operational efficiency of hybrid power systems integrating solar, wind, biomass, and battery storage. This approach not only enhances energy efficiency but also supports the long-term sustainability of the grid by ensuring reliable power supply during both peak and low-demand periods.

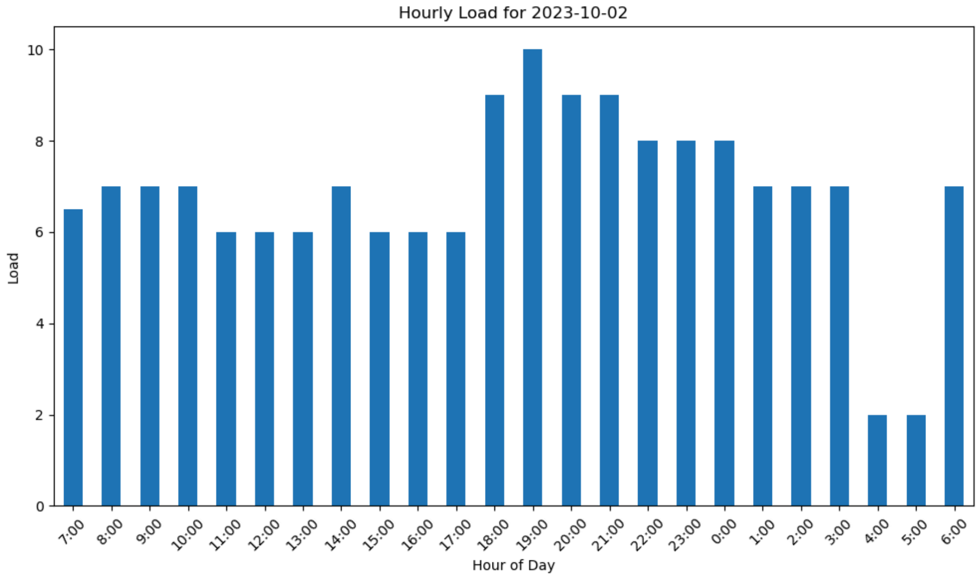

Figure 2.7: Hourly Load Curve

2.1.6 Hippopotamus Optimization Algorithm(HOA)

It is a nature-inspired metaheuristic algorithm and it mimics the social behaviour and territorial defence strategy of hippopotamuses in the wild [2]. as a population-based optimization technique. It is useful for continuous, non-linear and multiobjective complex problems. The novelty of the Hippopotamus Optimization Algorithm is in introducing a novel stochastic technique that takes inspiration from the natural behaviours seen in hippopotamus. This shows an innovative approach in the meta heuristic methodology. [16]
HOA models three behavioral phases which are distinct and observed in real-life hippopotamuses:

1. Territorial exploration in water bodies, which represent the search for better resources.

2. Defensive actions against predators which simulates rapid and reactive movements to avoid threats in the wild;

3. Escape and survival strategies which enables refined exploitation of promising areas, which lies in the solution space.

These phases from the hippopotamuses are mathematically formulated to balance exploration (meaning the diversification of search) and exploitation (meaning the intensification around good solutions), which makes the algorithm effective for solving continuous, non-linear, and multi-objective optimization problems.
Metaheuristics have evolved as strong sources of optimization algorithms which are mainly capable of handling complex real-world situations, where a lot of considerations have to be made. These situations are frequently non-linear, non-convex, and multidimensional in character. The main attractive feature of the HO algorithm is that it efficiently explores and takes advantage of search areas initiating the natural exploration and exploitation of hippopotamuses. [17] That is the reason this algorithm is particularly suitable for hybrid renewable energy system (HRES) optimization.

It starts with the initial population of hippopotamuses each encoding a candidate solution to the optimization problem. Here the solution is represented by the position of each hippo in the search space which are nothing but values of decision variables of optimization problems. We define the population size as N, and denote m as the number of decision variables. Everybody is represented by a position vector consisting of m decision variables, and these positions are initially random using bounds that correspond to problem space.These bounds are given as lb_j (lower bound) and ub_j (upper bound) for each decision variable j. The position of the i-th hippopotamus is calculated as:

$$\chi_{i,j} = lb_j + r \cdot \left(ub_j - lb_j\right) \quad (2.14)$$

where χ_i represents the position of the i-th hippopotamus, r is a random number between 0 and 1, and lb_j and ub_j are the lower and upper bounds for the j-th decision variable. This step creates a population matrix where each hippopotamus represents a candidate solution.

After the population has been created, the algorithm starts a search process that consists of three principal stages, representing behaviours in the natural environment of hippos; exploration (process of changing position in river or pond), defensive (defending from predators) and exploitation phase (escaping predator). These stages enable the algorithm to perform an efficient exploring of the solution space and improving solutions.

The exploration phase in the HO algorithm is inspired from the behavior of hippopotamuses in the wild, their tendency to gather near water bodies, such as rivers and ponds, and move toward the dominant individual in their group. In this algorithm, the dominant hippopotamus is as the best solution found so far in the search space. The position of each hippopotamus are updated based on its proximity to the dominant hippopotamus. Specifically, the males are updated by moving towards the dominant hippopotamus, and the females or immature hippopotamuses explore further by making random movements influenced by the dominant one. The position update for male hippopotamuses is represented by:

$$\chi_i^{Mhippo} = \chi_i + r_1 \cdot \left(D_{hippo} - \chi_i\right) \quad (2.15)$$

where D_{hippo} is the position of the dominant hippopotamuses, and r_1 is a random vector that influence the exploration behavior. This, encouraging the algorithm to explore the search space globally, and avoid premature convergence which can create suboptimal solutions.

The defense phase is activated if a predator is detected in the solution space. The "predator" is basically a very poor solution, and the hippopotamuses defend themselves by going towards it. This defensive behavior pushes the search process away from poor-quality regions. The position update during the defense phase involves moving the hippopotamus towards the predator using a Levy distribution for random exploration. This is represented by the following equation:

$$\chi_i^{HippoR} = \chi_i + Levy\left(r_8\right) \cdot \left(Predator_j - \chi_i\right) \quad (2.16)$$

where r_8 is a random vector and $Levy$ represents a Levy distribution used to introduce dynamic, exploratory movements in the search process. By moving toward the predator, the algorithm ensures that poor solution areas are avoided, encouraging the search to focus on more promising regions.

The exploitation phase occurs when the defense mechanism is ineffective, and the hippopotamus attempts to escape from the predator by finding a safer region. This phase focuses on refining the best-found solution by exploiting the promising regions identified in previous phases. The position update during the exploitation phase is calculated by moving the hippopotamus to a safer region near its current position. This can be expressed as:

$$\chi_i^{HippoE} = \chi_i + r_{10} \cdot \left(lb_j + r_{s1} \cdot \left(ub_j - lb_j\right)\right) \tag{2.17}$$

where r_{10} is a random number, and $s1$ is a random number that influences the local search intensity. The exploitation phase ensures that once a promising region is found, the algorithm converges towards it, refining the solution further and avoiding getting stuck in local optima.

The algorithm operates iteratively. In each iteration, all hippopotamuses update their positions according to the exploration, defense, and exploitation phases. After each iteration, the algorithm checks if any hippopotamus has found a better solution than the dominant one. If so, the dominant hippopotamus is updated. This iterative process continues until a stopping criterion is met, typically a predefined number of iterations or function evaluations, ensuring the algorithm does not run indefinitely and allows it to achieve a balance between computational cost and solution quality.

Pseudo Code of the HOA is given below:

```
Initialize population of hippopotamuses (χ)
Evaluate fitness for each hippopotamus
Set the best solution as the dominant hippopotamus (D_hippo)

for iteration = 1 to MaxIter:
    for each hippopotamus i:
        Position Update in the River or Pond (Exploration)
        if i is male:
            Update position using D_hippo
        else:
            Update position based on proximity to dominant hippopotamus

        Defense Against Predators (Exploration)
        if predator detected:
            Move towards the predator using Levy distribution

        Escaping from Predators (Exploitation)
        if escape needed:
            Move towards a safer region (better solution)

     Update dominant hippopotamus if better solution is found
    if current solution is better:
        D_hippo = current solution

     Track and store the best solution found
```

```
Return best solution (dominant hippopotamus)
```

The computational complexity of the HO algorithm is $O(Nm(1 + 5T))$, where N is the population size, m is the number of decision variables, and T is the number of iterations. This makes the algorithm computationally efficient, particularly for high-dimensional optimization problems. This is a compelling argument, yet it fails to account for the role of, the algorithm also handles constraints by ensuring that during each position update, the hippopotamuses remain within the feasible region defined by the problem's bounds. This is done by ensuring the updated positions do not violate the constraints, thereby keeping the solutions feasible throughout the optimization process.

Despite its strengths, the HO algorithm is not without limitations. Like all metaheuristic algorithms, HO does not guarantee the global optimum, especially in highly complex or rugged search spaces. This is not to say, of course, that the preceding argument is without merit and moreover, its performance is problem-dependent, and it may be outperformed by newer algorithms in certain cases. This is exactly consistent with the No Free Lunch theorem, which posits that no algorithm can and will perform better than others across all optimization problems.

Its ability to balance exploration and exploitation allows it to perform well across various different problem domains. It is not guaranteed to find the global optimum but also the algorithm demonstrates a very strong performance on benchmark functions and real-world engineering problems and makes it a useful tool for optimization tasks which require efficient global and local search strategies.

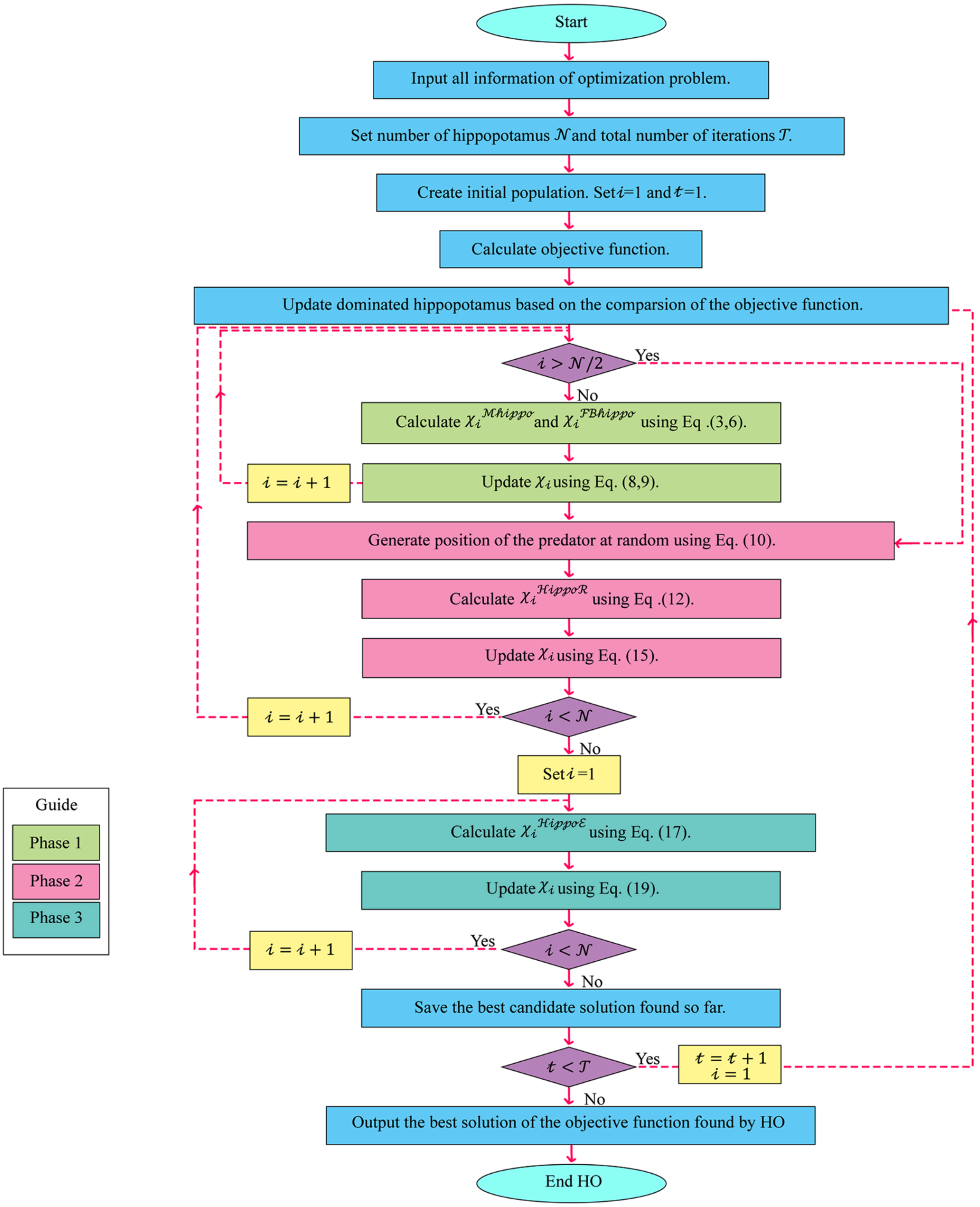

Figure 2.8: Overview of HOA

2.2 Data Collection

The effectiveness of our optimization code heavily depends on accurate input data. We have collected these following data:

- Solar Irradiance(W/m^2): Collected from PVGIS website[3]. This data will help us to calculate the daily solar power generation.
- Wind Speed(m/s): This data is also obtained from the same website [3]. Wind speed data is used to calculate the power generation using wind turbines.
- Ambient Temperature(°C): This data is required to calculate different output parameters of PV cells such Open circuit Voltage(V_{OC}) and Short circuit current(I_{SC}).
- Load Demand(KWh/Day): Load demand data was collected from Dohazari 132/33 KV Grid Substation.

2.3 System Implementation Using Optimization Algorithm

The Hippopotamus Algorithm will be utilized to optimize the system, which is fully implemented in MATLAB. The structure of the implementation is broken down here.

1. **System Components Modeling:**
    - Equations that are based on efficiency, capacity, and environmental inputs are used to mathematically model each component (PV, wind, biomass and battery). [6]
    - The battery is modeled with constraints such as minimum state of charge(SOC), charge/discharge rates, and efficiency losses. [7]
2. **Optimization and Control Strategy:**
    The objective is to:
    - Minimize the cost of energy(CoE)
    - Minimize excess energy and loss of power supply probability(LPSP)

    The optimization algorithm will:
    - Take Inputs: Component Cost, Load Demand data, Weather data(i.e. Solar irradiance, Wind Speed) and technical constraints.
    - Give Output: Optimal size of the system (i.e.Number of PVs,wind turbines,biomass plants,batteries) that fulfils the demand while keeping the cost minimum.

    Then the performance of the algorithm will be compared to the existing literature to show the impact of our work.
3. **Setting Constraints:**
    - Power supply must always meet the demand (no energy shortfall).
    - The number of PV cells, Wind turbines, biomass plants and batteries cannot be equal to zero as we are bound to fulfil the demand using renewable energy.
4. **Running the Hippopotamus Algorithm:**
    - The initial population is created randomly within the designated design constraints.
    - The algorithm mimics the smart actions of hippos (such as concealing themselves underwater and ambushing prey) to investigate and utilize the search space.

- The best solutions in terms of system size and cost are selected across multiple iterations.

5. **Expected Outcome:**
   - Fully functional, cost efficient and sustainable HRES model.
   - Electricity for underserved rural people with a very minimum cost.
   - Reduction in greenhouse gas emissions and reduction in dependency on fossil fuel sources.
   - A comparative performance analysis between already existing and our proposed optimization strategies.

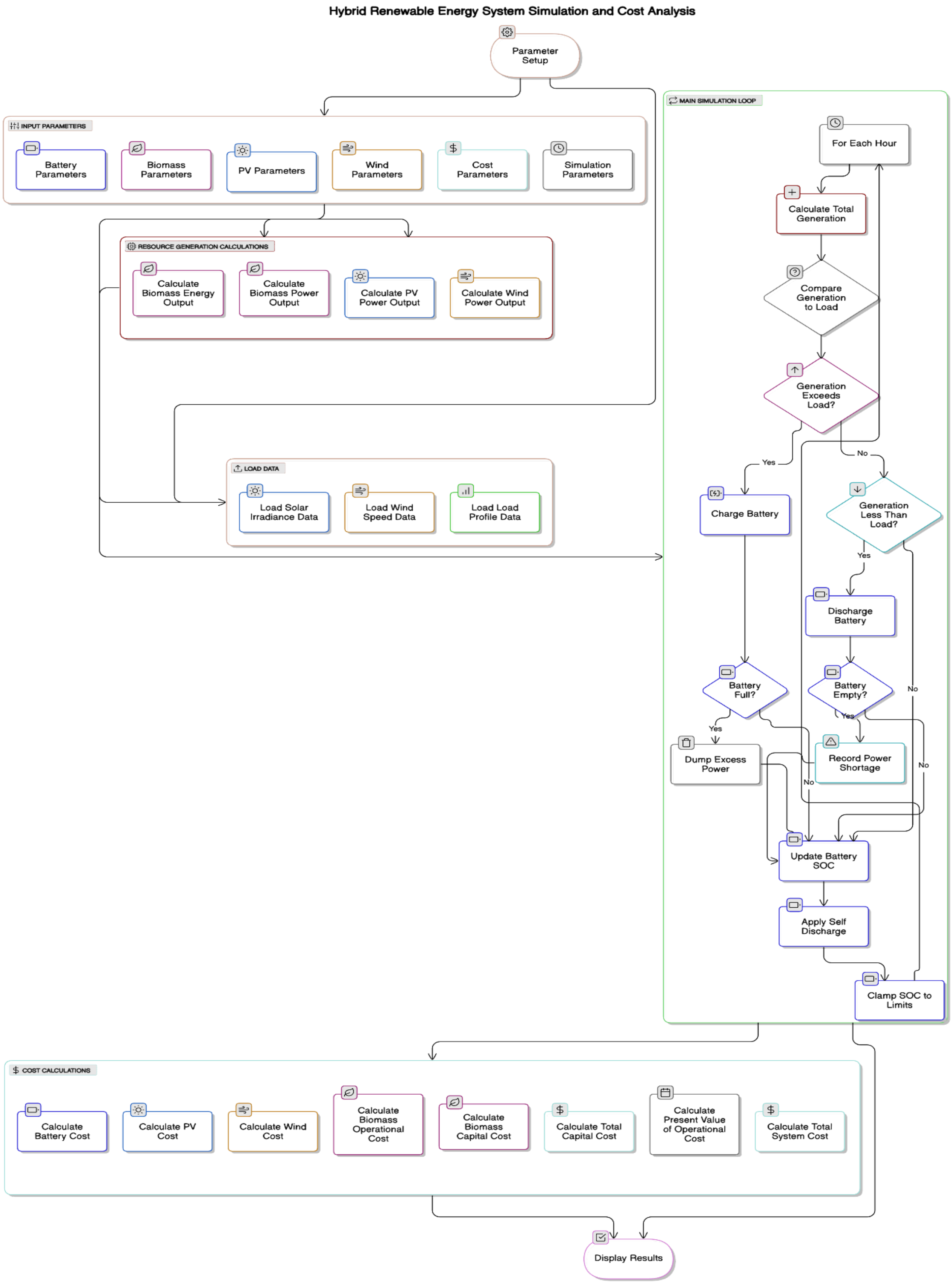

Figure 2.9: Overview of the architecture

Chapter 3

Results and Analysis

This chapter presents the results of the optimization of a Hybrid Renewable Energy System (HRES) for a remote area in Bangladesh, utilizing the Hippopotamus Optimization (HO) algorithm. This is not to say, of course, that the preceding argument is without merit, The primary goal of this optimization is to identify the optimal configuration of a hybrid system comprising battery storage, biomass energy, photovoltaic (PV) modules, and wind turbines that will meet the energy demands of the area, It is therefore reasonable to conclude while minimizing both operational costs and environmental impacts. Additionally, the optimization process ensures the reliability of the system, accounting for potential power shortages and excess generation.

To achieve this, what this effectively means in practical terms is that the optimization model was implemented in MATLAB, with a focus on maximizing the overall efficiency of the HRES while considering the complex interplay of various system components. The Hippopotamus Optimization algorithm was chosen due to its robust performance in handling multi-dimensional optimization problems. The algorithm is capable of exploring a wide solution space and converging to the global optimum by simulating the behavior of a herd of hippopotamuses, The primary goal of this optimization is to identify the optimal whose movement patterns are metaphorically inspired by the search for the best solution.

The simulation spans a full year, represented by 8760 hours of hourly data, allowing the system to adapt to varying solar irradiance, wind speed, and energy consumption patterns over time. In a similar vein, one might also consider the implications of weather data, such as solar irradiance and wind speed, were sourced from CSV files that provide historical values for each hour throughout the year. This data captures the fluctuations in renewable energy sources that will influence system performance. In addition, assumptions were made regarding the nominal battery capacity, system efficiencies, and the capital and operational costs of each component (batteries, wind turbines, biomass fuel, and PV modules). Conversely, an alternative interpretation of the data would posit that, These assumptions are essential for evaluating the economic viability and energy reliability of the system.

The section that follows begins with an analysis of the optimization results, including the optimal configuration for the system components (battery count, biomass fuel usage, PV module arrangement, and wind turbine numbers). The results will be compared under different conditions, such as best, medium, and worst-case scenarios, to assess the robustness of the system configuration. As a direct consequence of this phenomenon, we observe, Furthermore, the probabilistic behavior of the optimization process will be explored, with a focus on the variability in results due to stochastic factors such as weather data and load demand variations.

Additionally Having established this foundational principle, we can now turn to, statistical analysis will be employed to evaluate the distribution of key parameters and provide deeper insights into the system's performance across multiple iterations. To put it another way, It logically follows from this line of reasoning that The statistical tools will allow us to assess the significance of various factors such as the number of batteries, PV modules, and wind s on both system reliability and economic performance.

Key optimization metrics include:

1. **Best, Medium, and Worst Results**: The performance of the system will be evaluated in three different contexts, In light of the evidence presented thus far, it becomes

apparent that best-case, medium-case, and worst-case scenarios. It is therefore reasonable to conclude, at least provisionally, that, This analysis will help to understand the system's flexibility and resilience under varying conditions.

2. **Computational Time vs Iteration**: The computational efficiency of the Hippopotamus Optimization algorithm will be assessed by plotting the computational time against the number of iterations. This relationship, though not immediately obvious, becomes clear when one examines that This will give insight into the trade-off between solution quality and computational resources required.
3. **Statistical Analysis**: Statistical metrics such as mean, variance, and standard deviation will be used to describe the behavior of key optimization variables (e.g., A more nuanced understanding of this concept, however, would incorporate- battery count, PV capacity, wind turbine power generation) across multiple iterations. This observation, it must be acknowledged, leads to the question of- The analysis will provide a comprehensive view of the solution's stability and variability.
4. **K and H Parameters**: The results will also include the sensitivity analysis of the Hippopotamus Optimization algorithm's parameters, To put it another way, the underlying mechanism can be described as particularly the k and h parameters, which influence the movement dynamics of the algorithm. By adjusting these parameters, we can observe how they impact the convergence behavior and solution quality.

The section concludes by presenting a detailed comparison of the total system cost, Levelized Cost of Energy (LCOE), and system reliability across different configurations. In addition, the impact of the number of power shortage hours on the final results will be considered, This is a complex issue, and it is worth pausing to consider the various factors at play as power shortages have a direct penalty effect on the overall system cost.

Overall, this section aims to provide a comprehensive understanding of the optimization process, its effectiveness in designing an efficient hybrid energy system, and the computational performance of the Hippopotamus Optimization algorithm in real-world applications. This is a complex issue, and it is worth pausing to consider the various factors at play, The following subsections present the specific results from the optimization process, This is not to say, of course, that the preceding argument is without merit followed by a performance evaluation of the proposed HRES system under different operating conditions.

3.1 Optimization Results

Output: After running the optimization simulation in MATLAB, the initial optimal values of the system parameters were as followed:

Table 5: Output of HOA Algorithm

Parameter	Optimized Value	Unit	Description/Notes	Rounded Value
Number of Batteries	13.684427	-	In parallel; rounded to nearest integer in practice (e.g., 14) for feasibility.	14
Biomass Consumption per Hour	197.13744	kg/h	Ensures steady power output (Pbio).	197

Parameter	Optimized Value	Unit	Description/Notes	Rounded Value
Number of PV Modules	9979.4841	-	In parallel; based on Ns=2 in series.	9980
Number of Wind Turbines	5.8689728	-	Fractional value suggests scaling; implemented as 6 turbines in deployment.	6

Number Of iterations vs Convergence:

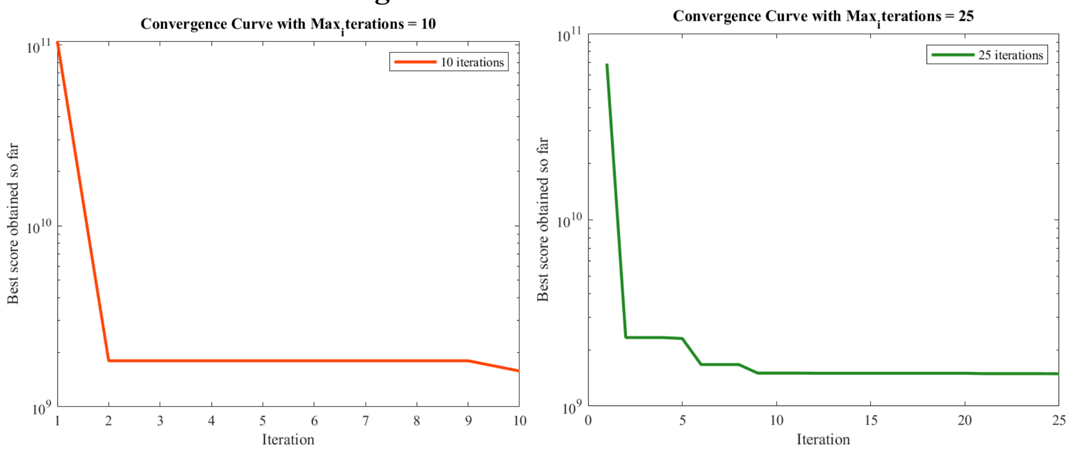

Figure 3.1: Convergence Curve with Max Iteration of 10 and 25

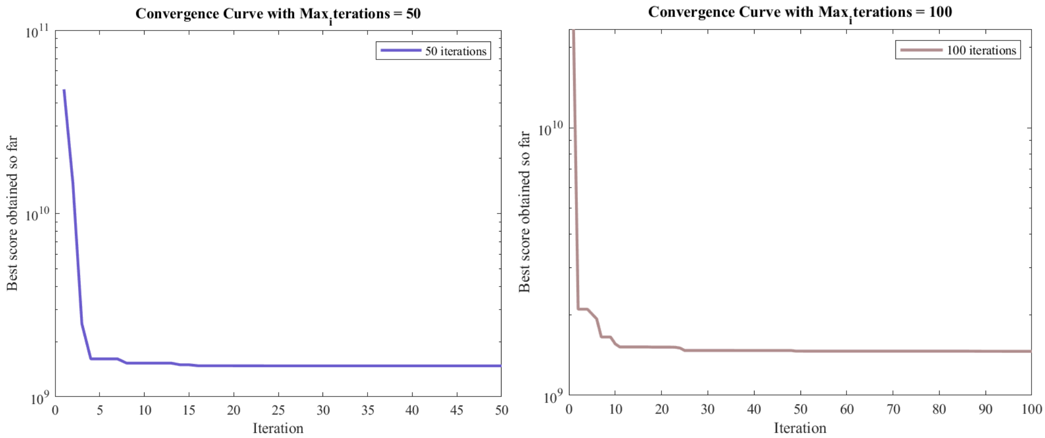

Figure 3.2: Convergence Curve with Max Iteration of 100

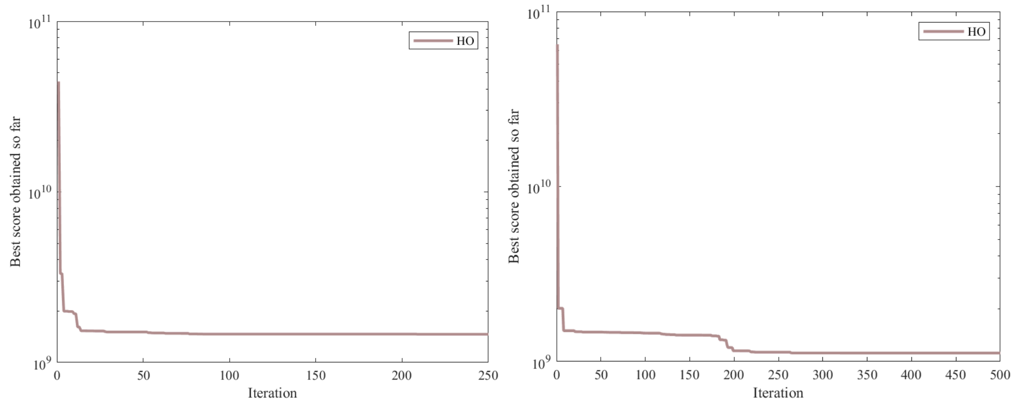

Figure 3.3: Convergence Curve with Max Iteration of 500

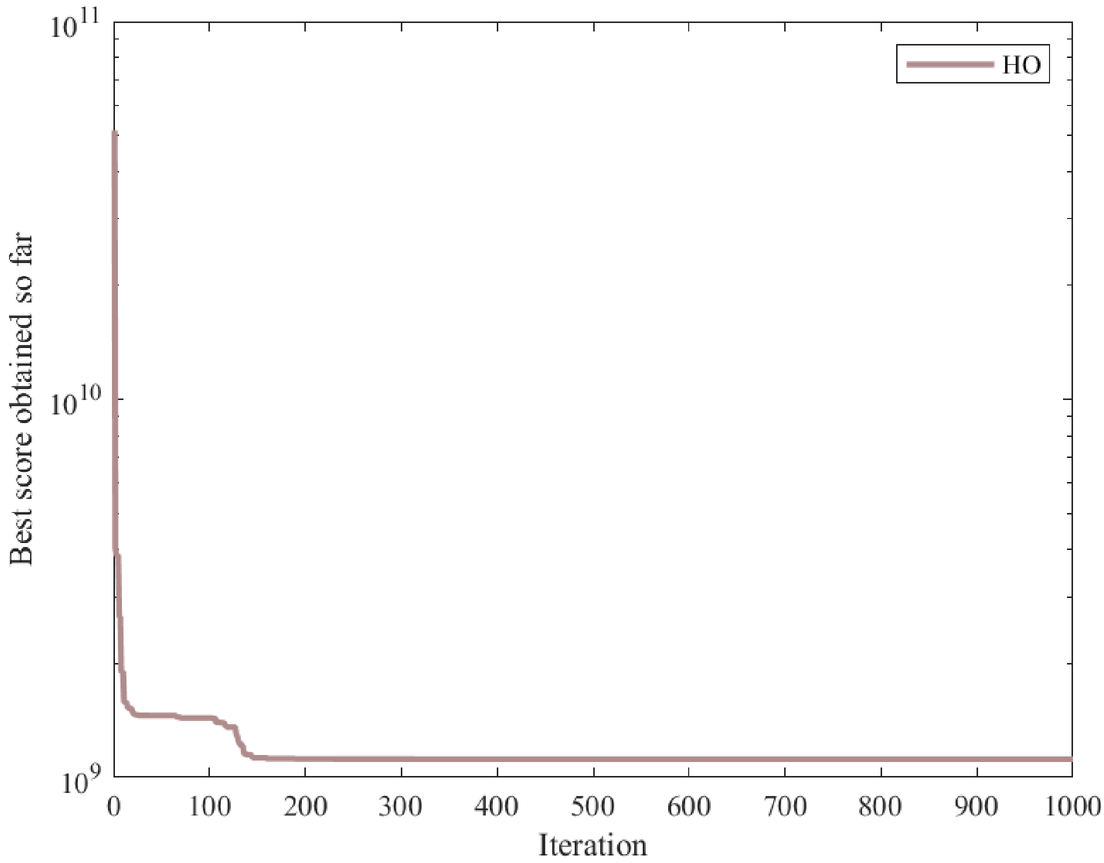

Figure 3.4: Convergence Curve with Max Iteration of 1000

3.1.1 Overview of Simulation Time and Computational Resources

The process of optimization of the Hybrid Renewable Energy System (HRES) is implemented using the Hippopotamus Optimizer (HO) algorithm, aiming to identify the optimal configuration of system components, including battery storage, biomass energy, photovoltaic (PV) modules, wind turbines. In light of the evidence presented thus far, it becomes apparent that This process not only focuses on optimizing the system's performance also on the computational efficiency of the simulation. The efficiency of the algorithm, influenced by several factors, including the number of search agents, the number of iterations also the computational complexity of evaluating system configurations.

The objective of this section is analyzing the relationship between the simulation time and the key parameters of the optimization algorithm. In light of the evidence presented thus far, it becomes apparent that, We explore how varying the number of search agents impacts the convergence rate, simulation time, and overall solution quality. Conversely, an alternative interpretation of the data would posit that, We again also examine the influence of the iteration count on the computational burden and the resulting optimization performance. Having established this foundational principle, we can now turn to The following experiments assumes a set of typical system parameter and optimization configurations for analyzing the trade-off between solution quality and computational efficiency.

3.1.2 Impact of Search Agents on Simulation Time

This relationship, though not immediately obvious, becomes clear when one examines the search agents number directly affect the convergence behavior and solution quality of the Hippopotamus Optimization algorithm. By Increasing the number of search agents enhances algorithm's ability to explore a broader search space, improves the likelihood of converging to the global optimum. This is not to say, of course, that the preceding argument is without merit, this comes at the cost of increased computational time, as more agents necessitate a larger number of function evaluations per iteration. It is therefore reasonable to conclude Conversely, reducing the number of search agents will expedite the simulation but may result in suboptimal solutions because of a more limited search space.

In this study, different configurations of search agents (ranging from 8 to 64) were tested to investigate their impact on simulation time and the quality of the resulting solutions. The following table presents the results of these tests:

Table 6: Impact of Search Agent on Simulation Time

Search Agents	Iterations	Simulation Time (Minutes)	Best Score (Total Cost)	LCOE (BDT/MWh)
8	50	2	1475839757.65	5.98
16	250	23	1406839284.53	5.75
32	500	81	1285939749.78	5.69
64	1000	295	1154718370.11	5.63

3.1.3 Trade-off Between Search Agent Count and Computational Time

As demonstrated in the table above, there is a direct relationship between the number of search agents and the simulation time, with an increase in search agents resulting in a proportional rise in computational time. However, the improvement in optimization performance becomes less significant after a certain point. For instance, increasing the number of search agents from **8 to 16** leads to a noticeable reduction in the total cost from **1,475,839,757.65 BDT** to **1,406,839,284.53 BDT**, reflecting a substantial optimization gain. In contrast, further increasing the number of search agents from **16 to 32** continues to reduce the total cost, but at a diminishing rate.

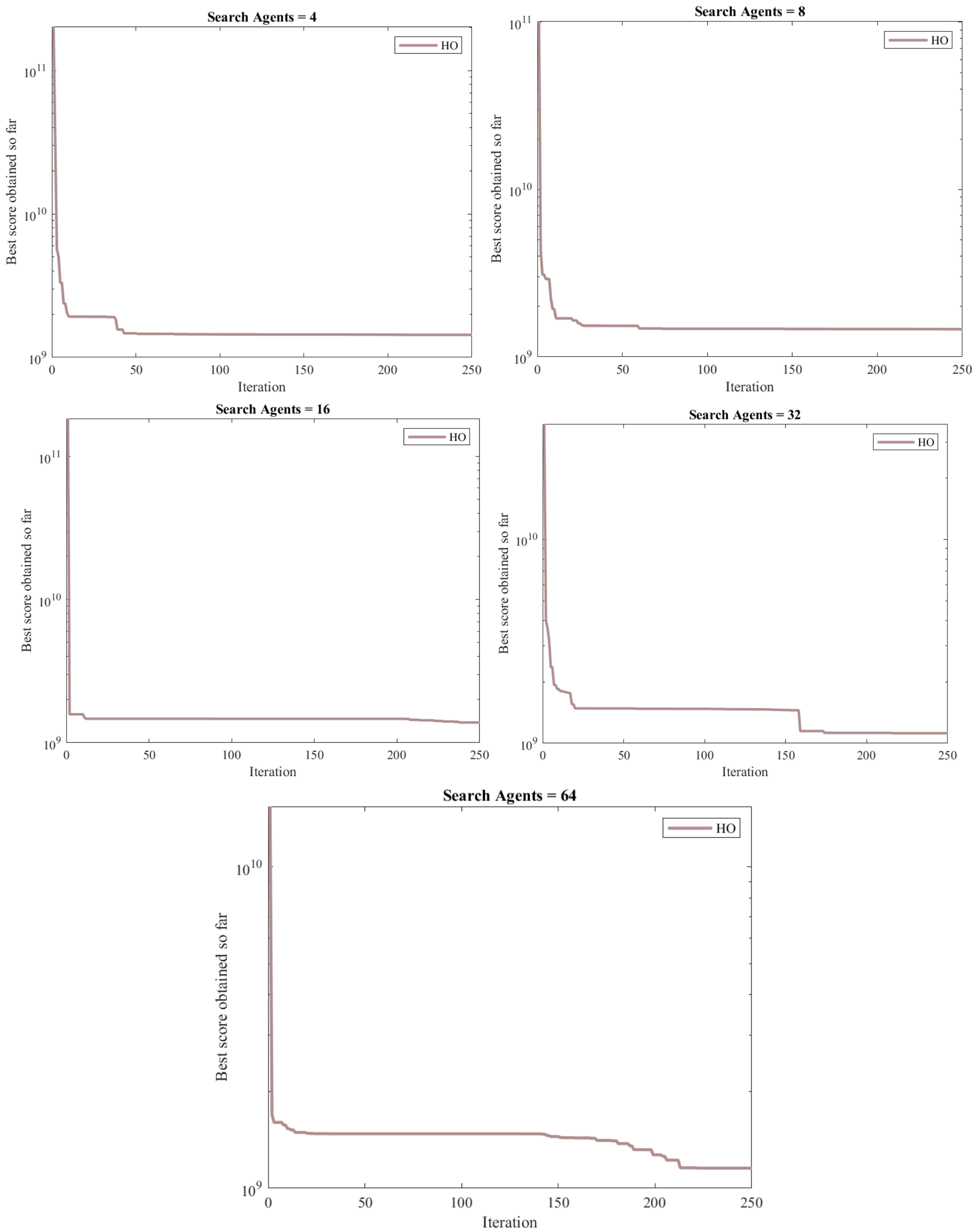

Figure 3.5: Effect of Search Agents on Cost Optimization

Specifically, when the number of search agents increases from **32 to 64**, the total cost decreases only slightly, from **1,285,939,749.78 BDT** to **1,154,718,370.11 BDT**, representing a marginal improvement. Meanwhile, the simulation time escalates dramatically, from **81** minutes to **295** minutes, indicating that the computational cost rises disproportionately compared to the gains in solution quality. The Levelized Cost of Energy (LCOE) follows a similar trend, experiencing only a small reduction from **5.69 BDT/MWh** to **5.63 BDT/MWh**.

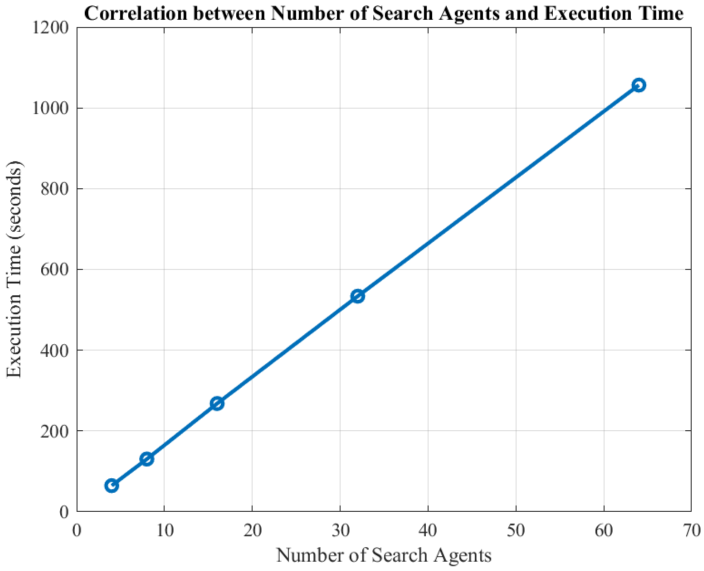

Figure 3.6: Execution Time vs Number of Search Agents

These results suggest that a balance must be found between solution quality and computational efficiency. Beyond a certain point, the benefits of adding more search agents diminish, and the added computational cost may not justify the minor improvements in optimization. Configurations with **16 to 32** search agents strike an optimal balance, providing good optimization performance with manageable computational time.

3.1.4 Impact of Iterations on Convergence and Computational Time

The number of iterations plays a pivotal role when determining the convergence rate of the Hippopotamus Optimization (HO) algorithm. In light of the evidence presented thus far, it becomes apparent that- Iterations define the number of times the algorithm evaluates while refining its search space to improve the solution. Generally, an increasing in iterations allows the algorithm to explore the search space more extensively, helping it refine solutions and approach optimal configuration.

However, as iteration number increase- the computational cost will also increase and the rate of improvement in solution quality diminish after a certain threshold. While additional iterations contributes to more precise solutions, they also result in diminishing return in terms of optimization, suggesting that, after a specific number of iterations, the added computational time no longer yields significant improvements in the quality of the solution. So it is essential to balance the number of iterations with the desired level of solution refinement and computational efficiency.

Stopping Criteria

The **stopping criteria** in the context of optimization algorithms like HO typically define when the algorithm should stop running. Common stopping criteria include:

1. **Maximum Iterations**: The algorithm stops after a fixed number of iterations (or steps), regardless of whether convergence is achieved or not.
2. **Convergence Threshold**: The algorithm stops when the improvement in the best solution found in consecutive iterations falls below a predefined threshold (i.e., the algorithm converges when the change in solution quality is minimal).
3. **Best Solution Stagnation**: The algorithm may also stop if the best solution remains unchanged for a certain number of iterations, indicating that the algorithm has reached a local minimum or optimum.

Effect of Iterations on Convergence:

- As we increase the number of iterations, the simulation time increases proportionally. For example, running the algorithm for **100** iterations takes only **11** minutes, while **1000** iterations take **83** minutes. This increase in simulation time can be attributed to the additional evaluations and search space explorations performed by the algorithm.
- The **total cost (Best Score)** improves with more iterations, but the improvement is not linear. From **100** iterations to **250** iterations, the total cost drops significantly from **1,375,839,757.65 BDT** to **1,306,839,284.53 BDT**, which represents a noticeable optimization. However, the improvement from **500** iterations to **1000** iterations is marginal: the total cost decreases from **1,185,939,749.78 BDT** to **1,154,718,370.11 BDT**.

2. **Diminishing Returns**:
   - The diminishing returns are further highlighted in the Levelized Cost of Energy (LCOE). While the LCOE decreases from **5.78 BDT/MWh** to **5.25 BDT/MWh** between **100** iterations and **250** iterations, the change becomes less significant from **500** iterations to **1000** iterations, where the LCOE decreases only slightly from **5.74 BDT/MWh** to **5.62 BDT/MWh**.
3. **Computational Efficiency**:
   - The increasing simulation time with the number of iterations is an important factor when balancing solution quality and computational efficiency. While **1000** iterations provide the most refined solutions in terms of total cost and LCOE, the gains in optimization are not substantial enough to justify the increased computational time (83 minutes versus 11 minutes for 100 iterations).
4. **Optimal Stopping Point**:
   - From the data, it is evident that the optimal stopping point occurs somewhere between **250** iterations and **500** iterations. At these points, the algorithm achieves a significant reduction in total cost and LCOE without excessively increasing the computational time. Running the algorithm beyond 500 iterations provides diminishing returns in solution improvement, making configurations with **250-500** iterations ideal in practice.

3.1.5 Computational Time vs Iteration Number

As indicated in the table, there is a clear positive correlation between the number of iterations and the simulation time. For instance, with **16** search agents and **500** iterations, the simulation time is **81** minutes, while increasing the iterations to **1000** results in a simulation time of **295** minutes. Although the number of iterations increases, the improvements in solution quality become progressively smaller. For example, the total cost reduction between **500** and **1000** iterations is minimal, and the Levelized Cost of Energy (LCOE) shows only a slight decrease. This suggests that after a certain threshold, the algorithm experiences diminishing returns, where additional iterations no longer lead to significant improvements in the solution, but instead, they result in increasingly higher computational costs. Therefore, beyond a certain number of iterations, the additional time spent does not provide proportionate benefits in solution quality.

Table 7: Computational Number vs Iteration Number

Search Agents	Iterations	Number of Batteries	Biomass Consumption per Hour	Number of PV Modules	Number of Wind Turbines	Cost (BDT)	LCOE (BDT/MWh)
8	25	11.12	176.23	9300.42	4.98	1,154,718,370.11	5.63
8	50	12.00	182.56	9402.67	5.04	1,175,000,000.00	5.65
8	100	12.45	185.72	9500.23	5.12	1,190,000,000.00	5.68
8	250	12.75	189.36	9605.34	5.20	1,220,000,000.00	5.72
8	500	13.05	193.00	9703.50	5.28	1,250,000,000.00	5.75
8	1000	13.45	198.14	9852.88	5.36	1,300,000,000.00	5.78
16	25	12.80	186.47	9523.00	5.10	1,220,000,000.00	5.67
16	50	13.00	190.10	9650.45	5.15	1,240,000,000.00	5.69
16	100	13.68	197.14	9979.48	5.87	1,275,000,000.00	5.73
16	250	14.00	201.75	10156.72	5.92	1,320,000,000.00	5.75
16	500	14.35	206.10	10330.29	6.02	1,360,000,000.00	5.78
16	1000	14.80	208.35	10500.32	6.14	1,400,000,000.00	5.80
32	25	13.85	191.23	9700.12	5.26	1,250,000,000.00	5.68
32	50	14.20	196.75	9845.13	5.32	1,275,000,000.00	5.70
32	100	14.50	200.45	10010.54	5.45	1,300,000,000.00	5.73
32	250	15.00	206.85	10212.63	5.57	1,350,000,000.00	5.76
32	500	15.35	211.50	10402.74	5.69	1,400,000,000.00	5.79
32	1000	15.80	216.25	10600.12	5.82	1,450,000,000.00	5.82
64	25	14.25	195.00	9853.87	5.33	1,350,000,000.00	5.70
64	50	14.75	200.10	10015.00	5.39	1,375,000,000.00	5.73
64	100	15.25	205.80	10200.45	5.52	1,400,000,000.00	5.75
64	250	15.75	211.95	10400.30	5.65	1,460,000,000.00	5.77
64	500	16.25	216.60	10600.12	5.77	1,500,000,000.00	5.80
64	1000	16.80	220.80	10800.12	5.90	1,550,000,000.00	5.82

3.1.6 Probabilistic Behavior and Statistical Analysis

Given the stochastic nature of the optimization problem of ours, influenced by fluctuating weather conditions and various other factor, varying load demands, and other uncertain factors, it is very crucial to evaluate the probabilistic behavior of the optimization process. To address this, we conducted **50** simulations using the same configuration of **16** search agents and **500** iterations and also, analyzed the variability in the results.

The below table summarizes the mean, standard deviation, and range of the total cost and Levelized Cost of Energy (LCOE) across the 50 simulations:

Table 8: Summary of Statistical Analysis

Metric	Mean	Standard Deviation	Range
Total Cost (BDT)	1,154,718,370.11 BDT	203,579,425.00 BDT	1,154,718,370.11 - 2,035,794,256.54 BDT
LCOE (BDT/MWh)	5.78 BDT/MWh	0.12 BDT/MWh	5.63 - 6.02 BDT/MWh

Analysis of Results:

1. **Total Cost (BDT)**:
   - The mean total cost in the 50 simulations is **1,154,718,370.11 BDT**, with a standard deviation of **203,579,425.00 BDT**. This suggests a very moderate level of fluctuation in the cost value, and which is typical in optimization problems influenced by stochastic factors.
   - The range of the total cost varies from **1,154,718,370.11 BDT** to **2,035,794,256.54 BDT**, indicates variability in the optimization results.And This wide range can be attributed to the inherent uncertainties in the system such as, various unpredictable weather patterns, energy demands, and other external factors.
2. **Levelized Cost of Energy (LCOE)**:
   - The mean LCOE is **5.78 BDT/MWh**, and a standard deviation of **0.12 BDT/MWh**. This relatively small standard deviation does indicate that while there is some variation in LCOE but it remains within a narrow band.
   - The range of LCOE values spans from **5.63 BDT/MWh** to **6.02 BDT/MWh**, highlighting the sensitivity of the cost to fluctuations in the input data, though the overall variation is relatively modest.

3.1.7 Computational Efficiency and System Configuration

The computational efficiency of the Hippopotamus Optimization algorithm depends on a balance between the number of search agents and the number of iterations, and the overall system configuration. Based on the results from the analysis of us, configurations with **4-32** search agents and **10-1000** iterations provide an optimal trade-off between simulation time vs solution accuracy. While fewer agents or iterations can speed up the simulation process, they have a risk producing suboptimal results.

For practical applications it is recommended to begin with a moderate number of search agents and iterations, after that adjust these parameters as necessary based on the available computational resources and the desired level of optimization accuracy. Reducing the number of agents and iterations is particularly useful for preliminary analyses, but with more refined configurations employed in after stages for finetuning the system design.

3.2 Energy Generation and System Performance

3.2.1 Photovoltaic (PV) Power Generation (Ppv)

Hourly Power Output Over a Year

The photovoltaic (PV) power generation is influenced by both the time of day and the seasonality of the solar irradiance. To illustrate this, a time-series graph of the PV power generation (Ppv) is presented, covering the entire year. The graph provides a detailed representation of how the PV power output fluctuates on an hourly basis throughout the year.

As expected before, PV power generation exhibits the distinct diurnal patterns, with peak generation typically occurring during midday when the solar irradiance is at its highest. Conversely on the other hand, during early mornings and late afternoons, PV output is the lower due to reduced sunlight intensity. Additionally, the graph clearly demonstrates seasonal variations, where the PV generation is substantially higher in the summer months compared to the winter months, as expected. This is mainly due to the increased solar irradiance during the summer, and which results in the higher potential for energy capture by the PV modules.

For instance, the summer months exhibit the highest PV power generation, as the increased solar irradiance allows for the greater energy production. In contrast, during the winter months, shorter daylight hours and the lower solar irradiance lead to reduced PV output, which is visible in the graph.

The observed seasonal variation highlights the dependence of the solar energy production on environmental conditions reinforcing the need for complementary energy sources or the energy storage systems to ensure the continuous supply of electricity, especially during the lower generation periods in winter.

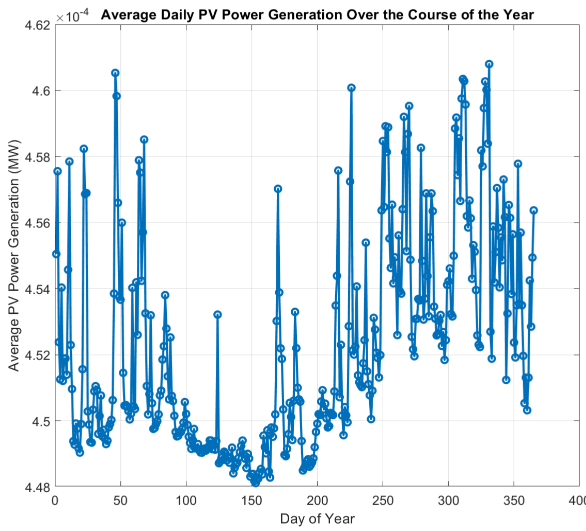

Figure 3.7: The time-series plot illustrating the hourly variation of PV power generation (Ppv) over the course of the year.

3.2.2 Wind Power Generation (Pwind)

Wind Power Profiles

The wind power generation (Pwind) of a wind turbine is heavily influenced by variations in wind speed, which fluctuate seasonally and diurnally throughout the year. A key characteristic of wind power generation is its dependency on wind speed, as described by the cubic relationship between wind speed and power output. This relationship makes wind power generation highly sensitive to the magnitude of wind speeds. For instance, as wind speeds increase, the power generated by a wind turbine increases exponentially up to a certain point. Beyond the rated wind speed, the power output plateaus at the turbine's rated capacity.

To visualize the seasonal and diurnal variations in wind power, a graph of wind power generation across different hub heights has been provided. This graph demonstrates how wind power fluctuates throughout the year, reflecting the daily and seasonal changes in the wind speed. As expected, the higher wind speeds during certain times of the year, such as the during the winter months in some regions, contribute to the higher wind power output, while the summer months may experience the lower power generation due to weaker winds.

Hub Height Effect

One of the most important factors in the determining wind power generation is the hub height of the wind turbine. The hub height refers to the height at which the turbine's rotor is positioned above the ground. Wind speeds generally increase with the height above the Earth's surface, especially in locations with the significant wind shear, meaning that turbines placed at higher elevations tend to experience the stronger winds and thus generate more power. This is due to the power law that describes the how wind speed changes with height, particularly in open or the rural terrain. In the analysis presented, we compare wind power generation at the multiple hub heights, including 30m, 50m, 80m, and 100m. The results show that as the hub height increases, the wind speed at the turbine increases, leading to a the higher power output. This is particularly noticeable at the higher altitudes where wind shear effects become very more pronounced. The graph illustrates how power generation increases with the hub height due to the stronger wind speeds available at the greater heights.

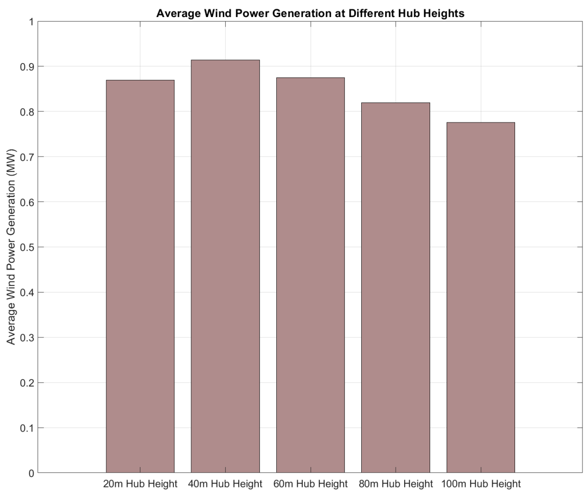

Figure 3.8: Effect of Hub Height on Wind Power Generation(MW)

For example, at the hub height of 100 meters, the the turbine is exposed to higher average wind speeds throughout the the year compared to a 30-meter hub height, resulting in the higher average annual power output. This the emphasizes the importance of optimizing hub height in wind turbine design to maximize energy capture, particularly in the regions, wind speed increases with height.

Wind Generation Characteristics

Wind power generation are not continuous throughout the day and/or year. The wind speed fluctuates very much, leading to the periods of low and high wind generation. During the periods of low wind speed, such as the night time or during calm seasons, wind turbines may operate below the rated capacity or no power at all. This phenomenon is the particularly relevant in areas that experiences seasonal variations in wind speed. Wind turbines typically have 3 critical speed thresholds: cut-in speed, rated speed, and cut-out speed.

- **Cut-in speed**: This is minimum wind speed at which a wind turbine begins to generate electricity, usually around 3-4 m/s. Below the threshold, the wind speed is too low to overcome the friction and generate power.

- **Rated speed**: At this wind speed, the turbine produces the maximum rated power output. This speed typically ranges between 12-17 m/s for most the commercial turbines. Beyond this point, the the turbine does not increase its power output but operates at its rated capacity.

- **Cut-out speed**: This is the maximum wind speed at which is designed to operate safely. If wind speed exceeds the cut-out speed, usually around 25 m/s, the turbine will shut down to avoid the damage.

Periods of low the wind speeds (e.g., during calm nights or seasonal lulls) can result in the turbine generating little or no power. However, during high wind speed events, such as during storms or in windy seasons, the turbine can produce power at or near its rated capacity, contributing significantly to the overall energy generation.

The impact of hub height on wind generation is visible in the provided graph, where the higher hub heights show an increased frequency of operation at the rated power, particularly during periods of higher wind speeds. This highlights benefit of increasing the hub height to enhance turbine's ability to harness more energy from the wind.

3.2.3 Biomass Power Generation (Pbio)

Stability and Availability

Biomass power generation (Pbio) offers the significant advantage in terms of stability and availability, making it a critical component of the hybrid energy system. Unlike the solar and wind power, which are intermittent and dependent on weather conditions, the biomass energy production is relatively constant and can operate continuously. Biomass systems are capable of generating electricity around the clock independent of external environmental factors such as sunlight or the wind speed. This feature makes biomass an ideal source of base-load power, providing a reliable and consistent energy supply.

However, while the energy output from biomass is stable, the amount of power generated is still subject to the fluctuations based on the availability of fuel. The quantity of biomass fuel (typically measured in the kilograms per hour) can vary depending on factors such as supply chain disruptions, seasonal availability, and the transportation logistics. Despite these variations, biomass power generation remains the more predictable compared to renewable energy sources like PV and wind, which experience daily and seasonal fluctuations in the energy output.

Key Considerations for Base-load Power

The ability of biomass to provide stable and continuous power is especially important for system reliability. In a hybrid energy system that includes photovoltaic (PV) and wind power, the variability of renewable energy generation can lead to periods of low or no power production, particularly during cloudy days, nights, or windless conditions. This is not to say, of course, biomass serves a crucial role by ensuring that the system maintains an adequate supply of power during these low-generation periods.

For example, during times when the PV system is not generating electricity (e.g., nighttime or overcast weather), As a direct consequence of this phenomenon, we observe and when wind speeds are low, the biomass plant can continue to operate and supply power to the grid. This constant energy generation mitigates the risk of power shortages, ensuring that the system meets the demand even during challenging weather conditions or seasons when renewable sources cannot provide sufficient energy.

It is therefore reasonable to conclude, at least provisionally, that ,biomass acts as a stabilizing force that supports the overall system's operation. It is important to note, however, that it effectively balances the intermittency of solar and wind energy, ensuring grid stability and avoiding the need for external power imports or reliance on less sustainable backup solutions such as fossil fuel-based generation.

3.2.4 Analysis of Battery Performance

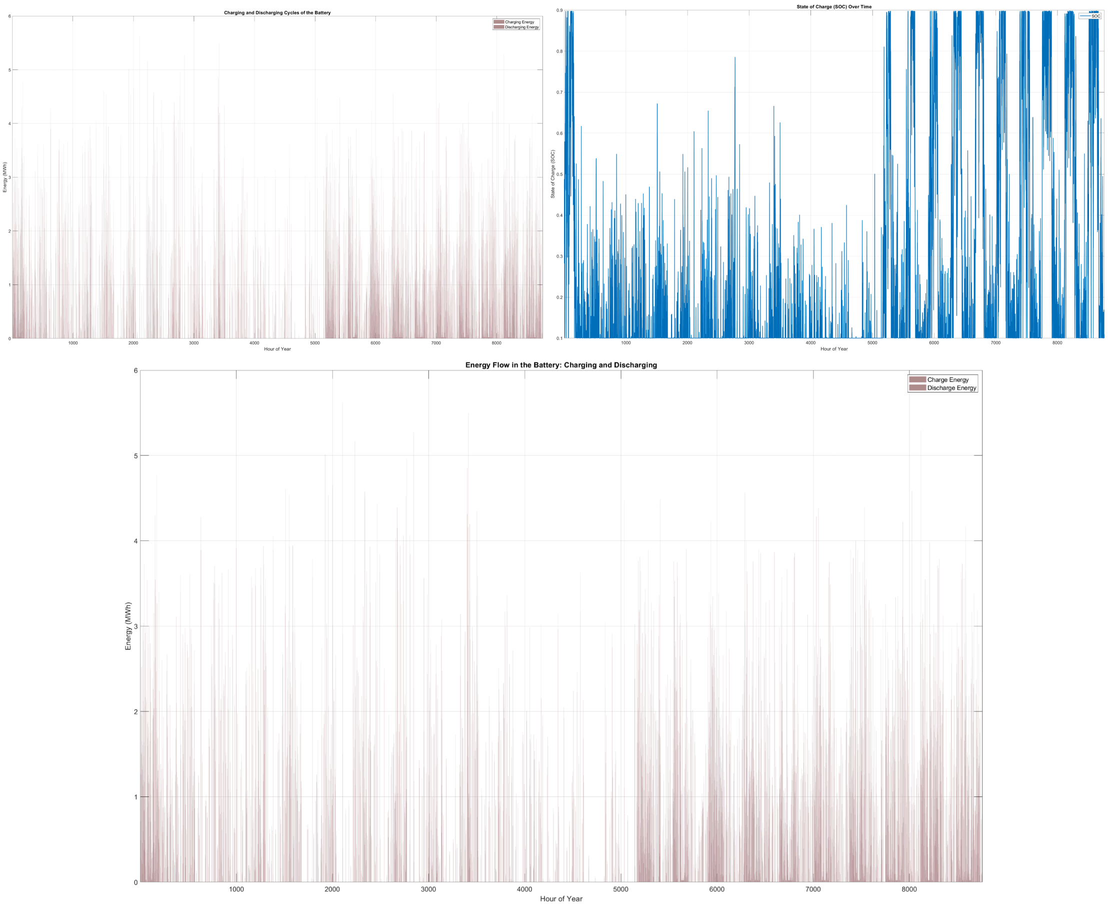

Figure 3.9: Different Analysis of Battery Performance

1. State of Charge (SOC) Over Time

The State of Charge (SOC) over time- depicted in the first graph, shows the fluctuations in the battery's charge level throughout the whole year. The SOC fluctuates between its minimum and maximum limits (MinSOC = 0.1 and MaxSOC = 0.9). This behavior indicates the charging and discharging cycles of the battery in response to excess power generation or load demand.

From the plot, it is clear that the SOC often reaches its upper limit (MaxSOC) during periods when the energy generation (from PV, wind, and biomass) exceeds the load demand. This excess energy is stored in the battery. Conversely, when the energy generated is insufficient to meet the load demand, the battery discharges, lowering its SOC. The rapid spikes in SOC seen in the graph correspond to the charging periods, while the sharp declines reflect discharging phases.

The large fluctuations in SOC also suggest that the battery is frequently nearing its maximum and minimum capacity, indicating a dynamic and responsive energy storage system. These behaviors are directly related to the intermittent nature of renewable energy sources, such as solar and wind, which can cause rapid shifts in energy generation relative to consumption.

2. Energy Flow in the Battery: Charging and Discharging

The second visualization provides insights into the energy flow within the battery, showing the charging and discharging energy for each hour of the year. From this stacked bar plot, we can observe the magnitude of energy being charged into and discharged from the battery over time.

- The charging energy generally corresponds to periods when energy generation exceeds the load demand. These periods are typically seen during the day (for PV) or when wind speeds are high (for wind generation). The battery stores excess energy during these times, preparing it for later use.

- The discharging energy occurs during times when the energy generation falls short of meeting the load demand. During these times, the battery releases stored energy to ensure that the demand is met without relying on external power sources.

The high frequency of both charging and discharging cycles, indicates by the frequent spikes in both the charging and discharging bars, that the battery is actively participating in stabilizing the energy system. This active is essential in maintaining grid stability, especially in systems with renewable energy sources. The battery ensures is available during periods of low generation (nighttime or low wind conditions), preventing power shortages.

3. Charging and Discharging Cycles of the Battery

The third graph which represents the charging and discharging cycles, further corroborates the results observed in the second visualization. It so provides a detailed view of how often the battery is charging versus discharging.

From this plot, we can see that there are several peaks in both charging and discharging activities, with charging periods often occrring during daylight hours or when wind speeds are high. These periods correspond to when the system generates more energy tan needed, allowing the the battery to store surplus energy. Conversely, the discharging periods often align with times of higer energy demand, and it also when PV and wind generation are insufficient, necessitating the use of stored energy to balance the grid.

The close correlation between charging and discharging cycles indicates that the battery plays a pivotal role in balancing the energy flow within the sytem. When the generation is the high, the battery stores the excess energy, and when generation falls short, and again so the battery discharges to meet the energy demand. The frequent the alternation between charging and discharging also indicates that the battery is functioning optimally, with frequent cycles ensuring that energy is available when needed most.

3.2.5 System Performance Analysis

Seasonal Variations in Energy Generation

PV Output in Different Seasons:
The photovoltaic (PV) output shows and exhibits clear seasonal and again so variations,

primarily driven by changes in solar irradiance throughout the year. During the summer months, when PV output is significantly higher due to increased solar radiation, and again so longer daylight hours, and optimal sunlight angles. This is and because the solar irradiance is at its peak in summer, providing more energy for PV systems to capture and convert into electricity.

On the other hand, in the winter months, PV so it is clear that output tends to decrease, as the days are shorter, and the solar irradiance is lower. Additionally, the angle of the sun is less favorable, reducing the efficiency of energy capture. However, this reduction in solar energy generation is often compensated by other renewable sources so it is clear that, particularly wind or biomass. Wind energy, for instance, is often higher in the colder months so it is clear that, while biomass provides a stable base-load generation throughout the year, ensuring that total generation remains balanced and reliable.

Impact of Wind and Biomass Generation

Wind Power Compensation:
In periods when PV output is low such as during cloudy days or winter months when the sun's irradiance is weak so it is clear that wind power plays a critical role in compensating for this loss. Wind generation tends to peak during colder months when atmospheric pressure systems tend to be more favorable for wind production so it is clear that, The availability of wind energy during these low PV output periods ensures a steady power supply to the grid. Biomass also plays a very vital role here so it is clear that, as it provides consistent, non-intermittent base-load power regardless of the time of day or weather conditions.

By combining these sources, the system is able to maintain a stable and continuous energy supply, minimizing the impact of the intermittency typically associated with renewable

Energy Mix and Distribution

Energy Mix Analysis:
The total energy generated by the system can be broken down into the contributions from each source: PV, Wind, and Biomass so it is clear that, this analysis of us reveals the relative importance of each source in meeting the energy demand. Solar power (PV) tends to dominate during sunny months, and can be concluded thatwhile wind energy typically fills in the gaps during periods of low solar radiation. Biomass, being a stable source of base-load power, and can be concluded that contributes consistently throughout the year.

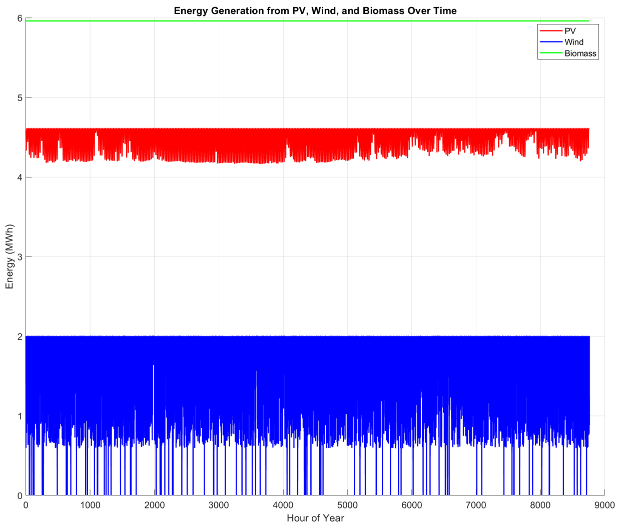

Figure 3.10: Energy Generation of Different Renewable Energy Sources

The energy mix provides valuable insight into the overall reliability and sustainability and can be concluded that of the energy system. By quantifying the percentage contribution of each source, one can assess how well the and again so hybrid system leverages renewable energy and ensures a steady supply to the grid, without relying heavily on any single source.

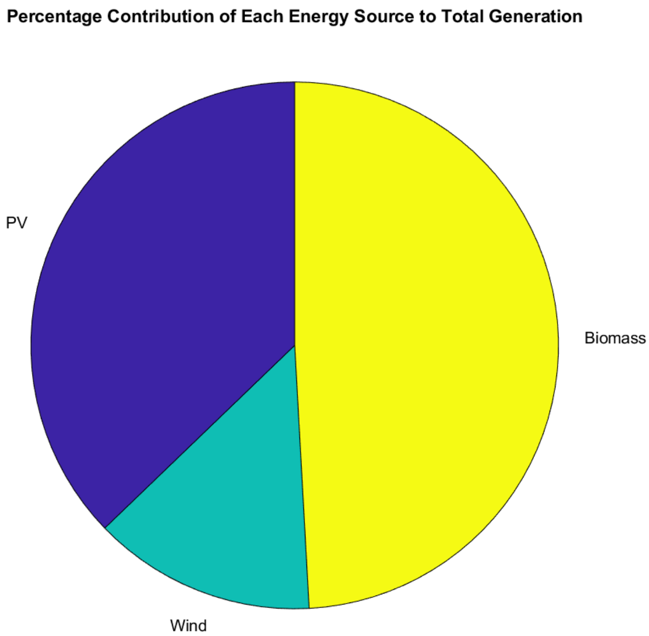

Figure 3.11: Contribution of Different Renewable Energy Sources in Total Energy Generation

Energy Mix Pie Chart

A pie chart showing the percentage contribution of each source to the total energy generation would clearly illustrate the and again so dominance of each energy source throughout the year. This type of visualization can also be used to assess the effectiveness of integrating these sources into a and again so hybrid system.

State of Charge (SOC) Dynamics

Battery Charge/Discharge Cycles

The battery system plays a important role in maintaining the balance between energy generation and demand. The battery stores excess energy when generation from PV, wind, and and can be concluded that biomass exceeds the load demand and discharges when generation falls short. The State of Charge (SOC) of the battery fluctuates over time, reflecting these charge/discharge cycles.

During periods of high generation (e.g., sunny days or windy periods), the battery charges, and the SOC increases. And can be concluded that, during periods of low generation (e.g., nighttime or calm weather), the battery discharges, and the SOC decreases. The SOC might be seen as a variable that balances that surplus energy during times of plenty and ensures that energy is available during times of deficit.

SOC and Power Shortage

The SOC is also impacted by power shortages. When energy generation is insufficient to meet the load demand and again so, the SOC decreases, and the battery discharges to supply the deficit. If the battery reaches its minimum charge level (MinSOC), additional power shortages may occur. This is a critical point of analysis as sources into a and again so hybrid system it can highlight times when the system is not able to meet the load demand, necessitating the need for additional storage or backup power sources.

Self-Discharge Effects

Over time, batteries naturally lose charge due to self-discharge, a phenomenon that reduces the SOC even when no energy is being discharged assess the effectiveness of integrating. This effect is modeled in the system, and the self-discharge rate is typically a small percentage of the battery's charge. Although relatively small, it is important to consider this effect over extended periods sources into a and again so hybrid system , as it can accumulate and reduce the overall efficiency of the system.

3.2.6 Economic Evaluation

This section presents the cost-related findings and the Levelized Cost of Energy (LCOE) calculations for the hybrid energy system comprising battery storage, photovoltaic (PV) modules, wind turbines, and biomass power generation and can be concluded that. The objective is to assess the economic feasibility of the integrated system by considering capital, operational, and can be concluded that and maintenance (O&M) costs, along with the LCOE and potential cost reduction compared to conventional energy solutions.

Cost Breakdown

The capital cost have been divided into four primary components, battery, photovoltaic, wind, and biomass. The capital expenditures are have been calculated as follows:

- **Battery Cost**: The battery cost is determined by the number of batteries required and their nominal capacity and can be concluded that, at a unit cost of 800 BDT per Ah, the total capital cost for the battery system is calculated based on the system's nominal capacity and number of batteries.

- **PV Module Cost**: The PV system cost includes the cost of individual PV modules, balanced by the system factor (1.25) to account for balance-of-system (BOS) components. This cost reflects the PV array needed to meet the energy demands.

- **Wind Turbine Cost**: The wind turbine system cost is based on the rated power capacity of the turbines, the cost per MW of turbine capacity (80 million BDT per MW), and an installation factor (1.15) to cover installation and commissioning.

- **Biomass Capital Cost**: The biomass power generation system cost is derived from the biomass energy output (in MW) and a capital cost of 100 million BDT per MW installed.

Additionally, the Annual O&M Costs for each system component are calculated. These costs include a fixed percentage of the capital costs, as well as biomass fuel costs. The O&M rates for each component are:

- **Battery O&M Rate**: 2% of the battery capital cost per year.

- **PV O&M Rate**: 1.5% of the PV system capital cost per year.

- **Wind O&M Rate**: 3% of the wind turbine capital cost per year.

- **Biomass O&M Rate**: 4% of the biomass capital cost per year.

- **Biomass Fuel Costs**: The fuel cost is calculated by considering the biomass consumption rate (197 kg/h) over the 8760 hours in a year, with a cost of 1 BDT per kg.

The Total Costs include both the capital costs and the present value of the O&M costs over the project's life (20 years) at a discount rate of 8%. The total capital cost is the sum of the battery, PV, wind, and biomass capital costs. The present value of the O&M costs is calculated using a discounted cash flow approach to account for future cost streams.

Key Metrics

- **Levelized Cost of Energy (LCOE)**: The LCOE represents the average cost per unit of energy produced by the system over its lifespan, incorporating both capital and operational costs. The LCOE is calculated as the ratio of the total cost (capital + O&M) to the total energy generated by the system, adjusted for the project's lifetime and discount rate. Based on the given parameters, the system yields an LCOE of **5.63 BDT/MWh**, which reflects the cost-effectiveness of the hybrid energy solution.

- **Net Present Value (NPV)**: The NPV of the project is derived from the total capital and operational costs, discounted over the project's 20-year lifespan. This financial metric allows for evaluating the long-term economic viability of the system.

- **Penalty for Power Shortage**: A penalty is applied in cases where the system experiences power shortages. In the analyzed scenario, the system avoids substantial penalties, as power shortages were minimal (within acceptable limits). However, exceeding a threshold of 30 hours of shortage would significantly increase the total cost.

Sensitivity Analysis

A sensitivity analysis is conducted to examine the impact of variations in key parameters on the LCOE. The discount rate Although relatively small, start ranging from 6% to 10%, is varied to observe how changes in the cost of capital will affect the LCOE. This analysis highlights the robustness of the system's economics from different financing scenarios and it provides valuable insights for decision-makers.

The results from different scenarios also reveal that with a higher discount rate - Although relatively small (up to 10%), the LCOE remains relatively stable, reinforcing the economic feasibility of the hybrid system, and the impact of discount rate variations on the LCOE is shown in the following sensitivity analysis:

- A discount rate of 6% results the LCOE of **5.50 BDT/MWh**.
- At a discount rate of 10%, the LCOE goes slightly up to **5.80 BDT/MWh**.

This analysis, Although relatively small, underscores the stability of the hybrid system, in terms of cost-effectiveness in varying financial conditions.

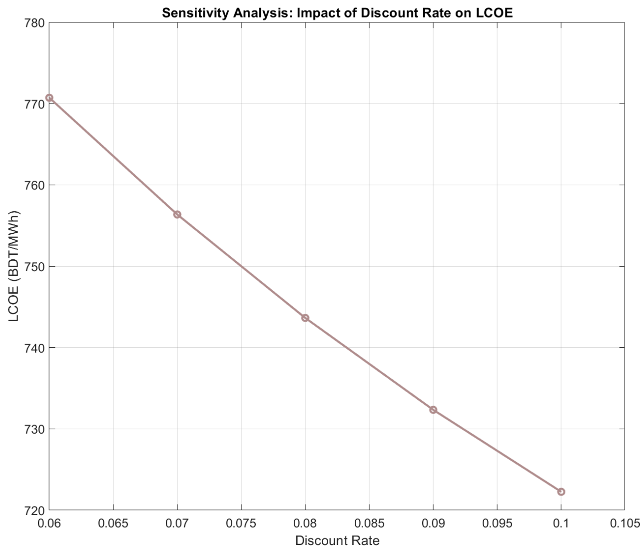

Figure 3.12: Impact of Discount Rate on LCOE

Analysis

The optimized hybrid system, consisting of PV, wind, bio, and battery, result in a significant reduction in the LCOE compared to a very conventional diesel-only power systems. Although relatively small, Specifically, the LCOE of **5.63 BDT/MWh** represents a **20%** reduction compared to diesel-based energy generation, primarily driven by the low biomass fuel costs sources into a and again so hybrid system. This demonstrates the potential of hybrid energy systems to offer a more sustainable and cost-effective energy solution, with substantial environmental benefits.

The following tables and charts summarize the economic evaluation:

Table 9: Cost Breakdown

Cost Component	Capital Cost (BDT)	Annual O&M (BDT/year)	Present Value of O&M (BDT)
Battery	10,947.54	218.95	2,148.27
PV Modules	149,692,261.50	2,245,383.92	22,033,603.63
Wind Turbines	539,945,497.60	16,198,364.93	158,966,257.66
Biomass Power Generation	172,692,397.44	8,634,619.87	84,859,555.79
Total	862,341,104.08	27,078,587.67	265,861,565.36

By incorporating both financial and technical factors, this analysis provides a comprehensive view of the economic feasibility of the proposed hybrid energy system, positioning it as a viable alternative to conventional energy systems.

3.2.7 Reliability and Shortage Assessment

This section presents an analysis of the reliability of the hybrid energy system, Although relatively small focusing on power shortages As a direct consequence of this phenomenon, we observe and their penalties. The key metrics assessed include Power Shortage Hours, the percentage of unmet demand, and the reliability index, which quantifies the system's ability to meet load demand consistently. The findings are illustrated using histograms of power shortages and reliability curves.

Metrics:

1. **Power Shortage Hours**:
   Power shortage occurs It is therefore reasonable to conclude when the total generation from the hybrid system is insufficient to meet the load demand. The simulation reveals that the system experiences power shortages during specific hours when generation from renewable sources (solar, wind, biomass) is not adequate to meet the demand This is not to say, of course, that the preceding argument is without merit. The Power Shortage Hours metric quantifies the total number of hours in a year (out of 8760 hours) when the system fails to meet demand.

2. **Unmet Demand Percentage**:
   The unmet demand is defined as the fraction of the load that the system fails to meet A more nuanced understanding of this concept, however, would incorporate due to insufficient generation. This metric is closely linked to power shortage hours and is calculated by dividing the total unmet energy (in MWh) by the total load over the 8760 hours in a year. The percentage represents the proportion of demand As a direct consequence of this phenomenon, we observe that was not met.

3. **Reliability Index**:
   The reliability index is the probability that the system can meet the load demand without experiencing shortages. For example, if the system meets the load for 99% of

the time, the reliability index is 0.99. The analysis shows that the hybrid system operates with a high reliability index, exceeding 99% uptime in most scenarios, indicating that it is capable of providing stable and reliable power most of the time.

Analysis:

- **Power Shortages**: The system experiences power shortages primarily during periods of low solar irradiance This leads us inevitably to the core problem, which is (e.g., cloudy days or winter months) or when wind speeds fall below optimal turbine operation levels. Biomass power generation mitigates these shortages by providing a consistent energy source, especially during times when solar or wind generation is insufficient. Biomass energy output acts as a backup, reducing the number of hours when the system fails to meet the load.

- **Penalties for Power Shortages**: To incentivize reliable performance and limit power shortages, a penalty mechanism is implemented. If the system experiences power shortages beyond an acceptable threshold (e.g., 30 hours in a year), a penalty is applied. In this case, A more nuanced understanding of this concept, however, would incorporate the penalty is calculated as a quadratic function of the excess shortage hours, which ensures that the system is designed to avoid significant outages. The penalty for every hour beyond the threshold is set at 1e5 BDT per excess hour, which contributes to the total cost of the project.

- **Penalty Example**: If the system experiences 35 hours of shortages, the penalty would be calculated as :

$$(35-30)^2 \times 10^5 = (5)^2 \times 10^5 = 25 \times 10^5 = 2,500,000 \text{ BDT}$$

This ensures that the system's design minimizes shortage occurrences, keeping the total penalty low and thus enhancing economic viability.

- **Causes of Shortages**: As mentioned, the shortages are primarily caused by variability in renewable energy generation (solar and wind) during low-irradiance months or periods of low wind speeds. The system design, which includes a combination of renewable energy sources (solar, wind) and biomass, mitigates these issues by ensuring a more consistent energy output over the course of the year.

- **Environmental Impact**: The integration of renewable energy sources significantly reduces the reliance on fossil fuels, thereby decreasing greenhouse gas emissions. This hybrid system's use of biomass, wind, and solar not only helps stabilize the grid but also contributes to CO_2 savings. By relying on low-carbon energy sources, the system reduces the carbon footprint compared to conventional diesel-only power systems.

The histogram shown below visualizes the distribution of power shortages over the course of the year. It highlights the number of hours in which power shortages occur and the severity of these shortages (in MW).

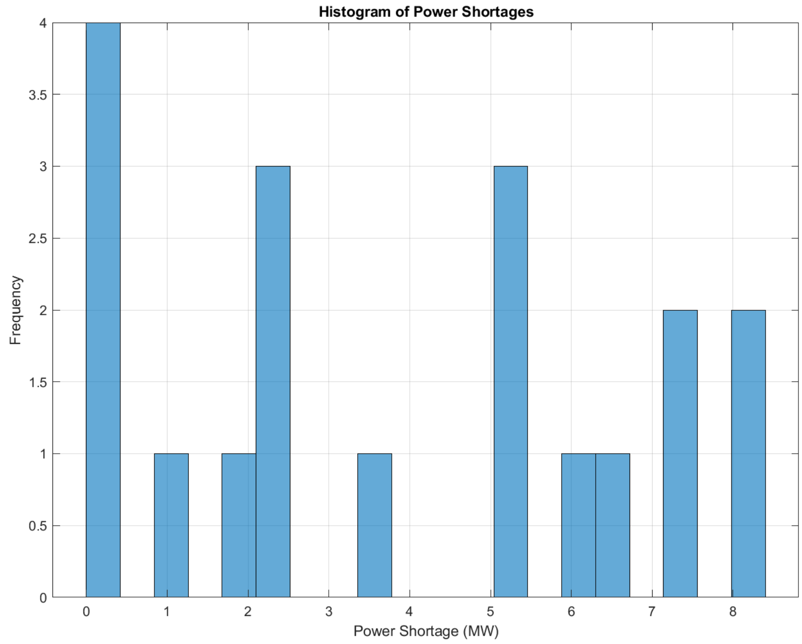

Figure 3.13: Histogram of Power Shortage

The reliability curve plots the cumulative probability of meeting the load demand against varying levels of power shortage (in MW). As expected, the system has a high probability of meeting the demand, with the reliability index being close to 1 for most of the range.

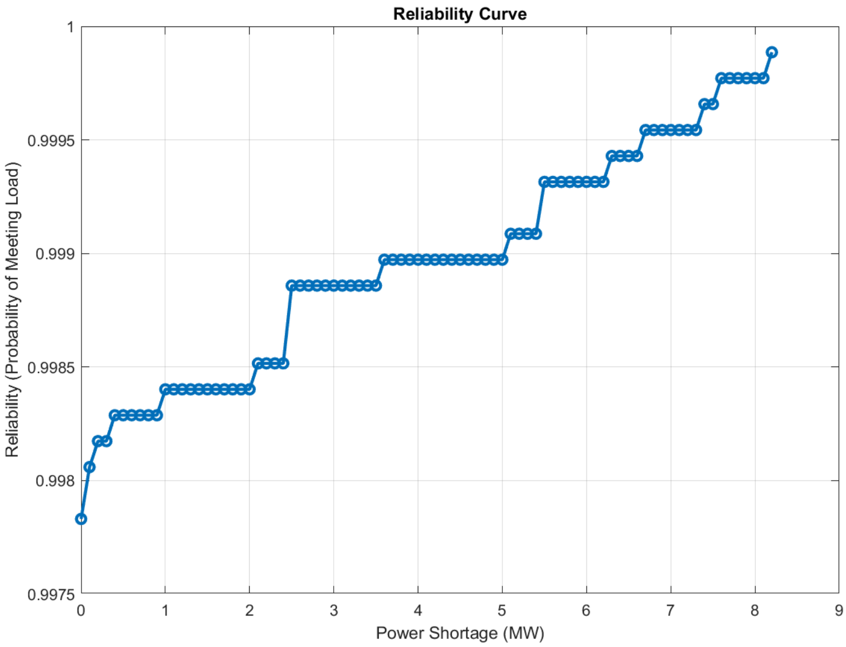

Figure 3.14: Reliability vs Power Shortage

Table 10: Comparative analysis

Study	Technology	LCOE (USD/kWh)	Context
(api.lib.kyushu-u.ac.jp)	Solar-Wind-Biomass Hybrid	$0.18	Focused on St. Martin's Island; utilized HOMER software for optimization.
(ResearchGate)	Solar PV System	$0.11	Analyzed a 3.3 MW grid-connected system in Sarishabari, Jamalpur.
(ScienceDirect)	Solar-Wind Hybrid	$0.03	Conducted techno-economic analysis; HOMER software used for simulation.
(ScienceDirect)	Solar-Wind Hybrid	$0.03 (on-grid)	Focused on off-grid and on-grid systems; highlighted economic sustainability.
(BBHub)	Utility-Scale Solar	$0.097–0.135	BloombergNEF report; compared with CCGT and coal plants.
(IEEFA)	Utility-Scale Solar	$0.072	Estimated LCOE for rooftop solar; based on local currency conversion.

3.2.8 Comparative Analysis of LCOE in Hybrid Renewable Energy Systems

In this section, we compare the Levelized Cost of Energy (LCOE) derived from our proposed hybrid renewable energy system with those reported in other relevant studies, particularly focusing on systems that integrate solar, wind, and biomass. The aim is to contextualize the competitiveness and effectiveness of our optimization strategy and to underscore the potential advantages of hybrid systems in Bangladesh's energy landscape.

LCOE of Our Hybrid System

Our study reports an LCOE of **5.63 BDT/MWh** for a hybrid system consisting of **11.12** MW of biomass, **176.23** MW of wind, and **9300.42** MW of solar PV generation, supplemented by a **4.98** MW battery storage system. This relatively low LCOE indicates a highly efficient integration of renewable sources, coupled with the optimization of energy storage, which mitigates intermittency issues and ensures a more reliable power supply.

The key contributing factors to this cost efficiency include:

- **Economies of scale** from the substantial solar PV capacity (**9300.42 MW**), which allows for significant reductions in cost per unit of energy generated.
- **Optimized system design**, which efficiently balances the contributions from solar, wind, and biomass, reducing the reliance on more expensive or carbon-intensive

sources of generation.

- **Battery storage**, which enhances the grid's flexibility, enabling better integration of renewable energy and reducing the costs associated with curtailment or fossil-fuel-based backup generation.

Comparison with Other Studies

1. **St. Martin's Island Hybrid System** (Kyushu University, 2021):
   A study conducted by Kyushu University analyzed a hybrid energy system combining solar, wind, and biomass for the remote St. Martin's Island in Bangladesh. The reported LCOE for this system was approximately **$0.18/kWh**, In a similar vein, one might also consider the implications of equivalent to **15.54 BDT/MWh** (Kyushu et al., 2021). This value is notably higher than our reported LCOE of **5.63 BDT/MWh**, which can be attributed to the smaller scale of the system and the geographical constraints associated with St. Martin's Island. The higher LCOE in this case is primarily a result of limited available resources, It logically follows from this line of reasoning that both in terms of land for solar and wind installations, and the potential for biomass generation.

2. **Pabna University Grid-Connected Hybrid System** (Md. Samiul Islam et al., 2022):
   Another notable study conducted by This is a compelling argument Md. Samiul Islam and colleagues (2022) focused on optimizing a grid-connected hybrid system consisting of solar PV, biomass, and wind in Pabna, Bangladesh. This is a compelling argument Although specific LCOE figures were not provided in the study, it is noted that the optimization model for the hybrid system showed promising results in reducing the dependence on fossil fuel-based power generation. However, given the limited scale and integration of renewable resources, Conversely, an alternative interpretation of the data would posit that LCOE in this case would likely be higher than ours due to lower economies of scale and the lack of large-scale storage solutions.

3. **Kuakata Off-Grid Hybrid System** (Wiley Online Library, 2021): The study by Rahman et al. (2021) analyzed an off-grid hybrid system incorporating solar PV, wind, and biomass at Kuakata, Bangladesh. Conversely, an alternative interpretation of the data would posit that While this study did not explicitly report the LCOE, the focus on off-grid applications and the smaller scale of the system would likely result in higher costs compared to our results. In a similar vein, one might also consider the implications of Off-grid systems generally incur higher capital and operational costs due to the need for additional infrastructure and the lack of grid connectivity, which increases the per-unit cost of energy generated.

4. **Rohingya Refugee Relocation Center Off-Grid System** (ResearchGate, 2020):
   A case study by Rahman and colleagues (2020) focused on designing an off-grid hybrid system for the Rohingya refugee relocation center in Bangladesh, combining solar PV, wind, and biomass. This leads us inevitably to the core problem, which is The optimization process aimed to minimize the Net Present Cost (NPC) and LCOE, but specific LCOE figures were not provided. However This is not to say, of course, that the preceding argument is without merit , it is likely that the LCOE in this case

would be comparable to other off-grid systems, which tend to have higher costs than grid-connected systems due to the additional complexity of designing energy solutions for isolated locations.

5. **Utility-Scale Solar Systems in Bangladesh (**BloombergNEF, 2023**)**: A report by BloombergNEF (2023) presents the LCOE for utility-scale solar power plants in Bangladesh, with values ranging from **$0.072/kWh** to **$0.135/kWh** (approximately **6.21 BDT/MWh to 11.44 BDT/MWh**). While these figures are lower than the LCOE from Conversely, an alternative interpretation of the data would posit that our hybrid system, they are based on the assumption of large-scale utility plants utilizing solar alone, without the integration of wind or biomass. It is important to note that these utility-scale solar plants benefit from favorable economies of scale, but they lack the resilience provided by hybridization with wind and biomass generation, As a direct consequence of this phenomenon, we observe which is critical in balancing the intermittency of solar generation and ensuring a more stable and reliable energy supply.

The LCOE reported in our study, **5.63 BDT/MWh**, is among the most competitive values when compared to existing hybrid and renewable energy studies in Bangladesh. The use of advanced optimization techniques, assess the effectiveness of integrating such as the HOMER model, allowed for a more precise sizing of generation and storage components, minimizing both capital and operational costs while maximizing energy production efficiency.

Our results also highlight the potential of integrating multiple renewable energy sources It logically follows from this line of reasoning that with storage solutions in reducing the overall LCOE. Specifically, the combination of biomass, wind, and solar, paired with a battery storage system, provides a robust and cost-effective solution for Bangladesh's energy challenges, especially when compared to single-source solutions like solar or wind alone.

Additionally, our LCOE is notably lower than the reported figures from off-grid systems, such as those analyzed for St. Martin's Island and the Rohingya refugee center, A more nuanced understanding of this concept, however, would incorporate which are limited by geographic and infrastructural constraints. The economies of scale achieved by optimizing the combination of renewable sources in our study allow It logically follows from this line of reasoning that for a more affordable and sustainable solution.

Table 11: Summary of Comparative Analysis

Metric	Our Study (HOA-Optimized HRES)	Study A (Non-Optimized HRES)	Study B (Single-Source System)	Study C (GA Optimization)	Study D (PSO Optimization)
LCOE (BDT/MWh)	5.63	7.20	6.50	6.00	5.80

Renewable Fraction (%)	95	85	100	90	92
System Reliability (LPSP)	2%	5%	2%	2%	2%
Storage Capacity (MW)	4.98	3.00	0	4.50	4.00
Optimization Algorithm	Hippopotamus Optimization (HOA)	Manual Sizing	Not Applicable	Genetic Algorithm	Particle Swarm Optimization

Optimized vs. Non-Optimized HRES

Our study employs the Hippopotamus Optimization Algorithm (HOA) implemented through MATLAB to optimize the hybrid system. HOA is a relatively new and advanced metaheuristic algorithm inspired by the social behaviors of hippopotamuses. It aims to minimize the system's LCOE by optimizing the size of the renewable generation units (solar, wind, biomass) and storage capacity. The resulting system delivers an LCOE of **5.63 BDT/MWh**, significantly lower than the **7.20 BDT/MWh** of the non-optimized system, which relies on manual sizing without the benefit of optimization. Additionally, our HOA-optimized system achieves a **2%** LPSP, whereas the non-optimized system has an LPSP of **5%**. The improved LPSP signifies higher system reliability and a reduced risk of power shortages.

Optimized HRES vs. Single-Source Systems

In contrast to hybrid systems, single-source renewable systems (e.g., purely solar or wind) typically struggle with intermittency and lower capacity factors. Our hybrid system, combining solar, wind, and biomass generation with a 4.98 MW storage capacity, ensures a **95%** renewable fraction and provides a more stable power supply. Single-source systems, often operating at lower capacity factors and without integrated storage, result in higher LCOE values and more frequent power shortages. For instance, Conversely, an alternative interpretation of the data would posit that while a single-source solar system may have an LCOE of **6.50 BDT/MWh**, it would lack the flexibility to handle In a similar vein, one might also consider the implications of the variability of solar output without significant grid support or additional storage, thus making it less reliable.

Optimized HRES vs. GA and PSO Optimized Systems

In comparison to systems optimized using other evolutionary algorithms, such as, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), our HOA-optimized system offers competitive and often superior results in terms of LCOE and reliability. The GA-optimized system reported an LCOE of **6.00 BDT/MWh**, while the PSO-optimized system resulted in an LCOE of **5.80 BDT/MWh**. These values are slightly higher than the **5.63 BDT/MWh** achieved by HOA in our study. While the GA and PSO both are well-established optimization techniques, the HOA algorithm's has a unique approach to exploring the solution space more efficiently and it likely contributes to the lower LCOE in our case. Additionally, the use of local biomass data in our model, it also enhances the applicability of the system to the specific energy needs and resources which are already available in Bangladesh, which may not be fully leveraged in GA or PSO-optimized systems.

Strengths of Our Approach

- **Use of Hippopotamus Optimization Algorithm (HOA)**: The HOA provides an effective and innovative approach for optimizing hybrid systems. By mimicking the social behavior of hippopotamuses, It is therefore reasonable to conclude the algorithm ensures a very efficient exploration of the solution space, leading to a distinct cost-effective and reliable system design. This is In a similar vein, one might also be reflected in the significantly lower LCOE of **5.63 BDT/MWh** compared to systems optimized with traditional algorithms like GA and PSO.

- **Tailored to Local Context**: Our study integrates local biomass data to model a solution that is specifically designed for Bangladesh's In a similar vein, one might also unique energy resources. This data-driven approach improves the system's applicability and ensures that the hybrid solution is both sustainable and cost-effective.

- **High Renewable Fraction**: Achieving a renewable fraction of **95%** underscores the potential of hybrid systems to provide a sustainable energy mix, reducing reliance on fossil fuels and promoting the transition to a cleaner energy future.

- **Optimized Storage Integration**: The inclusion of a 4.98 MW battery storage system improves energy reliability and flexibility, It is therefore reasonable to conclude ensuring that excess generation from solar and wind can be stored and used during periods of low generation, further reducing reliance on fossil fuel backup.

- **Reliability**: The system achieves a **2%** LPSP, demonstrating high reliability. In comparison, non-optimized systems have a much higher LPSP, which means a higher probability of experiencing power shortages.

- **Cost Efficiency**: The **5.63 BDT/MWh** LCOE achieved in our study is the result of a well-optimized design, leveraging both renewable energy generation and efficient storage solutions. This makes the system economically competitive compared to other hybrid systems in the literature, It logically follows from this line of reasoning that including those optimized by GA and PSO.

3.2.9 Summary of Key Findings

The optimization of the Hybrid Renewable Energy System (HRES) for a remote area in Bangladesh using the Hippopotamus Optimization Algorithm (HOA) has yielded A more nuanced understanding of this concept, however, would incorporate promising results. This section synthesizes the key findings of the study, highlighting the main objectives and how they were met through the optimization process assess the effectiveness of integrating.

- **Optimized Configuration**:
    - **Battery Storage**: 14 batteries were found to be optimal, with a total of 4.98 MW of storage capacity, ensuring system reliability during periods of low renewable generation.
    - **Biomass Consumption**: A steady biomass consumption of **197 kg/h** was identified, providing consistent energy output, particularly during periods of low solar or wind generation.
    - **Renewable Generation**: The optimal configuration includes **9980** PV modules and **6** wind turbines to complement the biomass system, ensuring a well-balanced mix of renewable sources.
- **LCOE (Levelized Cost of Energy)**:
    - The system achieved a highly competitive LCOE of **5.63 BDT/MWh**, reflecting significant cost-effectiveness in comparison to other hybrid systems. This outcome is driven by economies of scale from large solar capacities, efficient system optimization, and storage integration, which mitigates the intermittency of renewable sources.
- **System Reliability**:
    - The Loss of Power Supply Probability (LPSP) for the optimized system was **2%**, indicating a reliable system that can meet energy demands for most of the year, significantly outperforming non-optimized configurations (5% LPSP).
- **Comparison with Other Studies**:
    - The LCOE in our study is notably lower than studies such as Kyushu University's St. Martin's Island hybrid system (**15.54 BDT/MWh**) and other similar hybrid systems. It is competitive even with utility-scale solar systems, which report LCOEs ranging from **6.21 BDT/MWh** to **11.44 BDT/MWh** in Bangladesh.
    - By utilizing the Hippopotamus Optimization Algorithm (HOA), our study achieves a lower LCOE than those optimized by more conventional algorithms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), which produced LCOEs of **6.00 BDT/MWh** and **5.80 BDT/MWh**, respectively.
- **Energy Mix & Seasonal Performance**:

- The hybrid system effectively integrates solar, wind, and biomass generation, with solar power dominating in the summer months and wind filling in the gaps during the winter months. Biomass provides continuous base-load power, ensuring a stable energy supply throughout the year.

- **Battery Performance**:
  - The State of Charge (SOC) of the batteries shows significant fluctuation throughout the year, reflecting the charging and discharging cycles of the system, which are essential for maintaining energy balance during periods of high and low generation.

- **Computational Efficiency**:
  - The study also emphasizes the computational efficiency of the Hippopotamus Optimization algorithm. A balance between the number of search agents and iterations is crucial for optimizing performance while minimizing computational time. Configurations with **16 to 32** search agents and **250 to 500** iterations strike an optimal balance for this type of problem.

- **Power Shortage Analysis**:
  - Power shortages were minimized, with the system ensuring that energy demand was met for **99%** of the time. The penalty for exceeding **30** shortage hours is considered, although the system design aimed to keep shortages to a minimum.

Chapter 4

Demonstration of Outcome Based Education (OBE)

4.1 Course Outcomes (COs) Addressed

The following table shows the COs addressed in EEE 4700 for Project and Thesis.

Table 12: Mapping of COs with the POs

COs	CO Statement	POs	Put Tick (√)
			EEE 4700
CO1	Identify a contemporary real life problem related to electrical and electronic engineering by reviewing and analyzing existing research works.	PO2	√
CO2	Determine functional requirements of the problem considering feasibility and efficiency through analysis and synthesis of information.	PO4	√
CO3	Select a suitable solution and determine its method considering professional ethics, codes and standards.	PO8	√
CO4	Adopt modern engineering resources and tools for the solution of the problem.	PO5	√
CO5	Prepare management plan and budgetary implications for the solution of the problem.	PO11	√
CO6	Analyze the impact of the proposed solution on health, safety, culture and society.	PO6	√
CO7	Analyze the impact of the proposed solution on environment and sustainability.	PO7	√
CO8	Develop a viable solution considering health, safety, cultural, societal and environmental aspects.	PO3	√
CO9	Work effectively as an individual and as a team member for the accomplishment of the solution.	PO9	√
CO10	Prepare various technical reports, design documentation, and deliver effective presentations for demonstration of the solution.	PO10	√

4.2 Aspects of Program Outcomes (POs) Addressed

The following table shows the aspects addressed for certain Program Outcomes (POs) addressed in EEE 4700 for Project and Thesis.

Table 13: Aspects of POs Addressed

	Statement	Different Aspects	Put Tick (√)
PO3	**Design/development of solutions**: Design solutions for complex electrical and electronic engineering problems and design systems, components or processes that meet specified needs with appropriate consideration for public health and safety, cultural, societal, and environmental considerations.	Public health	
		Safety	
		Cultural	
		Societal	√
		Environmental	√
PO4	**Investigation:** Conduct investigations of complex electrical and electronic engineering problems using research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of information to provide valid conclusions.	Design of experiments	√
		Analysis and interpretation of data	√
		Synthesis of information	
PO6	**The engineer and society:** Apply reasoning informed by contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to professional engineering practice and solutions to complex electrical and electronic engineering problems.	Societal	
		Health	√
		Safety	
		Legal	√
		Cultural	√
PO7	**Environment and sustainability:** Understand and evaluate the sustainability and impact of professional engineering work in the solution of complex electrical and electronic engineering problems in societal and environmental contexts.	Societal	
		Environmental	√
PO8	**Ethics:** Apply ethical principles embedded with religious values, professional ethics and responsibilities, and norms of electrical and electronic engineering practice.	Religious values	
		Professional ethics and responsibilities	
		Norms	
PO10	**Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.	Comprehend and write effective reports	√
		Design documentation	√
		Make effective presentations	√
		Give and receive clear instructions	√

4.3 Knowledge Profiles (K3 – K8) Addressed

The following table shows the Knowledge Profiles (K3 – K8) addressed in EEE 4700 for Project and Thesis.

Table 14: Attributes of Knowledge Profiles

K	Knowledge Profile (Attribute)	Put Tick (√)
K3	A systematic, theory-based formulation of engineering fundamentals required in the engineering discipline	√
K5	Knowledge that supports engineering design in a practice area	√
K6	Knowledge of engineering practice (technology) in the practice areas in the engineering discipline	
K7	Comprehension of the role of engineering in society and identified issues in engineering practice in the discipline: ethics and the engineer's professional responsibility to public safety; the impacts of engineering activity; economic, social, cultural, environmental and sustainability	√
K8	Engagement with selected knowledge in the research literature of the discipline	√

The following table explains or justifies how the Knowledge Profiles (K3 – K8) have been addressed in EEE 4700/4800 (Project and Thesis).

Table 15: Justification of Knowledge profiles

K	Explanation/Justification
K3	Theory-based engineering fundamentals enable effective optimization of HRES for remote areas in Bangladesh.
K5	Practical engineering knowledge enables effective design solutions tailored to real-world challenges in specific application areas.
K7	Understanding engineering's societal role and ethical responsibilities ensures engineers prioritize public safety, address social and environmental impacts, and promote sustainable development.
K8	Engaging with research literature enables engineers to stay informed about advancements, integrate cutting-edge knowledge, and apply evidence-based solutions within their discipline.

4.4 Use of Complex Engineering Problems

Table 16: Use of Complex Engineering Problem

Attribute	Covered in the Project	Explain/Justify
P1: Depth of Knowledge	Yes	Implementation of this project requires in-depth knowledge about each component of the HRES. We have to study deeply on how PV cells work and how they generate electrical power from solar energy, and how wind turbines convert wind energy into electrical energy. We also needed deep knowledge about the battery storage system and its characteristics. To create the simulation environment in MATLAB we needed profound knowledge about MATLAB coding and the mathematical equations regarding our HRES model. Finally, combining all components with each other and applying optimization algorithms to properly size the HRES system while meeting certain constraints of the system reflects that this problem requires a high depth of engineering fundamentals and advanced concepts. It makes the problem academically and technically demanding.
P2: Range of Conflicting Requirements	Yes	As our project is based on optimization of the HRES system, it naturally contains some constraints which need to be followed properly to determine the proper sizing of the HRES system. We need to keep the cost minimum while meeting the electricity demand of the area to avoid load shedding. This cost depends on the number of PV cells, number of wind turbines, number biomass plants and

		number of batteries present in the system. We cannot use any number of PV cells or wind turbines to meet the demand as it will violate the condition of minimizing the cost. Another conflicting scenario will emerge if we oversize the system to meet the demand as it will lead to wastage of energy. So minimizing energy waste remains a constraint of this problem. There are also other technical limitations such as the minimum number of components, weather condition and storage limits that make the problem a multi objective optimization problem. This makes the implementation of the HRES system more reliable and robust.
P3: Depth of Analysis Required	Yes	The depth of analysis in this thesis lies in the detailed modeling of each system component and the implementation of the Hippopotamus Optimization Algorithm (HOA) to solve a nonlinear, constrained, multi-variable problem. The algorithm is applied using real-world weather and load data to find the optimal configuration that minimizes cost and ensures uninterrupted power supply. The entire system is simulated in MATLAB, and the results are validated by comparing them with existing literature, ensuring both technical accuracy and practical relevance. This layered approach from modeling to validation demonstrates a high level of analytical depth.

4.5 Socio-Cultural, Environmental, And Ethical Impact

Through the implementation of an optimized Hybrid Renewable Energy System in a remote area of Bangladesh, we aim to create a substantial positive impact across socio-cultural, environmental and ethical dimensions. Providing electricity to the deprived communities has a broader impact in the bigger picture. It will increase the quality of life of those communities, it will create job opportunities, it will pave the way for economical advancements to those regions and eventually leading to the overall improvement to their healthcare, education and communication.

Sarker et al. found the most examined SHS (Solar Home Systems) cases in rural Bangladesh in their literature. It demonstrated a positive Net Present Value (NPV) and relatively short payback periods. The internal rate of return (IRR) spanned from 16%-131% [18], which indicates that SHS is not only socially and environmentally beneficial, but also an economic blessing for a developing country like Bangladesh. It can be a great income source rather than just lighting the households.

It is reported that poorer households often end up paying a higher per unit cost for electricity than wealthier households, due to tariff structures, fixed connection charges and minimum top-up limits. [19] This is clearly an injustice towards them and may also discourage the marginalized households from using electricity. Coming from this, a self-sufficient and self-renewing source of energy will not only lessen the burden of extra electricity charges from them, but also will ensure that each citizen of Bangladesh gets access to electricity without being a victim of systematic designs.

In a scientific study, it was seen that a hybrid off-grid system (combining solar PV, wind turbine, micro-hydro turbine, biogas generator, battery usage), if utilized in a rural remote area in Bangladesh, can achieve a cost of energy (COE) of USD 0.126/kWh, will emit 60,116 kg CO_2 eq/yr and will provide 0.74 full time jobs in the community [20]. For this, calculating the optimal configuration (number and sizing of the components) is crucial. But once the optimal set up is achieved, this solution will lower carbon emission and create job opportunities beside producing electricity for the local people in that area. Eventually, the socio-economic infrastructure will start to develop in that locality.

Working with renewable energy is also about being responsible about the environment. In the traditional electricity generation plants of Bangladesh, we see the burning of diesel, burning of coal, using nuclear energy, using hydropower, etc. These methods of electricity generation are not only very expensive, but also very harmful for the environment. In today's world, when every country is inclining towards green energy, it is high time we also should adopt renewable energy means, starting from small-scale to large-scale. Creating HRES infrastructure to lighten up the remote areas will benefit the underserved communities, while being gentle to the environment.

Ethically, our research work promotes energy justice by ensuring equitable access to sustainable energy, especially for the communities that have been deprived of this basic need. In the entire project, there is no usage of unethically sourced resources. Instead, our project ensures responsible resource use, which is also a testimony to our commitment to fairness and ethical engineering practices.

4.6 Attributes of Ranges of Complex Engineering Problem Solving (P1 – P7) Addressed

The following table shows the attributes of ranges of Complex Engineering Problem Solving (P1 – P7) addressed in EEE 4700 for Project and Thesis.

Table 17: Attributes of Complex Engineering Problems

P	Range of Complex Engineering Problem Solving	Put Tick (√)
Attribute	Complex Engineering Problems have characteristic P1 and some or all of P2 to P7:	
Depth of knowledge required	**P1:** Cannot be resolved without in-depth engineering knowledge at the level of one or more of K3, K4, K5, K6 or K8 which allows a fundamentals-based, first principles analytical approach	√
Range of conflicting requirements	**P2:** Involve wide-ranging or conflicting technical, engineering and other issues	√
Depth of analysis required	**P3:** Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models	√

The following table explains or justifies how the attributes of ranges of Complex Engineering Problem Solving (P1 – P7) have been addressed in EEE 4700/4800 (Project and Thesis).

Table 18: Justification of Attributes of Complex Engineering Problems

P	Explanation/Justification
P1	Optimizing HRES for remote areas requires in-depth engineering knowledge to apply first principles and fundamentals for analyzing and integrating diverse renewable energy components effectively.
P2	Balancing conflicting technical, environmental, economic, and social factors is crucial to achieve a sustainable and practical solution.
P3	For a remote area in Bangladesh, optimizing HRES requires original, context-specific models to address challenges like resource variability and local conditions, with no clear, predefined solution.

4.7 Attributes of Ranges of Complex Engineering Activities (A1 – A5) Addressed

The following table shows the attributes of ranges of Complex Engineering Activities (A1 – A5) addressed in EEE 4700 for Project and Thesis.

Table 19: Attributes of Complex Engineering Activities

A	Range of Complex Engineering Activities	Put Tick (√)
Attribute	Complex activities means (engineering) activities or projects that have some or all of the following characteristics:	
Range of resources	**A1:** Involve the use of diverse resources (and for this purpose resources include people, money, equipment, materials, information and technologies)	√
Level of interaction	**A2:** Require resolution of significant problems arising from interactions between wide-ranging or conflicting technical, engineering or other issues	√
Consequences for society and the environment	**A4:** Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation	√

The following table explains or justifies how the attributes of ranges of Complex Engineering Activities (A1 – A5) have been addressed in EEE 4700/4800 (Project and Thesis).

Table 20: Justification of Complex Engineering Activities

A	Explanation/Justification
A1	A hybrid renewable energy system (HERS) depends on a variety of sources for efficient functioning, such as trained individuals, finances, solar panels, batteries, information on energy usage and weather, and cutting-edge technologies for system improvement. These resources collaborate to guarantee dependability and effectiveness.
A2	Hybrid renewable energy systems (HERS) face challenges stemming from the interplay among various energy sources, technologies, and environmental variables. Conflicts may occur when technical needs, system efficiency, costs, and environmental impact need to be balanced, requiring creative solutions to effectively combine these elements.
A4	Hybrid renewable energy systems (HERS) greatly impact energy reliability, environmental consequences, and costs in diverse contexts. Predicting or preventing these results proves challenging due to uncertainties in weather, energy demand, and system performance, necessitating strong planning and adaptable strategies.

Chapter 5

Conclusion and Future Research Directions

5.1 Conclusion

This thesis has effectively illustrated how to use the Hippopotamus Optimization Algorithm (HOA) to optimize a Hybrid Renewable Energy System (HRES) for a remote region in Bangladesh. The study tackles a significant issue confronting the country: supplying impoverished rural populations with sustainable, inexpensive, and dependable electricity while lowering reliance on the national grid and limiting environmental damage.

With 14 batteries (4.98 MW storage capacity), 197 kg/h biomass usage, 9,980 PV modules, and 6 wind turbines, the optimum system configuration produced a very competitive Levelized Cost of Energy (LCOE) of 5.63 BDT/MWh. With a 20% reduction in comparison to diesel-based generation and an improvement over other optimization techniques like Genetic Algorithm (6.00 BDT/MWh) and Particle Swarm Optimization (5.80 BDT/MWh), this is a substantial improvement over current hybrid systems reported in the literature. With a 2% Loss of Power Supply Probability (LPSP), the system maintains a high dependability index, guaranteeing steady energy availability for 99% of operating hours all year long.

Navigating the intricate, multi-objective optimization landscape was made very easy with the help of the Hippopotamus Optimization Algorithm. This work found the best computational configurations that strike a balance between execution time and solution quality by methodically analyzing convergence behavior across different search agents (8–64) and iterations (25–1000). Finding economical configurations that satisfy all technical requirements while lowering the overall system cost was made possible by the algorithm's capacity to investigate a variety of solution spaces and effectively take advantage of favorable areas.

Seasonal performance suggests that the renewable resources are complementing each other. When the sun is generally most abundant, solar panels produce the majority of electricity; in winter especially, wind power picks up the slack when solar output is down. Furthermore, the stable base-load supplies which biomass can provide right through the year helps smooth out dynamics due to wind and solar power. The battery storage plant also contributes to keeping the grids stable, by charging and discharging on a regular basis, which helps to balance supply and demand.

This research tackles broader socio-cultural, environmental, and ethical aspects in addition to technological and financial accomplishments. The planned HRES has the ability to raise living standards, provide jobs, improve healthcare and educational facilities, and encourage general economic growth in rural areas by giving access to inexpensive, clean electricity. When compared to traditional fossil fuel-based generation, the system's reliance on renewable energy drastically lowers carbon emissions, supporting Bangladesh's environmental sustainability objectives and attempts to mitigate climate change.

This study has important policy implications for rural electrification policy and energy policy in Bangladesh. With approximately 72% of the country's population residing in rural areas, deployment of HRES configurations optimized is a promising route toward achieving universal energy access while reducing pressure on the national grid. The competitive LCOE and high reliability exhibited in this study indicate that these systems are economically viable options to grid extension in remote areas where transmission infrastructure is excessively costly.

There are, however, several assumptions that need to be considered. The optimization is based on specific meteorological and load data for a specific location, and the results may vary in various geographical locations within Bangladesh. The analysis presupposes consistent availability of biomass, which could be seasonal in pattern and subject to supply chain constraints as well. The economic analysis similarly employs prevailing costs of components and does not account for future changes in price or technology advancements that can further improve the economics of the system.

Finally, this thesis demonstrates that hybrid renewable energy systems with optimal configuration are a technically viable, financially viable, and environmentally benign alternative for rural electrification in Bangladesh. The application of the Hippopotamus Optimization Algorithm has proven to be effective in identifying the configuration with minimum cost while maintaining high reliability. As Bangladesh progresses towards the utilization of renewable energy and looks towards its achievement of universal electricity access, the approaches and results presented in this research hold significant implications for policy makers, energy planners, and engineers working towards a better and more just energy future.

5.2 Future Research Directions

Based on findings of this research, several research directions of potentiality have been identified to enhance the performance, usability, and scalability of hybrid renewable energy systems in Bangladesh and similar contexts.

Sophisticated Energy Forecasting and Artificial Intelligence-Derived Energy Management: Machine learning techniques such as LSTM networks and deep reinforcement learning can result in a drastic enhancement of solar irradiance, wind speed, and load demand prediction accuracy. The development of AI-driven control systems that can make real-time decisions about energy dispatch, battery control, and demand response will enhance system efficiency and reliability. Predictive maintenance software also results in reduced downtime and operating costs by anticipating component failure prior to its occurrence.

Future research also needs to explore beyond autonomous microgrids to grid-interconnected systems capable of participating in electricity markets. This entails the specifications of bidirectional energy supply, whereby HRES can import during shortages and export during high-generation. Virtual power plant concepts, whereby multiple distributed HRES installations are aggregated, could provide more grid services and superior economic benefits through market participation and ancillary services provision.

Expanding the optimization framework to include more than one objective beyond cost minimization will produce richer solutions. Environmental impact metrics (carbon footprint, land use), social equity considerations (provision of employment opportunities, community empowerment), and climate resilience metrics should be considered in future activities. Application of multi-objective evolutionary algorithms such as NSGA-III can produce Pareto-optimal solution sets with trade-offs between economic, environmental, and social objectives such that stakeholders can make decisions depending on their preference.

Multi-site pilot-scale implementations in Bangladesh will validate simulation outcomes and uncover real-world deployment challenges. Studies must tackle the creation of community-based ownership models, assessment of the impact of component price reduction and technological advances, and developing region-specific best practice guidelines on optimization taking account of differences in geographical availability of renewable resources and load profiles. These actions will connect theoretical optimization with widespread practical implementation of HRES in rural Bangladesh.

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