Optimization of Hybrid Renewable Energy System (HRES) for Electrification of a remote rural area in Cox's Bazar

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List of Acronyms

SDGs - Sustainable Development Goals
HRES - Hybrid Renewable Energy Systems
HOMER - Hybrid Optimization Model for Electric Renewables
PV - Photovoltaic
COE - Cost of Energy
DG - Diesel Generator
BG - Biogas
BM - Biomass
RCF - Replacement Cost Factor
WT - Wind Turbine
SOC- State of Charge
NPC - Net Present Cost
LCOE - Levelized Cost of Energy
TSC - Total System Cost
ACS - Annual Cost System
SBA - Scenario-Based Analysis
MCS - Monte Carlo Simulation
PEM - Point Estimate Method
PDF - Probability Distribution Function
CDF - Cumulative Distribution Function
LPSP - Loss of Power Supply Probability
PSO - Particle Swarm Optimization
GA - Genetic Algorithm
SBX - Simulated Binary Crossover
GWO - Grey Wolf Optimization
ACO - Ant Colony Optimization

WOA -	Whale Optimization Algorithm
HPWOA-	Hybrid Particle Whale Optimization Algorithm
CS -	Cuckoo Search
ARO -	Artificial Rabbits Optimization
PGCB -	Power Grid Company of Bangladesh
PVGIS -	Photovoltaic Geographical Information System
SREDA -	Sustainable and Renewable Energy Development Authority

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Abstract

This thesis investigates a cost-reliable Hybrid Renewable Energy System (HRES) tailored for rural demand, emphasizing uncertainty in resources and load. We consider photovoltaic generation, a biomass unit, and battery storage, and model variability via probabilistic strategies—Monte Carlo Simulation (MCS), Point Estimation Method (PEM), and Scenario-Based Analysis (SBA). Hourly solar irradiance, ambient temperature–dependent PV output, biomass fuel availability, and community load are represented as random variables; sampling/aggregation produces scenario sets fed to an optimization framework. Two hybrid optimizers are implemented: a time-focused PSO–GA–GWO and an accuracy-focused PSO–GWO–WOA. The objective function minimizes total system cost under a loss of power supply probability (LPSP) constraint, with lifecycle economics over a 20-year horizon. Results show that the proposed HRES meets the target reliability of LPSP $\leq$ 3% while reducing levelized cost by a considerable margin when compared with a deterministic baseline. Sensitivity analyses over a particular range solar variance and load variance indicate robust performance, with optimal capacities of PV: [Npv] kWp, biomass: [Pbio] kW, and battery: [Ebat] kWh. The findings demonstrate that explicitly modeling uncertainty and optimizing against expected outcomes yields designs that are both economically competitive and operationally reliable, providing a defensible pathway for village-scale electrification.

Keywords: HRES, uncertainty modeling, LPSP, MCS, PEM, SBA, PSO, GWO, WOA, rural electrification

CHAPTER 1: INTRODUCTION

Energy access remains a critical barrier to socio-economic development in many remote regions of developing countries. Despite global efforts to expand electricity coverage, numerous rural communities in Bangladesh still lack reliable access to power . Any attempt that will be undertaken to extend the national grid to these localities will often be prohibitively expensive due to difficult terrain, low population density, and high infrastructure costs.The substantial environmental impact of greenhouse gas and local air pollutant effluent emissions has been amply illustrated by carbon footprint studies of fossil fuel power plants in Bangladesh.In addition, burning fossil fuels can exacerbate the greenhouse effect and increase the effects of climate change by releasing chemicals into the atmosphere, such as nitrous oxide (N2O) and sulfur dioxide (SO2). Additionally, these emissions have a major role in the development of air pollution, which causes respiratory conditions and other health issues for those who live nearby. On top of that, these power plants' emissions of sulfur dioxide (SO2) and nitrogen oxides (N2O) have the potential to produce acid rain, which can harm the marine environment, plants, and structural degradation.[1]

1.1 Background and Motivation

Bangladesh has made significant progress in electrification, yet over 10 million people, primarily in rural or isolated areas, still live without reliable access to electricity. Grid-based expansion is economically inefficient in many such cases due to high transmission costs and low return on investment. A study conducted by the authors in [2] showed that dynamic ordinary least squares approach was used to examine time series data of 20 years. This ranged from 2000 to 2020. The results showed that health spending will rise by 0.95% and 2.67%, respectively, for every 1% increase in carbon dioxide emissions and fossil fuel energy usage. Additionally, over time, a 1% increase in the use of renewable energy could lead to a 1.44% decrease in health spending. The conflict in Ukraine has made the global energy market crisis even more severe in terms of energy pricing and supplies, which has a multifaceted negative influence on emerging nations.[3] Therefore, the transition to renewable energy sources has become of paramount importance due to such critical factors. First and foremost, renewable energy significantly mitigates climate change by producing minimal to no greenhouse gas emissions, unlike fossil fuels.This reduction is vital for curbing global warming and its associated impacts.[4] The UN adopted the SDGs, often referred to as the Global Goals, in 2015.Among the 17 SDGs of the United Nations (UN), our work addresses SDG7 and SDG13. SDG 7 deals with reasonable, cost-effective and clean energy. It addresses renewable energy integration to meet demands of the people, both at micro level and macro level. SDG 13 which is for climate action, is also affected because of that integration[5]. Bangladesh, one of the countries to be worst affected by global climate change, desires to raise its share of usage of renewable energy by a considerable margin [6]. With this goal in mind, various researches have been undertaken to try and integrate renewable energy with studies being conducted on different hybrid energy system configurations in multiple , especially rural regions of Bangladesh. Hybrid Renewable Energy Systems (HRES) offer a long-term , concrete and decentralized alternative to conventional electrification. By integrating numerous and varied sources of renewable energy—each with unique characteristics and availability patterns—HRES can improve system reliability and optimize resource utilization. Among various combinations, a hybrid of solar photovoltaic (PV) and biomass energy is particularly suitable for rural Bangladesh, where both sunlight and agricultural residues are abundantly available

1.2 Basic Functionalities of HRES

HRES blends numerous renewable sources of energy. They often include solar, wind, geothermal, biomass, biogas , and it usually has backup storage system, to provide reliable and cost-effective electricity. Their basic function is to balance intermittency between sources, reduce dependence on fossil fuels, and lower long-term costs. Globally, HRES are widely applied in off-grid electrification, mini-grids, and community-based projects, offering both environmental and socio-economic benefits [7].

In Bangladesh, HRES are particularly significant because many rural and island areas remain underserved due to the high cost of grid extension [8]. The country benefits from good solar resources and abundant biomass potential, making solar–biomass hybrids a practical option [9]. Large-scale deployment of solar home systems has already improved rural livelihoods by reducing kerosene dependence and enabling longer study and business hours [10]. Moreover, the government has set renewable energy targets of around 15% by 2030, and hybrid systems are anticipated to be crucial in achieving these goals [11].

1.3 Literature Review

In order to determine the approaches used and their shortcomings, a comprehensive analysis of the previous works, is conducted in order to analyze and evaluate various HRES designs for various parts of Bangladesh. Given Bangladesh's tradition in rural regions of using biomass resources such as agricultural residue or cow dung on a day-to-day basis , study in [12] demonstrated how to design an off-grid system utilizing solar photovoltaic (PV) panels and biomass gasification to generate electricity for an off-grid rural community in a village near Barisal. The proposed system showed that it was a cost-effective and reliable solution . The COE was 10.183 BDT/kWh , which is lower than conventional diesel-based systems (which cost

20-25 BDT/kWh), and reliable in the sense that biomass gasification could provide continuous supply of energy even when solar radiation was low. Furthermore, in [13], the following distinct setups were examined: PV/DG/battery, PV/battery, and DG/battery for households in Patar Char village under Patuakhali district. The Hybrid PV-Diesel-Battery System demonstrated the lowest Net Present Cost (NPC), and it also significantly reduced the carbon emissions compared to the Diesel-Battery System. Similar to how rural settlements exhibit the potential for biomass fuel, the nation's coastal regions also offer the potential for harnessing wind energy. WT were therefore taken into consideration as part of HRES in research that concentrated on island or coastal regions. A research carried out in a secluded community in the Bhola area in [14] studied the feasibility of utilising the various resources available there. Here Wind energy is considered as a secondary energy source, complementing solar PV, biomass, and diesel generators. It also turned out to be an unreliable source because of its low and inconsistent speed. The Levelized Cost of Energy (LCOE) for wind energy is higher than that of solar PV in Bangladesh, making it less economically viable for rural off-grid applications. The Net Present Cost (NPC) of wind-integrated systems is found to be higher compared to PV-dominant hybrid systems. Further research findings of why wind-integrated systems are not feasible can be found in study[15] carried out in Pabna where the integration of photovoltaic panels with biomass generators in a grid-connected hybrid system offers a sustainable and economically viable solution, with the least COE, the connected to the grid PV–biomass generator system proved to be the most economical.. Initially, wind energy was considered as a potential component of the proposed HRES as a part of our research. However, after a detailed resource and economic feasibility analysis, wind was excluded from the final system configuration.The majority of research on HRES in the academic community focuses on technological and economical evaluation, component estimation, and computational simulatios.One of the main things to consider in the design is the sizing of HRES. An oversized HRES can easily satisfy the load demand,but it would become very costly, while on the other hand; an undersized HRES is economical but more often than not, fails to satisfy the load demand.Study in [16] summarizes the mathematical modeling of various renewable energy systems. So with the understanding that we need to find an optimal sizing for the HRES, in order for the system to be technically and economically viable. The research done on the optimization of various HRES in various parts of Bangladesh was constrained by a few aspects, even if it offered insights into various approaches and modeling tools. Before suggesting an HRES for a location, the data on renewable resources should be examined and contrasted with existing literature to determine the HRES's components. Because global minima finding is insufficient, relying just on one optimization technique or the default HOMERoptimizer may increase system costs. Because several probabilistic load profiles account for the variable behavior of the load demand pattern, they would probably give accuracy in estimating HRES cost and sizing. Accordingly, when recommending a PV/DG/battery system for Kuakata island in Bangladesh with an preliminary cost of $1.77M, the study in [17] found that the load demand variation was the most important metric that was accountable for errors in HRES. The literature review on HRES analysis in Bangladesh makes clear that the aforementioned approaches have not taken into account the intermittent nature of renewable resources as much, which means the suggested results are unreliable. This was also mentioned in study [18].

SBA, MCS, and PEM—were generally found in studies on uncertainty modeling techniques to take into consideration the uncertain variances among different HRESs. The research review highlighted the benefits of MCS over PEM and SBA over MCS since SBA provides greater independence and oversight for choosing parameters that are regarded as random in MCS. Another significant benefit of SBA is its ability to lessen the computational load through optimal distribution and state selection. The study examined various meta-heuristic optimization algorithms used for HRES analysis in addition to analyzing and interpreting uncertainty modeling techniques. In order to guarantee successful global minima results, the goal was to choose algorithms with complementing properties and high performance.As was already established, there are clear limits to previous study conducted in the Bangladeshi context. To name a handful of the algorithms investigated, a comparative performance study [19] was done between GA and PSO for an off-grid hybrid energy system. In this paper, the algorithms were evaluated based on their ability to minimize the COE and LPSP. Another optimization algorithm which is widely used for optimization purposes in various researches is the ACO, initially made available in the early 1990s by M. Dorigo , V. Maniezzo and A. Colorni[20]. A study [21] conducted in Madhya Pradesh, India also utilised the ACO. This research proposes a solar-wind photovoltaic standalone HRES for an unelectrified area in Madhya Pradesh, India. Another nature inspired algorithm, which showed promising results, is the GWO . GWO was developed by Mirjalili et al in [22]. This approach was inspired by the hunting patterns of the grey wolf pack . In 2019, the authors in [23] used the GWO algorithm for the sizing approach of their design. In order to provide uninterrupted power to many residences in a group of villages in India, the best possible design for a hybrid system based on solar, biomass, biogas, and batteries has been completed. In accordance with the ever evolving nature of this field, a new optimization technique, the WOA was crafted in study [24]. This optimization was utilized in numerous studies . For example, the study in [25] utilised 3 optimization algorithms and did a comparison analysis between them. The purpose of the study is to employ the following optimization approaches - ARO, GWO and WOA. to COE while enhancing the dependability of the energy supply for isolated regions. In study[26], researchers went one step deeper and created the grid-connected PV/DG hybrid system by utilizing a hybrid PSO–GWO technique. When the hybrid PSO–GWO algorithm was contrasted with PSO and GWO alone, the hybrid approach produced superior outcomes.. And there are many other occasions where the authors implemented a hybrid algorithm, which yielded better results. One such instance is the research done in [27], which combined PSO with WOA to present a hybrid method (HPWOA) that enhances performance in microgrid design. The HPWOA performs better than more conventional methods like PSO and WOA, offering increased environmental sustainability, reduced energy costs, and higher dependability.A new method for attaining the most cost-effective functioning of a HRES is suggested by another study in [28]. An innovative combination of the CS and ACO is used to optimize the resulting multi-objective function. The outcomes of the suggested hybrid algorithm are contrasted with those of CS and ACO optimization methods. A comparative performance investigation of the suggested ACO-CS algorithm with ACO and CS has revealed that using the suggested hybrid ACO-CS algorithm produces better results.

From the extensive literature review carried out on this topic,it is quite evident and safe to conclude that the hybrid optimization algorithms are currently in huge demand, as they are shown to be more reliable, flexible, robust and are showing better results than traditional algorithms. With that idea in mind, in this research, we have developed a HRES consisting of Solar PV panels-Biomass Generators-Battery (for backup) and we have also designed a hybrid algorithm to find the optimum system design for our proposed system. Our goal is to find the right balance between the cost, while maintaining a consistent energy output for meeting the load demand. The following chapters are organized as following. Chapter 2 provides the methodology maintained in the study, Chapter 3 discusses the location selection and data collection, Chapter 4 covers proposing and modeling the components of HRES with operational strategy, Chapter 5 addresses the uncertainty handling technique adopted in the study, Chapter 6 represents cost function formulation with defined constraints and algorithms selected for the optimization problem. Chapter 7 covers the simulation result and discussion, Chapter 8 shows the demonstration of OBE(Outcome Based Education) and finally, Chapter 9 provides the conclusion of the study

CHAPTER 2: METHODOLOGY

In this research, *Eidgaon*, located northwest of Cox's Bazar, Bangladesh (centroid ≈ 21.5527° N, 92.0684° E), was selected as the study region due to its limited grid access and noticeable energy demand–supply imbalance. Renewable-resource and load-demand data were collected for this location to develop a techno-economically optimized HRES comprising of photovoltaic, biomass, and battery storage units.

Hourly solar-irradiance and load-demand data were obtained for an entire year. To reduce computational complexity while preserving seasonal characteristics, the year was divided into four representative seasons ;summer, winter, spring, and fall. Each season represents three months (≈ 90 days × 24 hours = 2160 data points). From these, one representative day of 24 hours was selected for each season, creating a simplified annual dataset of 96 hours (4 × 24 = 96).

For every season, the real data were divided into discrete **states** that represent variability in solar irradiance and load behavior. Using these state values, the **PDF** and **CDF** were generated for each hour. Based on these, three statistical distributions—**Beta**, **Weibull**, and **Normal**—were fitted to the observed data using **log-likelihood estimation**, which evaluates how well each distribution represents the real measurements.

As an example, the 16th hour of the summer season contains 90 observations (one per day for three months). The log-likelihoods of the three fitted distributions were compared, and the one with the highest likelihood ,for example the Weibull was selected as the best fit for that hour. This process was repeated for all 24 hours, and the **mode distribution** (the one most frequently appearing among the 24 hours) was adopted as the representative distribution for that entire season.

Once the seasonal distributions were identified, a **roulette-wheel selection** technique was employed to generate multiple realistic hourly combinations of solar irradiance and load. Forty scenarios were produced for each season, forming two matrices of 40 × 24 (for solar and load, respectively). These were then merged across the four seasons to obtain the final **40 × 96 matrices** that represent annual variability and uncertainty through a **Situation-Based Analysis (SBA)** approach.

The generated probabilistic datasets were used as inputs for the optimization stage. Here, the main task was to determine the optimal number of PV panels (Npv), biomass generator capacity (Pbio), and battery units (Nbat) while satisfying predefined **system constraints** and **reliability limits**. The primary objective of the optimization process was to **minimize the Total System Cost (TSC)** under these constraints.

Six optimization techniques were applied for performance comparison—**PSO,GA,GWO**, **WOA**, **Hybrid PSO-GWO-WOA** , **Hybrid PSO-GA-GWO** framework. Each algorithm searched the multidimensional solution space using the same probabilistic input profiles to obtain the most cost-effective configuration of the hybrid system.

CHAPTER 3: LOCATION SELECTION & DATA COLLECTION

3.1 Location Selection

Eidgah (Eidgaon) Thana ,upgraded to Eidgaon Upazila in July 2021 ;lies in northern Cox’s Bazar District, bounded by Chakaria to the north, Ramu to the east, Cox’s Bazar Sadar to the south, and Maheshkhali across tidal channels to the west [29]. Within this upazila, Islampur Union sits in the Eidgaon riverine–coastal belt, with local nodes such as Islampur Bazar and Eidgaon Bazar marking access points [32]. A practical map centroid for Eidgaon is about 21.5527° N, 92.0684° E [30], placing it roughly northwest of Cox’s Bazar town (21.4272° N, 92.0050° E) [31]. Despite near-universal rural electrification on paper, the Cox’s Bazar grid has faced forced load-shedding in recent seasons due to overloaded 132 kV infrastructure at Cox’s Bazar substations; remedial works (ACCC conductor upgrades, additional transformers, and a new Chakaria 132 kV substation) are in progress [33]. Local consultations reported frequent load-shedding making electric cooking impractical, with outages cited up to 18–20 hours/day in parts of the district during crises [33]. The region's ongoing power outages and limited access to electricity are both direct and indirect effects of poor research that results in ineffective energy infrastructure design. In order to address the energy issues, the site was chosen for this study in order to offer a methodical approach to the integration of renewable energy. In Fig:1 , a flowchart is provided which shows the steps followed in carrying out this study.

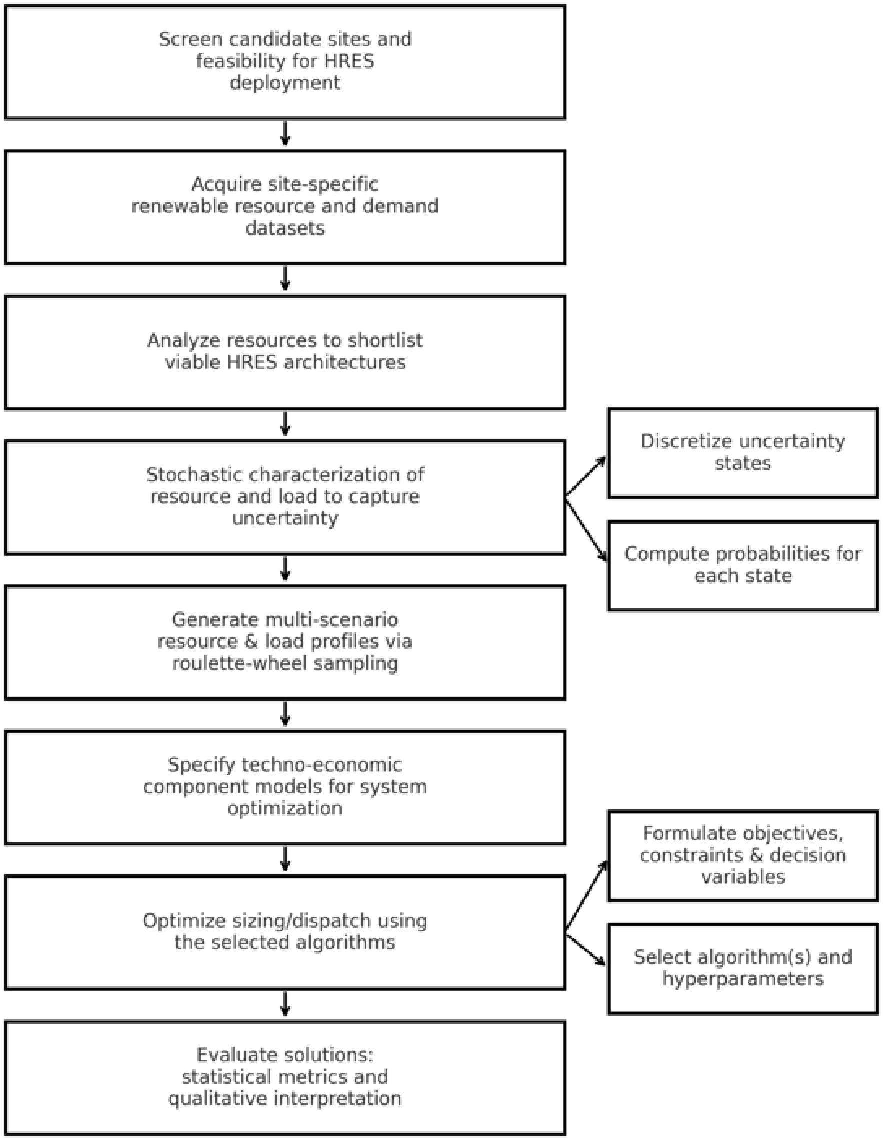

Fig. 1 Flowchart depicting the workflow maintained in the study

3.2 Solar Irradiance data

For a full year, hourly solar energy data for the chosen location is gathered from [34]. Fig. 2 shows the annual solar radiation data. According to data on solar irradiance, the summer months of July through September had the highest average availability of solar irradiance with an average of 270.56 W/m2 , and a maximum of 1061.03 W/m2. In spring(Apr-June), average irradiance and peak irradiance were 206.01 W/m2 and 1013.42 W/m2 respectively. Interestingly, in fall (Oct-Dec), the solar radiance reached an overall peak irradiance of 1066.65 W/m2, greater than that of summer, but its average irradiance of 256.91 W/m2 was less than that of summer. In winter(Jan-Mar) , both the average and maximum irradiances were lowest among the four seasons. With maximum irradiance being 902.43 W/m2 and average irradiance being 143.68 W/m2. This variance explains the unpredictability of the solar energy supply, which is then quantified and examined in this research.

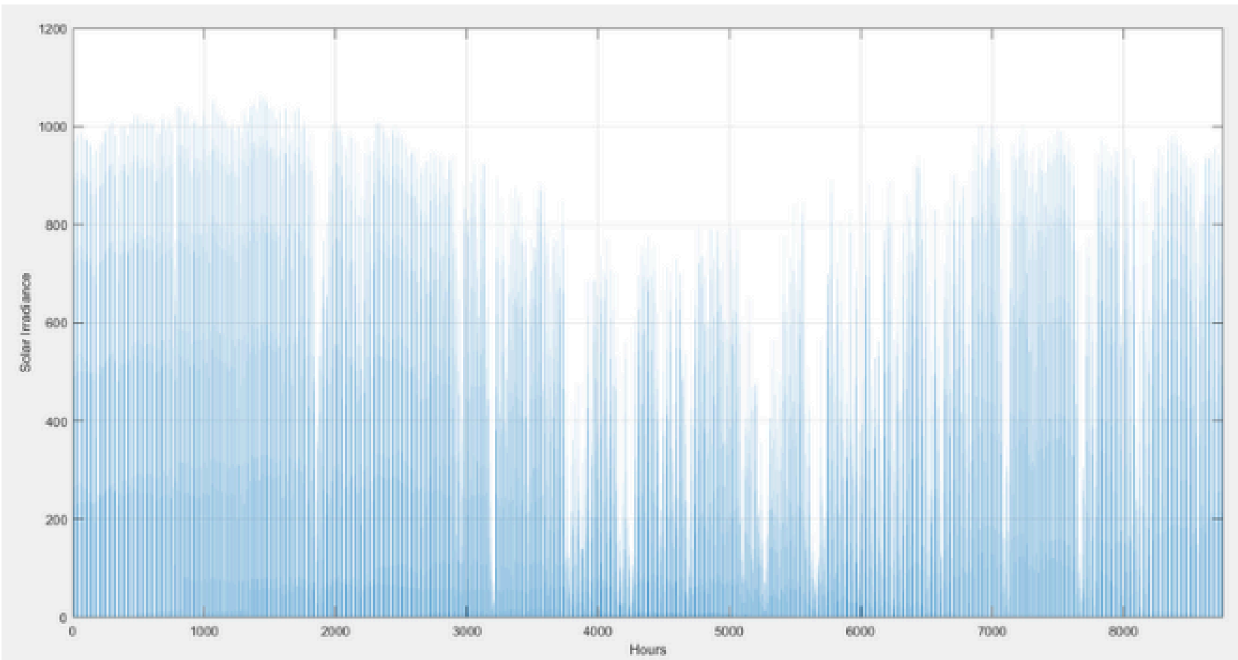

Fig. 2 Hourly solar radiation data for a full year

3.3 Wind Speed data

For a year, data regarding the hourly speed of wind is gathered at a height of ten meters at the chosen location [34]. Fig. 3 shows previously recorded wind speed data. Spring (April–June), summer (July–September), fall (October–December), and winter (January–March) had average wind speeds of 2.4 m/s, 2.51 m/s, 2.157 m/s, and 3.38 m/s, respectively. Unexpected peaks in the image, such as 12.62 m/s in the fall, represent variations in wind speed brought on by the environment. As a result, the wind speed profile is less patternable than that of solar radiation. As a result, probabilistic computing requires special handling, like more population creation or greater amount of states, and it has processing overhead in order to be accurate.

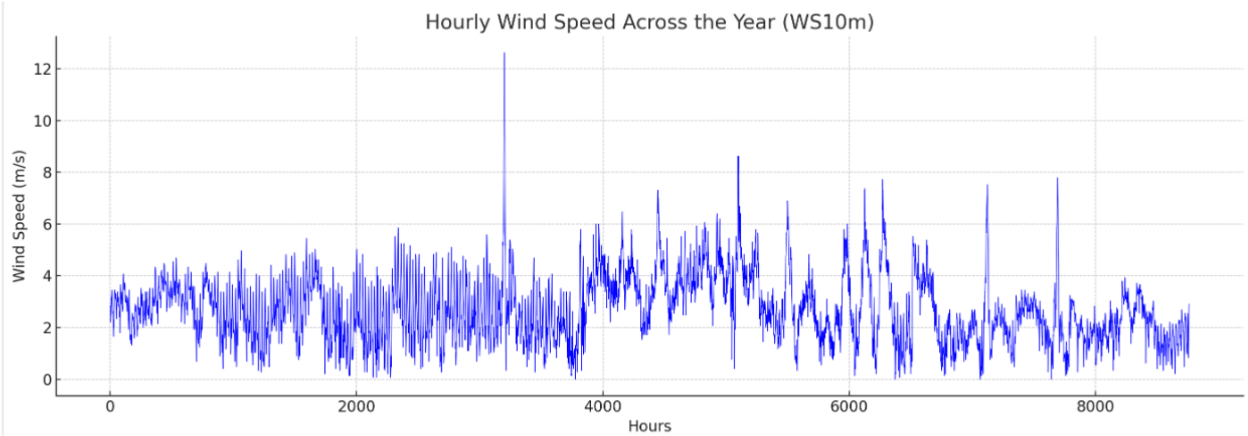

Fig. 3 Hourly wind speed data for a full year.

3.4 Load demand data

Load demand data for the year 2023 for a small village in Eidgah thana and Islampur union In Cox's bazaar were collected.The data for Cox's Bazar was not directly given. It had to be scaled by using population density metrics. To simulate the location's hourly load profile, the population of the chosen study region is multiplied by the electricity consumption per capita per hour.. The scaled load for the year 2023 is given below in Fig.4 .The data was taken from the PGCB website[35]. The database of PGCB provides load demand data on an hourly basis for both West and East grids.

Information regarding the seasonal shifts in power usage for the chosen region can be found in the load demand profile in Fig 4. Peak load demand was witnessed in spring(Apr-Jun) , which was 227 kW and it also had the maximum average load demand of 83kW, data shows that load requirement was highest in spring and conversely, minimum load demand was in winter(Jan-Mar), which was 71 kW, and it also had the lowest average load among the four seasons at 117.3375 kW. Average load demand in Winter was also significantly lower than that of summer, which has average load demand of 154.5125 kW.

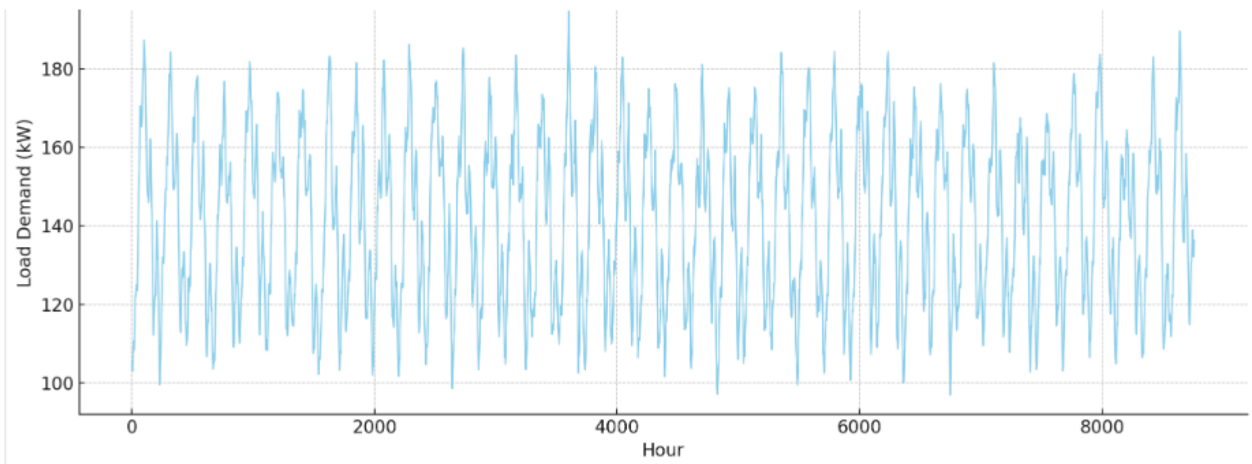

Fig. 4 Hourly load requirements for a full year.

The approach used here corresponds with the supposition of specific load elements that resemble the energy requirements of a geographic region, which has been used in literature, such as in studies [36] and [37]. It is true that this type of calculations for load pattern modeling cannot guarantee real life consumption of electricity features at a particular location. The calculation-based approach employed in this study is relatively better since it employs real-time load demand data from a larger area than the selected region is located in.

CHAPTER 4: Modeling of the System

4.1. Proposed HRES

A thorough report on the biomass fuel supply submitted with SREDA, Bangladesh [38], a trustworthy source, verified the biomass fuel availability of the Cox's Bazar region. The data gathered [34] also indicates that the chosen area has a tremendous potential for solar power generation. According to data from SREDA and the fuel calculation for biomass power in [39], the chosen area has the capacity to generate up to 240 kW of power from biomass fuel.
However, previous information on wind speeds(2.61 m/s yearly average) show that WT's potential is restricted because of its substantial investment and operating costs, as indicated by the study in [40].

From the observation and data inspection conducted in this work, a HRES consisting of solar PV modules, biomass generators and battery for storage of excess energy is suggested for the selected region. The system model is illustrated in Fig. 5 and Fig. 6 provides a visualization of a and the operational strategy of the proposed system.

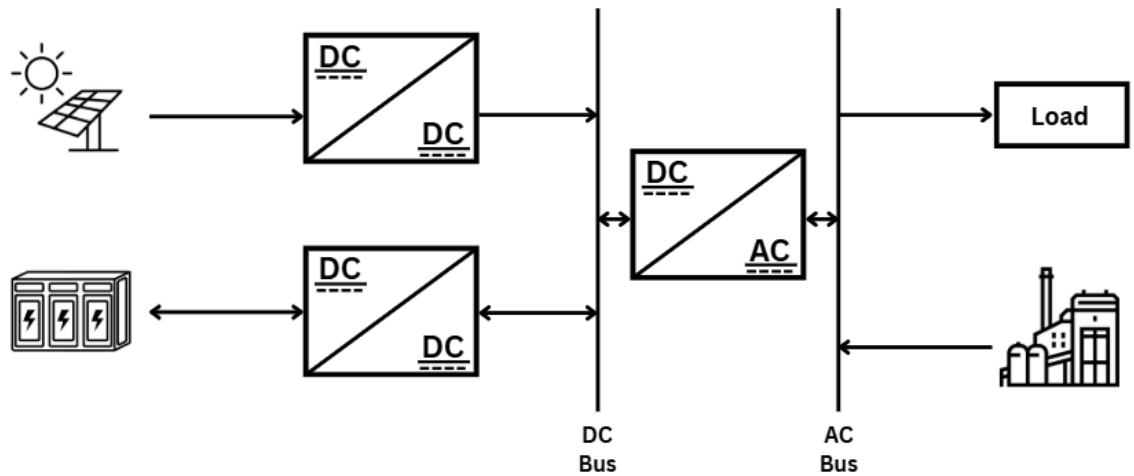

Fig 5. Proposed HRES consisting of PV module, biomass generator and battery

If the whole generation surpasses the need for load and if the battery's state of charge (SOC) is lower than its maximum SOC (SOC max), the excess power will charge the battery. But this same excess power will be fed to the dump load if SOC≥SOC max. Conversely, if the load demand surpasses generation and if the battery SOC is higher than the minimum SOC (SOCmin) then the battery will activate to satisfy the extra load demand. However, the power supply will cut off if a scenario occurs where the load demand exceeds the battery's production and SOC≤SOCmin.

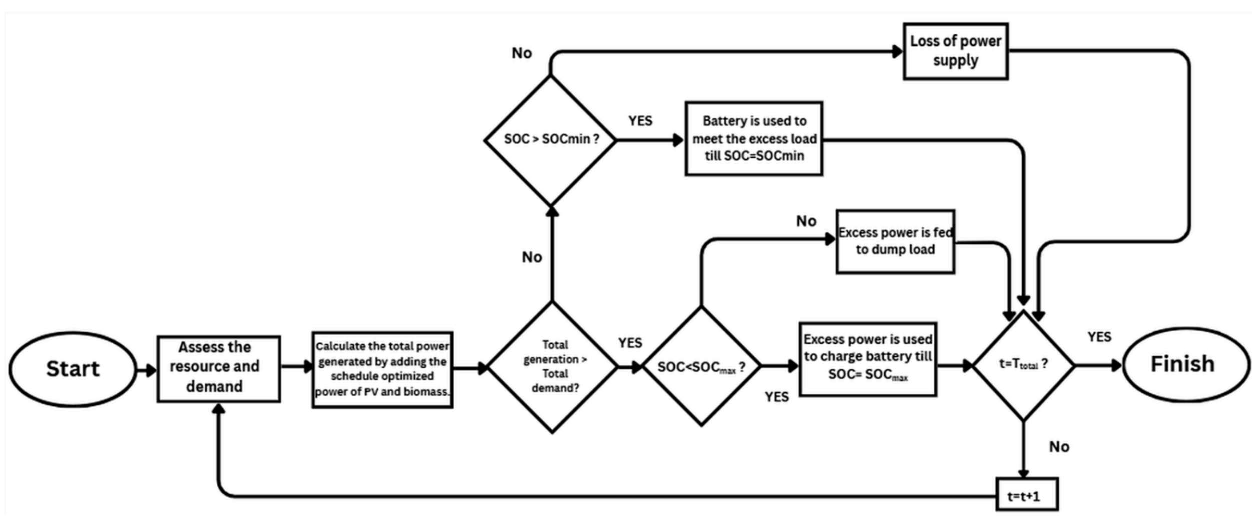

Fig. 6. Flow chart depicting the operational strategy of the proposed HRES.

4.2. Photovoltaic modeling

Various probability distributions were taken into account for solar radiation data in literature. The work in [41] considered beta distribution, discrete probability distribution is considered in [42] and in study [43] Weibull distribution is considered . Output PV power from the PV module depends on a number of various parameters of the module. Eqs.(1) to (5) determines power from a PV module [44] at any specific instant. These same sets of equations are used to calculate power in different states.

Parameters of the PV module considered in this study are listed in Table1.

$$P = V * I * FF \quad (1)$$

$$V = Voc - (Tcell * Kv) \quad (2)$$

$$Tcell = Tamb + Savg * ((T_{NOCT} - 20) / 0.8) \quad (3)$$

$$I = Savg * (Isc + Ki * (T_{cell} - 25)) \quad (4)$$

$$FF = (VM * IM) / (Voc * Isc) \quad (5)$$

Total output power from PV at any time instant can be calculated from Eq.(6) [45].

$$Ppv(t)=\eta pv*Npv*P \quad (6)$$

Table 1
Parameters of PV module

Technical parameters	
FF	Fill Factor(0.788)
Voc	Open circuit voltage(51.54 V)
Isc	Shortcircuitcurrent(14.79 A)
Tcell	Cell temperature(25 °C)
Tamb	Ambient temperature(25 °C)
Savg	Average solar irradiance of the state (1000 W/m2)
T_{NOCT}	Nominal operating cell temperature (45 ± 2 °C)

ηpv	Efficiency of module and converter(23.23 %)
VM	Maximum power point voltage(42.96 V)
IM	Maximum power point current(13.98 A)
Ki	Current temperature coefficient(0.046 A/°C)
Kv	Voltagetemperaturecoefficient(0.25V/◦C)
Npv	Number of PV module

Economic Parameters [45]

Capital Cost	640$
Lifetime	20 years

4.3. Biomass modeling

Biomass gasification is a process that yields an inflammable gas mixture [46]. CO2, CO, H2, O2 make up the majority of the gas mixture. Electric power is generated from this mixture. Eq. (7) is used to compute the biomass power [47].

$$P_{bio} = \frac{Totalbiomassavailable\left(\frac{Ton}{year}\right)*1000*CV_{biomass}*\eta_{biomass}}{365*860*\frac{operatinghours}{day}} \quad (7)$$

Technical and economic parameters for the selected biomass model are provided in Table 2 [48]

Table 2
Parameters of Biomass Unit.

Technical parameters	
CV_biomass	Calorific value of biomass (18 MJ/kg)
η_biomass	Conversion efficiency (21 %)
Economic Parameters	
Capital Cost	2300 $/kW

Replacement cost	1500 $/kW
Operation and maintenance cost	2 $/year
Life time	15000 h

4.4. Modelling of battery

Any renewable energy integration method must include battery or energy storage modeling since it offers a means of utilizing surplus or addressing the energy shortage by either storing energy or providing the load with excess stored energy. In the study, the instantaneous SOC of a lead-acid type battery is calculated using Eq (8) and Eq(9) [49].

$$SOC(t) = SOC(t-1)*\left(1-\frac{\sigma*\Delta t}{24}\right)+\frac{I_{bat}(t)*\Delta t*\eta_{bat}}{C_{bat}} \quad (8)$$

$$I_{bat}(t) = \frac{P_{pv}(t)+P_{bio}(t)-P_{load}(t)}{V_{bat}} \quad (9)$$

At any given hour, *Ibat(t),* current of the battery is calculated by the nominal voltage (*Vbat*) of each battery, the total generation from renewable sources (*Ppv*+*Pbi*o), and the load demand (*Pload*).

Parameters, considered for modelling of battery in this study, are provided in Table 3 [50].

Table 3

Parameters of Battery

Technical parameters	
σ	Self-discharge rate (0.2% per day)
C_{bat}	Battery capacity (357 Ah)
V_{bat}	Individual nominal charge
ηbat	Charging(0.8) and discharging(1) efficiency

Capital cost	1239 $
Operation and maintenance cost	12.39 $/year
Life time	5 years

4.5. Load demand modeling

A common model for load demand is the Gaussian distribution, sometimes referred to as the normal distribution [51–52]. Weibull distribution is also taken into account for load demand in the study [53]. Gaussian and Weibull distributions are used to test load demand data that was gathered from Bangladesh's national grid. The normal load distribution function can be defined as Eq. (10) [54].

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} * e^{\frac{-(x-\mu)}{2\sigma^2}} \tag{10}$$

Here, x represents the historical load demand data,whereas, μ and σ are the mean and standard deviation of the load data, respectively.

CHAPTER 5: Modeling of Uncertainties

5.1. Choosing a Strategy

Uncertainty is a first-order driver of cost and reliability in Hybrid Renewable Energy Systems (HRES). Solar irradiance, biomass feedstock availability, ambient temperature, and hourly demand all fluctuate in ways that cannot be captured by single “typical” profiles. Consequently, probabilistic modeling is preferred over deterministic point estimates when sizing components and scheduling dispatch. In this approach, uncertain quantities are treated as random variables described by probability distributions (e.g., seasonal irradiance PDFs, biomass supply variability, load profiles), and system performance is evaluated across many scenarios sampled from those distributions. Various Probabilistic strategies like MCS draws many realizations of stochastic inputs (e.g., weather, load, component failures) to estimate distributions of cost and reliability; it has been used extensively for hybrid microgrids, including sequential MCS for stand-alone HRES reliability evaluation and recent reviews of MCS across hybrid systems [55], [56], [57]. The Point Estimation Method (PEM)—notably the two-point or 2m+1 variants—approximates output moments with a few optimally chosen points, offering orders-of-magnitude speedups versus brute-force sampling; PEM has been applied to probabilistic power-flow with distributed renewables and to stochastic microgrid scheduling/energy management under RES and demand uncertainty [58], [59]. Scenario-Based Analysis (SBA) formulates a finite set of representative scenarios (with probabilities) and optimizes planning/dispatch against them; SBA is widely used for microgrid operation and planning under renewable/load uncertainty in both grid-connected and islanded contexts [60], [61]. Together, MCS, PEM, and SBA provide complementary trade-offs between fidelity and computational burden, enabling uncertainty-aware sizing and operation of HRES [55], [60].

5.2. State selection and probability

In this study, states are developed for solar radiation and load requirements data while balancing computational complexity and accuracy. For solar radiation and load requirements, state resolution or step size is taken into consideration as 25W/m2 and 12kW, respectively. In accordance with the past data's hourly deviation, states are chosen with the intention of allocating 45 states for solar irradiation and 15 for load demand. As previously said, SBA is already a computationally demanding procedure; therefore, even if adding more states will probably result in better estimation accuracy, the huge computation overhead and procedure call for a limited selection. Following the definition of the states, the average of the lower and upper limits for each state is used to compute the solar power and load demand for the states. Equations (14) and (15) are used to determine the CDFs of the states at each given hour using defined PDFs.

$$F_{solar}(s) = \int_{s_l}^{s_u} f_{beta}(s)^* ds \tag{11}$$

$$F_{load}(x) = \int_{x_l}^{x_u} f(x)^* dx \tag{12}$$

Here, $F_{solar}(s)$ represents the CDF of solar irradiance for a specific hour in a defined state whereas ,$F_{load}(x)$ represents the CDF for a specific hour in a defined state S_L and S_u are the lower and upper limits of solar irradiance of that state .Whereas, x_L and x_u are the lower and upper limit of load demand of that state.

With the CDFs defined, probability of each state for a specific hour is calculated from Eq. (13) and Eq. (14)

$$\mathbf{P}^{n}_{solar} = F^{n}_{solar}(s) - F^{n-1}_{solar}(s) \tag{13}$$

$$\mathbf{P}^{n}_{load} = F^{n}_{load}(x) - F^{n-1}_{load}(x) \tag{14}$$

Here, Pn solar is the probability of solar irradiance in nth state at a specific hour and Fn solar(s) is the CDF of solar irradiance in nth state at the same hour. Pn load is the probability of load demand in nth state at a specific hour and Fn load(x) is the CDF of load demand in nth state of the same hour.

5.3. Load-generation model

At this point, load demand and solar energy from a PV module is described for each state with a state probability in accordance with the 96 hourly data points which has been divided into four seasons with each season representing 24 hours. Solar power and load demand profiles are generated in multiple situations using a roulette wheel selection method. One of the most widely used probabilistic random generation techniques in advanced statistics is the roulette wheel [62]. To create 40 solar power profiles and 40 load demand profiles for each of the 96 hourly data points, the wheel is rotated 40 times.The wheel spinning number was chosen in order to lessen the computational load while maintaining a respectable level of correctness. 1600 load-generation models in total (40 generation profiles times 40 load profiles) are ready for optimization.Since increasing the number would require extensive computation, it may be claimed that this number is adequate for acceptable estimation.Because of this, the biomass model is thought to function without any related uncertainty. One way to express the load-generation matrix model is with Eq. (15). Fig. 7(a) and Fig 7(b) illustrates the Load Demand Matrix and Solar Power Generation Matrix

$$A = [\{A_{\mathrm{solar}},\ A_{\mathrm{biomass}},\ A_{\mathrm{load}}\} :\ N = 1 : x] \tag{15}$$

Here, *A* is load-generation matrix, *Asolar* is solar power generation matrix of x-by-96 dimension where, x is the total number of load generation models, *Abiomass* is a x-by-96 biomass power generation matrix and *Aload* is a x-by-96 load demand matrix.

$$
\begin{array}{cccc}
1^{st}\ \text{hour} & 2^{nd}\ \text{hour} & \cdots & 96^{th}\ \text{hour}
\end{array}
$$
$$
\left\{
\begin{array}{cccc}
P_{L1}^{1} & P_{L2}^{1} & \cdots & P_{L96}^{1} \\
P_{L1}^{2} & P_{L2}^{2} & \cdots & P_{L96}^{2} \\
\vdots & \vdots & & \vdots \\
P_{L1}^{40} & P_{L2}^{40} & & P_{L96}^{40}
\end{array}
\right\}
$$

40 x 96

Fig 7(a): *Aload*-
Load Demand Matrix

$$
\begin{array}{cccc}
1^{st}\ \text{hour} & 2^{nd}\ \text{hour} & \cdots & 96^{th}\ \text{hour}
\end{array}
$$
$$
\left\{
\begin{array}{cccc}
P_{pv1}^{1} & P_{pv2}^{1} & \cdots & P_{pv96}^{1} \\
P_{pv1}^{2} & P_{pv2}^{2} & \cdots & P_{pv96}^{2} \\
\vdots & \vdots & & \vdots \\
P_{pv1}^{40} & P_{pv2}^{40} & & P_{pv96}^{40}
\end{array}
\right\}
$$

40 x 96

Fig 7(b): *Asolar* -
Solar Power Generation Matrix

Chapter 6: Mathematical Expression of the Problem

6.1. Cost function and its related constraints

The goal of the cost function is to maintain a given LPSP while determining the best configuration for the suggested HRES for all load-generation models. A key metric for evaluating the viability of HRES is LPSP. LPSP is the probability that measures how often (or how much) the demand isn't met by the system that is available [61]. Zero LPSP is the ultimate goal, however achieving this is difficult and usually not economically feasible. In order to reduce the TSC under a tolerable maximum LPSP, the objective function looks for the ideal number of PV modules (Npv), biomass power capacity (Pbio), and batteries (Nbat) across all load-generation models and over the course of a 20-year project. Eq. (16) determines the objective function for our study.

Minimize: TSC

Minimize: f (Npv,Pbio,Nbat)

$$f\,(N_{pv},P_{bio},N_{bat}) = N_{pv}\,(C_{pv}+20M_{pv})+ [P_{bio}(C_{bio}+RCF*R_{bio})+20M_{bio}]+N_{bat}[C_{bat}+y_{bat}*C_{bat}+(20-y_{bat}-1)M_{bat}] \tag{16}$$

The capital costs of a PV module, a biomass gasifier unit (per kW), and a battery are shown above by the letters Cpv, Cbio, and Cbat, respectively. The associated yearly operating and maintenance expenses for the battery, biomass unit, and PV system are Mpv, Mbio, and Mbat. Over the course of the 20-year project horizon, ybat is the anticipated number of battery replacements. Rbio is the biomass unit's replacement cost (per kW), and RCF is the unit's replacement-cost factor, which is the number of times the unit is replaced over a 20-year period.

The constraints for the defined objective function considered in this investigation is expressed in Eqs. (17) to (20). In our study, *LPSPmax* is taken as 3% (0.03)

$$1 \leq N_{pv} \leq N_{pv}^{max} \tag{17}$$

$$1 \leq P_{bio} \leq P_{bio}^{max} \tag{18}$$

$$1 \leq N_{bat} \leq N_{bat}^{max} \tag{19}$$

$$LPSP < LPSP_{max} \tag{20}$$

6.2 Hybrid Optimization Algorithms

Selection of suitable algorithms is vital for solving complex optimization problems effectively. After reviewing extensive literature on renewable energy system optimization, two hybrid optimization frameworks were designed in this study by integrating well-established metaheuristic algorithms. PSO, GA,GWO and WOA were chosen for their complementary strengths in exploration and exploitation.

Combining these algorithms enables faster convergence, better search balance, and improved solution accuracy compared to using a single method. Detailed justification for each selected algorithm and the structure of the proposed hybrids is provided in the following sections.

6.2.1 Particle Swarm Optimization (PSO)

PSO is a nature-inspired, population-based metaheuristic originally proposed by Kennedy and Eberhart in 1995 [64]. The algorithm models the cooperative social behavior observed when birds fly in flocks or fish swims in schools, where individuals adjust their movement based on both personal experience and information shared by the group. Its appeal lies in conceptual simplicity, very few control parameters, and the ability to handle highly nonlinear and nonconvex optimization problems without requiring gradient information.

In PSO, a set of candidate solutions—called *particles*—fly through a multi-dimensional search space seeking the optimum of a fitness function *f(x)*. Each particle *i* is characterized by a position vector ***xi***=*(xi1,xi2,…,xiD)* and velocity vector **vi**=*(vi1,vi2,…,viD)* where D is the number of decision variables. The canonical update rules are done according to Eqs. (21) and (22)

$$\mathbf{v}_i^{t+1} = w\,\mathbf{v}_i^t + c_1 r_1\big(\mathbf{p}_i - \mathbf{x}_i^t\big) + c_2 r_2\big(\mathbf{g} - \mathbf{x}_i^t\big) \tag{21}$$

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_i^{t+1} \tag{22}$$

Here, ***w*** is **inertia weight**, controlling exploration vs. exploitation. A larger *w* drives wide search; a smaller www refines around promising regions. Linearly decreasing www from w_{max} to w_{min} during the run is common to maintain diversity early and promote convergence later. ***c1,c2*** are **acceleration coefficients** for the cognitive (self-learning) and social (group influence) terms, typically in the range 1.5−2.5. ***r1,r2~U(0,1)*** — independent random numbers adding stochasticity so particles do not collapse too quickly.$\mathbf{P}_i$ represents personal best position of particle *i and* $\mathbf{g}$ represents global best position found by the entire swarm (sometimes a local best in neighborhood topologies).

A major strength of PSO is its natural balance between *exploration* (searching new areas) and *exploitation* (refining good solutions). The *inertia weight w* plays a key role: initially larger to promote exploration, then gradually reduced to concentrate on exploitation. A widely used linear schedule is given in Eq (23).

$$w(t) = w_{\max} - \frac{w_{\max} - w_{\min}}{T_{\max}}\, t \tag{23}$$

where *Tmax* is the maximum iteration number and *t* is the current iteration.

Although the canonical PSO is powerful, many modifications have been proposed to improve robustness such as *Dynamic inertia PSO* where we change w nonlinearly or according to swarm diversity to avoid premature stagnation. Then we can use *Velocity clamping and boundary control* to keep solutions feasible in constrained engineering problems (as used in hybrid methods in this work) and *topology variations* where fully connected (global best), ring (local best), or von Neumann neighborhoods affect information flow and convergence speed.
These enhancements are particularly relevant in renewable energy system sizing, where the cost surface is multimodal and constraints such as power balance, capacity limits, and battery life must be respected. PSO has been applied widely in electrical and renewable energy engineering because of its speed and simplicity. For hybrid renewable energy system (HRES) planning, PSO can size photovoltaic, wind, and storage components to minimize levelized cost of energy while satisfying reliability constraints [65]. It has also been used in optimal power flow, microgrid scheduling, and maximum power point tracking for solar PV systems.

Its advantages include gradient-free and derivative-free optimization, quick convergence on smooth cost landscapes, few parameters to set (easier to tune than GA), strong global search ability in early iterations. However, limitations are also recognized: the algorithm can prematurely converge if swarm diversity decays early; it struggles with highly discrete search spaces; and performance depends on parameter tuning (especially *w,c1,c2*) [66]. These weaknesses motivate combining PSO with other metaheuristics, as done in the hybrid approaches developed in this thesis.

6.2.2 Genetic Algorithm (GA)

Genetic Algorithm (GA) is a population-based evolutionary optimization technique inspired by the principles of natural selection and genetics. First introduced by Holland in the 1970s and later formalized and popularized by Goldberg [67], GA searches for optimal solutions by iteratively evolving a population of candidate solutions through biologically inspired operators such as selection, crossover, and mutation. GA has been widely applied in complex engineering optimization problems, particularly when the search space is discrete, nonconvex, or discontinuous, and when derivative information is unavailable or unreliable.

GA begins with a population , *P0={x1,x2,…,xN},* where each individual (chromosome) ***xi*** represents a possible solution encoded as a vector of real numbers, binary digits, or other symbols. Each individual is evaluated using a fitness function ***f(xi)***. The population is evolved over generations through four main steps: *Selection, Crossover (Recombination) Mutation, Elitism and Termination*

Selection

Selection determines which individuals reproduce and pass on their genetic material to the next generation. The probability of selection is typically proportional to fitness; fitter individuals have higher chances of being chosen. One of the most widely used methods is ***tournament selection***, where a subset of individuals is randomly sampled, and the one with the highest fitness wins. Another common approach is *roulette-wheel selection*, where each individual is assigned a slice of probability proportional to its fitness.

Mathematically, the probability of selecting individual iii using fitness proportionate selection is provided in Eq(24)

$$P_i = \frac{f(\mathbf{x}_i)}{\sum_{j=1}^{N} f(\mathbf{x}_j)} \tag{24}$$

Crossover (Recombination)

Crossover combines the genetic information of two selected parent chromosomes to produce offspring. In real-coded GA, a widely used scheme is **Simulated Binary Crossover (SBX)**, which maintains the distribution of offspring close to the parent solutions. Given two parents *x1* and *x2*, the SBX operator generates offspring *x1′* and *x2′* as given in Eqs (25) and (26).

$$x_1' = \frac{1}{2}[(1+\beta_q)x_1 + (1-\beta_q)x_2] \tag{25}$$

$$x_2' = \frac{1}{2}[(1-\beta_q)x_1 + (1+\beta_q)x_2] \tag{26}$$

Here,βq. is a spread factor calculated based on a random number u~$U(0,1)$ and a user-defined distribution index ηc. Refer to Eq(27)

$$\beta_q = \begin{cases} (2u)^{1/(\eta_c+1)}, & u \leq 0.5, \\ \left[\frac{1}{2(1-u)}\right]^{1/(\eta_c+1)}, & u > 0.5. \end{cases} \tag{27}$$

SBX provides a controllable search radius: higher ηc makes offspring closer to parents (local search), while lower ηc increases diversity.

Mutation:

Mutation introduces random changes to offspring to maintain population diversity and help escape local optima. A common method for real-coded GA is polynomial mutation, defined for each gene xk given in Eq(28).

$$x_k' = x_k + \Delta_k(x_k^{\max} - x_k^{\min}) \tag{28}$$

where Δk is a small perturbation derived from a polynomial probability distribution controlled by a mutation index ηm . Lower ηm results in larger perturbations and higher diversity, while higher ηm makes mutation more conservative.

Elitism and Termination :

To avoid losing the best-found solutions, *elitism* copies a fraction of the top-performing individuals directly to the next generation. The GA cycle repeats until a stopping criterion is met — such as reaching a maximum generation number, achieving a target fitness value, or no significant improvement over several generations.

GA is highly flexible and robust for many types of optimization problems because it does not rely on gradient information and can work on discrete or mixed-variable search spaces. It has been successfully used in renewable energy system sizing, economic dispatch of power systems, layout optimization of microgrids, and parameter tuning of controllers [68]. GA is particularly powerful when the search space is rugged with many local minima, as crossover and mutation can help the algorithm escape suboptimal traps.

Advantages include Global search capability and resilience to local minima, flexible encoding (binary, real-valued, combinatorial), applicability to multi-objective and constraint-handling frameworks. Limitations include: Relatively slower convergence compared to swarm-based methods such as PSO, high sensitivity to parameter choices (population size, crossover and mutation probabilities) and possible loss of diversity leading to premature convergence if mutation is too weak or elitism too strong [69]. These trade-offs motivate combining GA with other metaheuristics (e.g., PSO, GWO) to improve exploration and convergence, as done in the hybrid frameworks proposed in this study.

6.2.3 Grey Wolf Optimization (GWO)

GWO is a nature-inspired metaheuristic algorithm [70]. It mimics the cooperative hunting pattern of grey wolves in nature, balancing exploration and exploitation through mathematically modeled social behaviors. Because of its simplicity, few control parameters, and competitive search capability, GWO has gained increasing popularity in engineering design, renewable energy optimization, and power system planning [71].

The algorithm models a **hierarchy of wolves**: the best candidate solution is denoted as the **α** wolf, the second and third best as **β** and **delta δ** wolves, while the remaining are **omega (ω)** wolves. The α, β, and δ wolves guide the search, while ω wolves follow and explore. This leadership structure provides adaptive information flow, allowing exploitation around promising solutions while keeping diversity.

The GWO hunting process is described using encircling, hunting, and attacking phases.

Encircling prey :

Grey wolves encircle prey by updating positions relative to the best leaders according to Eqs (29) and (30).

$$D=|C\cdot Xp-X(t)| \tag{29}$$

$$X(t+1)=Xp-A*D \tag{30}$$

where *X(t)* is the current position, *Xp* is the prey position (here approximated by α, β, δ wolves), and *A ,C* are coefficient vectors controlling the encircling dynamics as given in Eqs (31) and (32)

$$A=2a*r1-a \tag{31}$$

$$C=2*r2 \tag{32}$$

Here, r1,r2~U(0,1) are random vectors and a decreases linearly from 2 to 0 over iterations following Eq. (33)

$$\mathbf{a} = 2 - 2\frac{t}{T_{\max}} \tag{33}$$

This parameter drives the exploration–exploitation tradeoff: larger $|\mathbf{A}|>1$ promotes exploration (search far from leaders), while $|\mathbf{A}|<1$ triggers exploitation (move closer to leaders).

Hunting and position update

To better approximate the prey's location, each search agent updates its position relative to α, β, and δ wolves simultaneously. Eq(30) provides the general equation for position update of the wolves. And Eqs (34) - (39) provides the update individually for α, β, and δ. Lastly, in Eq. (40), the average is taken to find out the next position.

$$D\alpha = |C1 \cdot X\alpha - X| \tag{34}$$

$$D\beta = |C2 \cdot X\beta - X| \tag{35}$$

$$D\delta = |C3 \cdot X\delta - X| \tag{36}$$

$$X1 = X\alpha - A1 * D\alpha \tag{37}$$

$$X2 = X\beta - A2 * D\beta \tag{38}$$

$$X3 = X\delta - A3 * D\delta \tag{39}$$

Finally, the next position is averaged:

$$\mathbf{X}(t+1) = \frac{\mathbf{X}_1 + \mathbf{X}_2 + \mathbf{X}_3}{3} \tag{40}$$

This mechanism lets each wolf consider three leaders instead of only the single best, improving balance and reducing the chance of early stagnation.

At the start of the search, parameter ***a*** is near 2, making $|\mathbf{A}|>1$, encouraging wide exploration. As iterations progress, ***a*** shrinks toward 0, forcing $|\mathbf{A}|<1|$ and driving the swarm to converge around α, β, and δ. This linear decay has been shown to be effective for convergence stability and is easy to implement, but adaptive or nonlinear strategies exist to further improve performance. GWO has several attractive features such as needing only a few control parameters (only the maximum number of iterations and population size; exploration is automatically adjusted by ***a***). It gives a faster convergence compared to GA due to direct guidance from leaders and it provides a balanced global–local search by using multiple top wolves instead of a single global best, reducing premature convergence risk. And it also provides an ease of hybridization with other metaheuristics such as PSO or WOA (exploited in this thesis). However, GWO also has some limitations. Its exploration capability may diminish early in highly complex, multimodal landscapes, causing stagnation near local minima [72]. Performance may also degrade in discrete combinatorial problems without suitable encoding strategies. To address these issues, variants with adaptive a, chaotic maps, and hybrid frameworks have been developed and are employed in this study's hybrid algorithms. Since its introduction, GWO has been successfully applied to renewable energy system sizing, including hybrid PV–wind–battery systems, where it showed competitive cost minimization and reliability performance [71]. It has also been used in power flow optimization, load forecasting, and parameter estimation of control systems. Its low parameter count and fast convergence make it especially attractive when many scenario evaluations are required, as in this research.

6.2.4 Whale Optimization Algorithm (WOA)

The Whale Optimization Algorithm (WOA) is a swarm intelligence–based metaheuristic proposed by Mirjalili and Lewis in 2016 [73]. WOA is inspired by the cooperative foraging behavior of humpback whales, especially their unique **bubble-net feeding strategy**. The algorithm models two key patterns observed in whales: encircling prey and spiral bubble-net attacks. This approach provides an adaptive balance between global search and local exploitation, making WOA competitive with established metaheuristics while maintaining algorithmic simplicity. WOA uses three main search behaviors: **encircling prey**, **bubble-net attack (exploitation)**, and **search for prey (exploration)**.

<u>Encircling prey :</u>

WOA assumes the current best candidate solution is close to the prey (optimal solution). Whales update their positions relative to this best solution using Eqs (41) and (42)

$$D = |C \cdot X^* - X(t)| \tag{41}$$

$$X(t+1) = X^* - A \cdot D \tag{42}$$

Here, $X(t)$ is the current position of the whale, X^* is the position of the current best-known solution. A and C are coefficient vectors controlling the encircling dynamics as given in Eqs (43) and (44).

$$A=2a*r1-a \tag{43}$$

$$C=2*r2 \tag{44}$$

Here, $r1,r2 \sim U(0,1)$ are random vectors and ***a*** decreases linearly from 2 to 0 over iterations:

The vector **A** controls movement. When $|\boldsymbol{A}|<1|$, it leads to exploitation (moving toward the prey), while $|\boldsymbol{A}|>1$, it encourages exploration (searching beyond the current best).

<u>Bubble-net attacking mechanism (exploitation) :</u>

Humpback whales use a spiral motion to herd and attack prey. This is mathematically modeled in WOA by a logarithmic spiral equation given in (45):

$$\mathbf{X}(t+1) = \mathbf{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \mathbf{X}^* \tag{45}$$

Here, $D'=|\ X^* - X(t)|$ is the distance to the best solution, b is a constant defining the spiral shape, and $l \sim U(-1,1)$ is a random number controlling the spiral's direction and tightness. At each iteration, whales probabilistically choose between the shrinking encircling mechanism and the spiral update with probability p according to the equation provided in (46)

$$p \sim U(0,1): \quad \begin{cases} \text{Shrink encircling} & p < 0.5 \\ \text{Spiral motion} & p \geq 0.5 \end{cases} \tag{46}$$

<u>Searching for prey (exploration)</u>

To avoid local minima, whales sometimes search for prey randomly by updating positions relative to randomly selected individuals rather than the global best. Eqs(47) and (48) gives us a guideline on how to proceed with that.

$$D=|C * Xrand-X(t)| \tag{47}$$

$$X(t+1)=Xrand-A * D \tag{48}$$

where Xrand is a randomly chosen whale from the population. This exploration step occurs when $|A|>1$, forcing the whales to search new, unexplored regions. The main exploration–exploitation balance in WOA is controlled by the parameter *a*, which decreases linearly from 2 to 0. Early iterations ($|A|>1$) favor exploration, while later iterations ($|A|<1$) encourage exploitation around the current best. The random switching between spiral and shrinking encircling further improves search diversity.

WOA provides several key benefits such as few control parameters (only population size and maximum iterations in practice), effective exploitation due to spiral motion and adaptive shrinking., and it is simple to implement and consumes low computational power . It also has a good global search capability in continuous optimization. However, WOA also has limitations: it may explore less effectively in very high-dimensional spaces or problems with complex constraints, potentially leading to premature convergence [74]. Performance can also be sensitive to the linear decay of *a*; adaptive or nonlinear strategies have been proposed to improve diversity late in the search [75]. Hybridization with other algorithms, as done in this thesis, can strengthen exploration and improve convergence reliability.

However, WOA also has **limitations**: it may explore less effectively in very high-dimensional spaces or problems with complex constraints, potentially leading to premature convergence [74]. Performance can also be sensitive to the linear decay of a; adaptive or nonlinear strategies have been proposed to improve diversity late in the search [75]. Hybridization with other algorithms, as done in this thesis, can strengthen exploration and improve convergence reliability. WOA has been successfully applied in renewable energy system design, including photovoltaic/wind/battery hybrid system sizing [74], maximum power point tracking, and distribution network reconfiguration. Its simplicity and competitive accuracy make it an appealing alternative when fast implementation and few tuning parameters are desirable.

6.3 Development of the Hybrid Optimization Algorithm

While individual metaheuristic algorithms such as PSO, GA, GWO, and WOA each demonstrate strong performance in many engineering applications, practical renewable energy system design often involves highly nonlinear, multi-modal, and constrained cost functions that can cause single algorithms to stagnate or converge slowly. To overcome these limitations and exploit the complementary strengths of different search strategies, this study develops **two custom hybrid optimization algorithms**, each integrating three distinct metaheuristics in a staged manner. The **first hybrid** is **time-focused**, combining**PSO**, **GA** and **GWO** , and to accelerate convergence and deliver near-optimal solutions quickly; PSO rapidly explores the search space, GA injects diversity and prevents early stagnation, and GWO stabilizes and refines the best candidates. The **second hybrid** is **accuracy-focused**, sequentially applying **PSO**, **GWO**, and **Whale Optimization Algorithm (WOA)** to achieve deeper local exploitation and improved final solution quality, particularly when computational time is less constrained. Both hybrids adopt a dynamic phase-switching mechanism driven by stall detection and relative improvement thresholds to decide when to move from one algorithm to the next. This design allows each optimizer to operate in the region where it is strongest — fast global search at the start, diversity restoration in the middle, and fine-grained exploitation at the end. By constructing these two hybrid frameworks, the research aims to provide a robust and adaptable approach to the complex sizing and cost-minimization problem of hybrid renewable energy systems, outperforming the reliability and accuracy of using any single algorithm alone. In the following sections, the working principle of these two hybrid algorithms have been described in detail , and their flowchart has been drawn

6.3.1 PSO-GA-GWO(Time focused)

The **time-focused hybrid optimization algorithm** is designed to quickly reach high-quality solutions by letting each metaheuristic operate where it performs best and switching phases adaptively based on progress. The process starts by **initializing a population** of candidate solutions (particles/agents) randomly within the decision variable bounds. Each candidate is evaluated using the objective (fitness) function, and both the **personal best** (*pbest*) and **global best** (*gbest*) solutions are recorded. The flowchart has been attached in Fig: 8

Phase 1 — PSO (fast exploration)

Each particle updates its **velocity** and **position** using the inertia-weighted PSO equations. Refer to equations given in the section number 6.2.1 which describes the PSO algorithm.The velocities are clamped to limits to keep solutions feasible.If fitness improves beyond a defined threshold, the phase continues; otherwise, the **stall counter** increments. In our study, the threshold has been set at 15.

<u>Phase Switch Condition</u>

After each iteration, relative improvement is computed using Eq(49).

$$\text{improvement} = \frac{\text{last\_best} - g_{\text{best}}}{\text{last\_best}} \tag{49}$$

If improvement stays below a user-defined minimum for a certain number of consecutive iterations (**stall count ≥ stall_threshold**), the algorithm transitions to the next phase and resets the stall counter. In our study, the threshold for relative improvement has been set at 1%.

Phase 2 — GA (diversity & recombination)

When PSO stagnates, the algorithm triggers **genetic search**: **Tournament selection** picks parents biased toward better fitness. **Simulated Binary Crossover (SBX)** recombines parent solutions. **Polynomial**

mutation perturbs offspring to restore diversity. The newly created offspring replace weaker solutions, and *gbest* is updated. For details , refer to section 6.2.2 If GA also stalls, the algorithm switches to GWO.

Phase 3 — GWO (deterministic convergence)

The population is reorganized into α, β, δ, and ω wolves. Candidate updates follow the encircling/hunting model. For details and mathematical equations , refer to section 6.2.3 which explains the GWO algorithm. This stage focuses on refinement and fast local convergence.

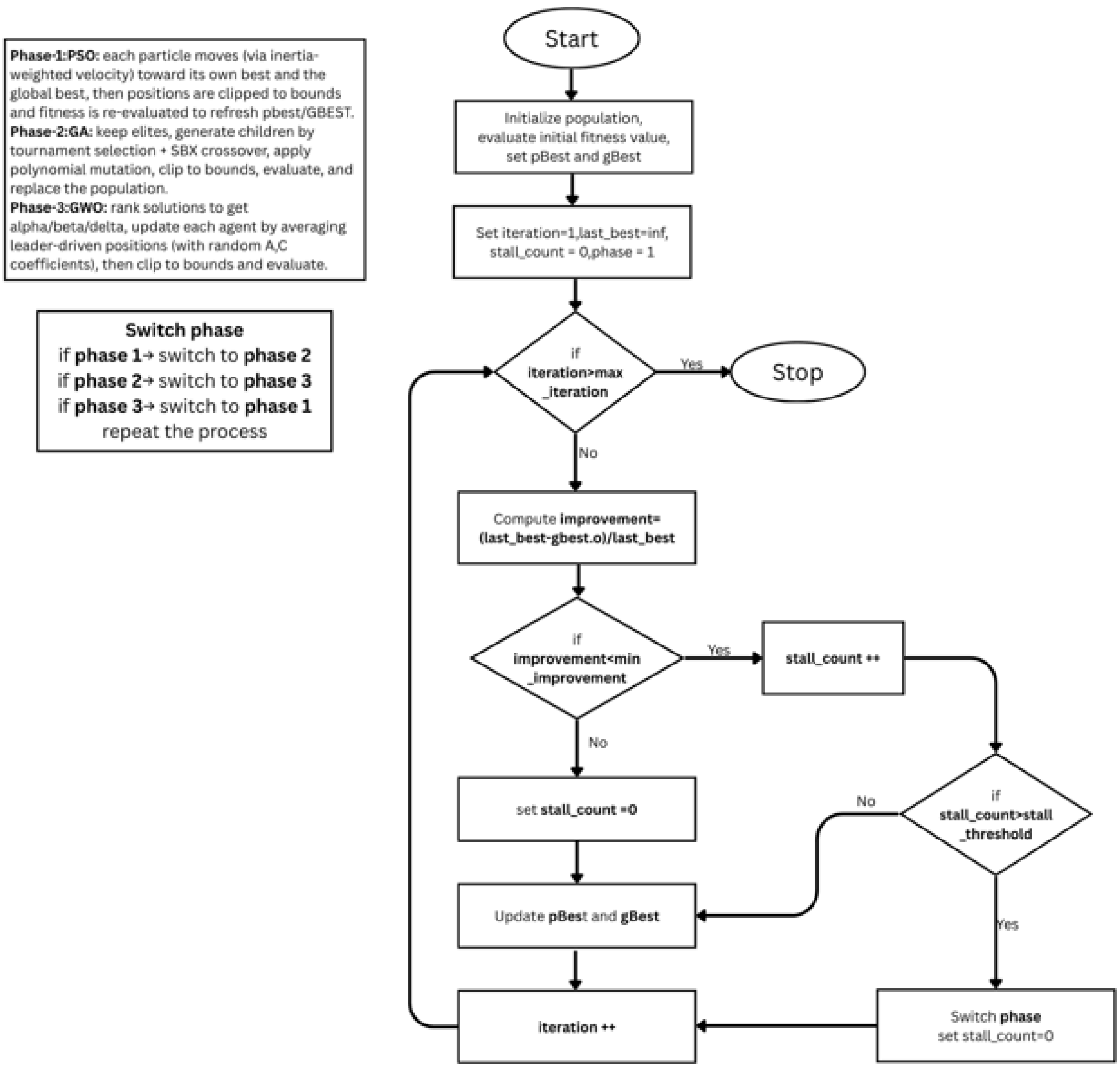

Fig:8 - Flowchart of *PSO-GA-GWO (Time focused)* algorithm

If GWO also stagnates before the stopping criteria (max iterations or acceptable error) are reached, the system can optionally loop back to PSO to reintroduce exploration, though in the time-focused hybrid the main cycle is typically PSO → GA → GWO. The algorithm stops when the maximum number of iterations is reached or when no meaningful improvement is observed for a prolonged period. The Key idea here is to use **PSO for speed**, **GA to escape local minima**, and **GWO for fast final tightening** — switching phases only when improvement stalls ensures efficiency

6.3.2 PSO-GWO-WOA(Accuracy focused)

The **accuracy-focused hybrid optimization algorithm** is designed to maximize final solution quality by allowing each constituent metaheuristic to contribute in a coordinated, performance-driven sequence. Unlike the time-focused strategy, which switches phases adaptively on stagnation, this framework runs controlled exploration phases, then selects the most promising optimizer to refine the search further.The process begins with **population initialization**: candidate solutions are randomly generated within the decision variable bounds and evaluated with the objective function. Both **personal best** (*pbest*) and **global best** (*gbest*) solutions are recorded, and algorithm-specific control parameters are prepared for **PSO)**, **GWO)**, and **WOA**. The flowchart for this algorithm has been attached in Fig: 9

Phase 1 — Parallel Independent Search (PSO, GWO, WOA)

For the first segment of iterations (e.g., 150), each optimizer runs **independently** on the same population:PSO explores rapidly using inertia-weighted velocity updates and stochastic acceleration toward both individual and global best positions.GWO forms α, β, δ leaders and guides wolves with adaptive encircling and hunting equations, offering structured exploitation while still exploring. WOA performs adaptive encircling and spiral bubble-net search, balancing exploration and local refinement.Each algorithm updates its own *pbest* and *gbest* during this phase. Running them simultaneously gives a comparative picture of their relative search effectiveness on the problem at hand. After the first search stage, the algorithm evaluates the **cost values** from the best solutions of PSO, GWO, and WOA. The optimizer with the **lowest objective cost** becomes the "winner," effectively adapting to the landscape instead of relying on a predefined order.

Phase 2 — Focused Refinement

The selected "winner" optimizer continues alone with the entire population for further refinement.
For example, if GWO produced the best cost after the initial 150 iterations, the swarm reorganizes under α, β, δ wolves; if WOA was better, bubble-net exploitation is used to fine-tune; if PSO leads, its adaptive

velocity and social learning refine the region. The remaining iterations (up to ~300 total) focus on intensification around the best solution found so far, improving precision and convergence reliability. The algorithm stops after the maximum set iteration count or if the improvement becomes negligible, outputting the final **best cost and system sizing**. Key Characteristics include Data-driven adaptivity**,** i.e. instead of a fixed switching sequence, the framework lets the cost outcome decide which metaheuristic is most effective for the given problem instance. It provides us a diverse hybrid strength by combining PSO's fast coarse search, GWO's balanced tightening, and WOA's fine exploitation, but activates the latter two only if they prove beneficial and it is designed for scenarios where runtime is less constrained, but the final optimality of cost and sizing matters most. Its advantages include automatically tailoring itself to the problem's landscape — no need to guess which algorithm will perform best. It reduces risk of premature convergence by testing three different search dynamics before intensification and it can achieve higher-quality solutions than using any single algorithm or a fixed sequence.

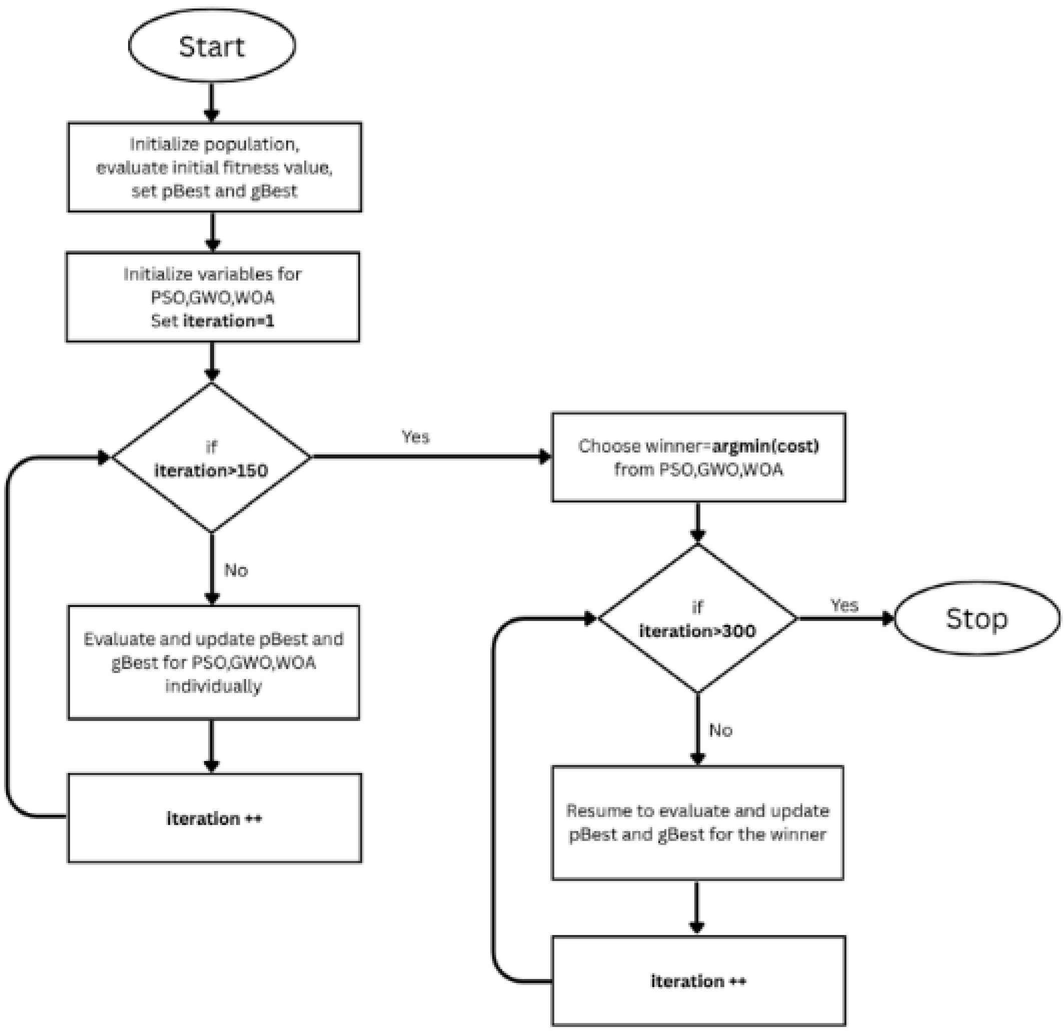

Fig:9 - Flowchart of *PSO-GWO-WOA (Accuracy focused)* algorithm

Chapter 7: Results and discussion

7.1 Uncertainty Modelling and Situation-Based Analysis (SBA)

To account for the stochastic nature of renewable resources and load demand, a **Situation-Based Analysis (SBA)** framework was developed. Real-world solar irradiance and load data were first divided into four representative seasons ; **summer, winter, spring, and fall** ,corresponding to a total of **96 hours** (24 hours × 4 seasons).

For each season, hourly datasets (e.g., the 16th hour of summer comprising 90 daily observations) were fitted to **three candidate probability distributions**: **Normal**, **Beta**, and **Weibull**. The fit quality was evaluated using the **log-likelihood method**, as illustrated in *Fig.10(a & b)*, which shows the empirical probability density and cumulative distribution functions. The Weibull distribution exhibited the highest log-likelihood (−370.6) and was thus selected as the best-fitting model for that hour.

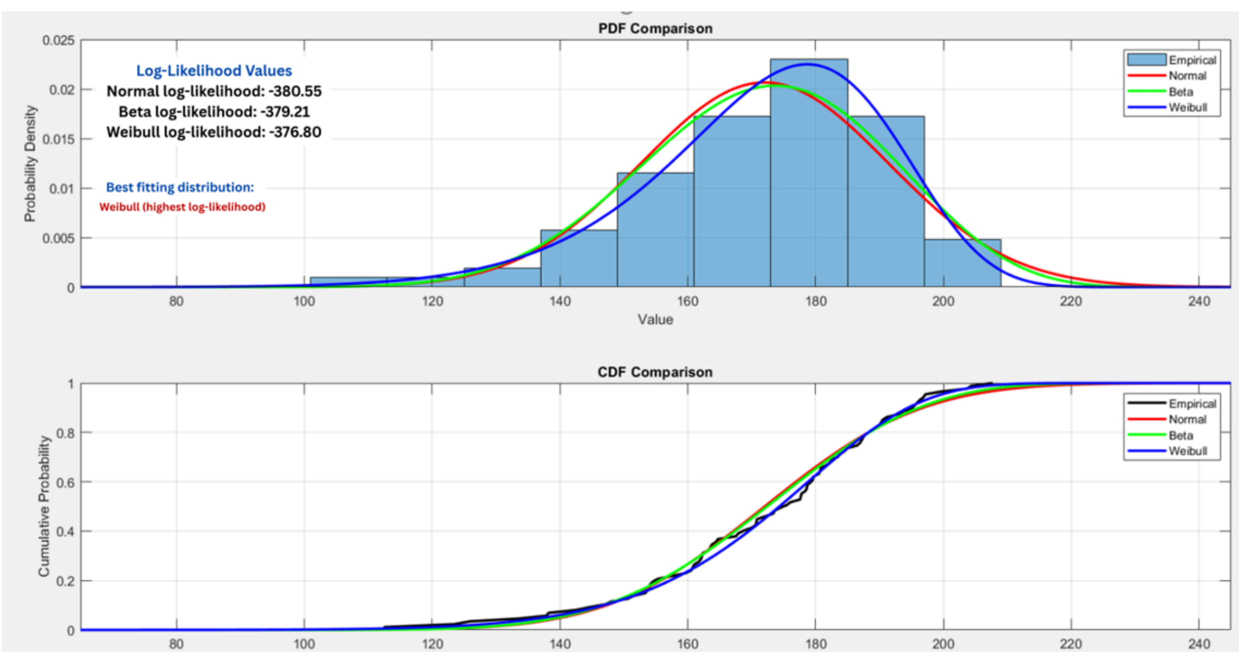

Fig.10 PDF and CDF fitting for load data (Weibull best fit via log-likelihood comparison with Normal and Beta distributions)

Repeating this process for all 24 hours of each season, the modal (most frequent) distribution was assigned as the **dominant seasonal distribution**. Using these best-fit seasonal distributions, a **roulette-wheel selection** procedure generated **40 probabilistic cases** per season, yielding two final **40 × 96 matrices** — one for solar irradiance and one for electrical load. These datasets formed the stochastic input base for all subsequent optimization algorithms.

While SBA provides structured, distribution-based uncertainty modeling, other probabilistic methods such as **Monte Carlo Simulation (MCS)** or **Point Estimate Method (PEM)** are also widely used in renewable-energy planning [76]. SBA was selected here because it combines data-driven realism with computational efficiency suitable for large-scale hybrid optimization.

7.2 Seasonal Load and Solar Characterization

The generated probabilistic profiles captured inter-seasonal variability effectively.
Fig. 11 shows the **annual load profile** across 40 probabilistic cases, with the orange curve representing the mean and the shaded region indicating the 5–95 % confidence band. The profile reveals higher demand peaks around the mid-year period, corresponding to the summer cooling load.

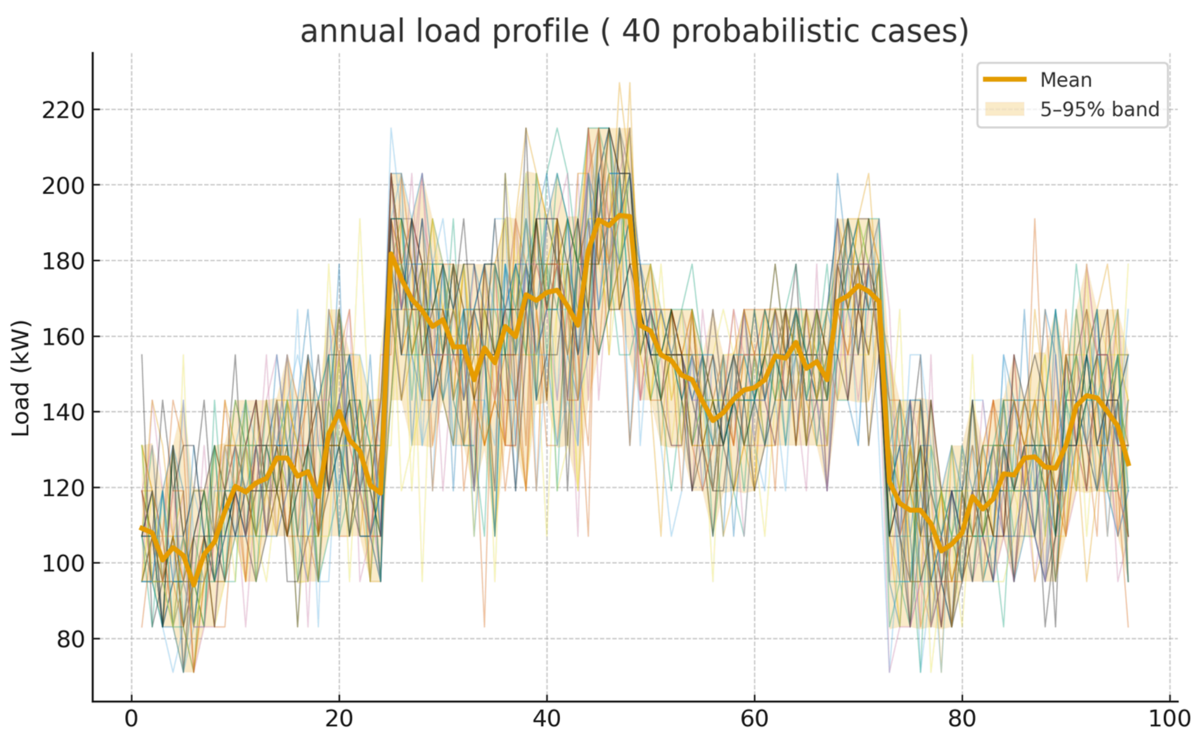

Fig.11 Annual load profile showing mean and 5–95 % probabilistic band across 40 cases

Seasonal decomposition of load (see *Figs. 12 and 13*) demonstrates that the **average load** was highest during **April–June (≈ 170 kW)** and lowest during **January–March (≈ 115 kW)**, confirming the impact of temperature-driven demand.

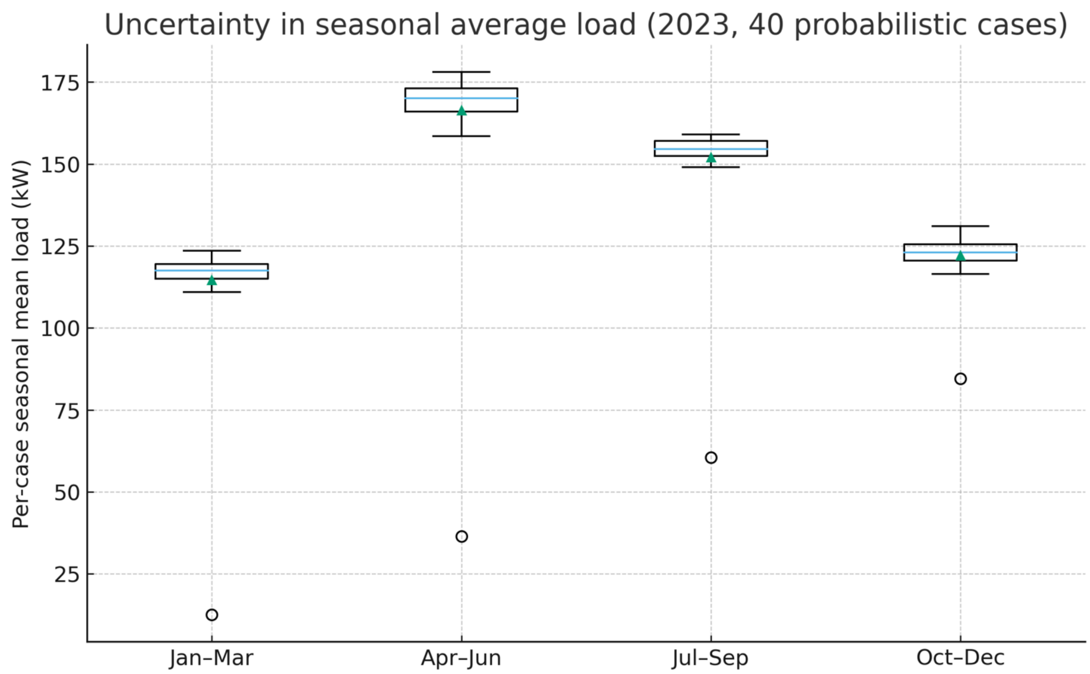

Fig. 12 Seasonal load uncertainty boxplots for Jan–Mar, Apr–Jun, Jul–Sep, and Oct–Dec

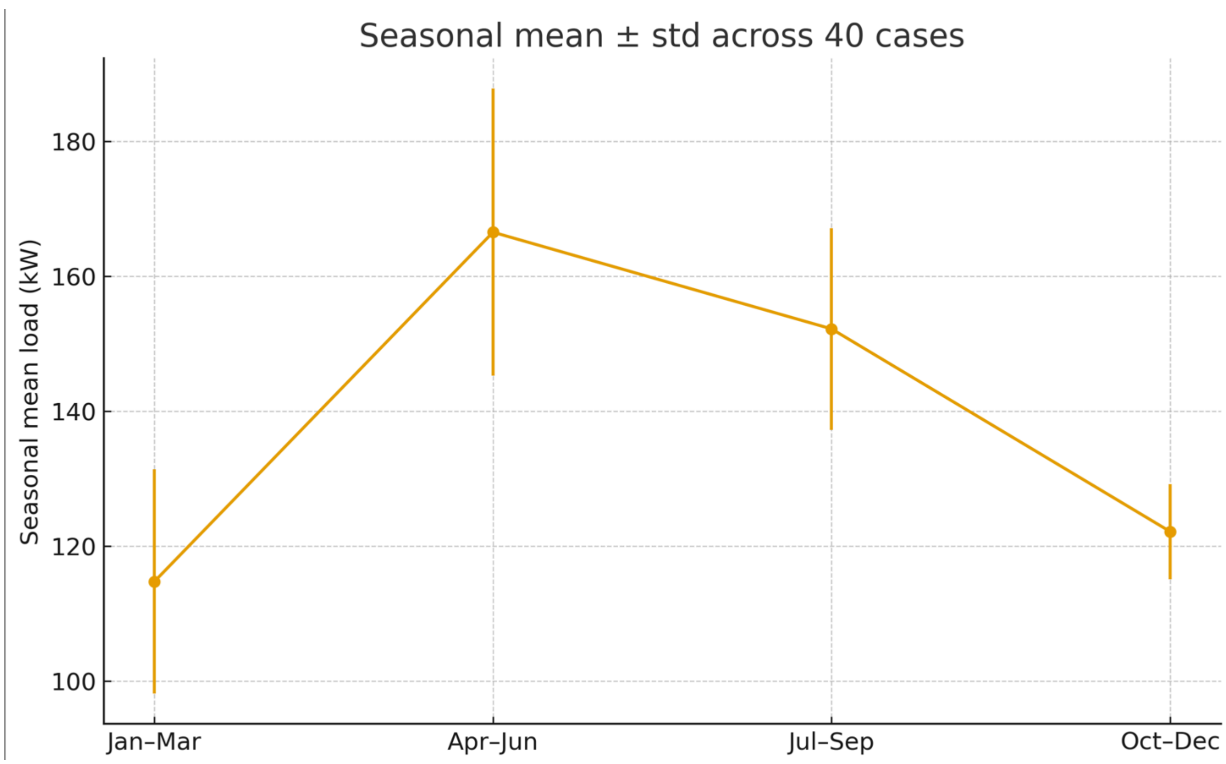

Fig. 13 Seasonal mean ± standard deviation of load across 40 cases

Similarly, *Figs. 14 – 16* illustrate the **solar irradiance** uncertainty. Irradiance was highest in **January–March (≈ 98 kW/m²)** and lowest in **July–September (≈ 58 kW/m²)**, reflecting monsoon-season attenuation. The standard-deviation bars capture natural daily variability, while the probabilistic envelopes quantify expected fluctuation for optimization input.

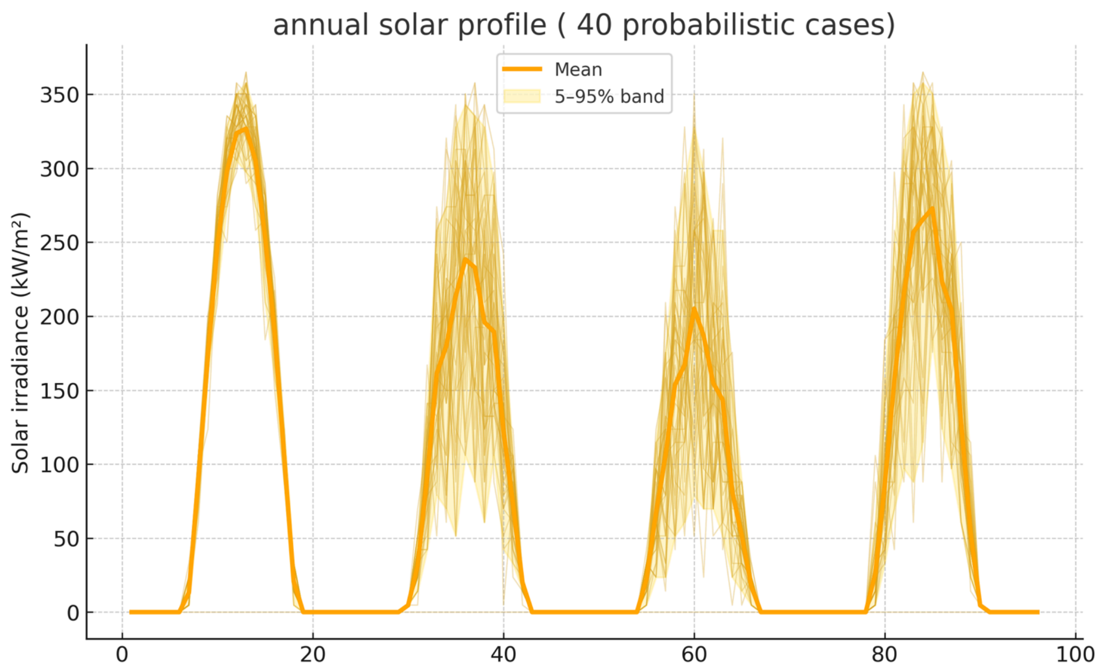

Fig. 14 Annual solar irradiance profile for 40 probabilistic cases (mean and confidence band)

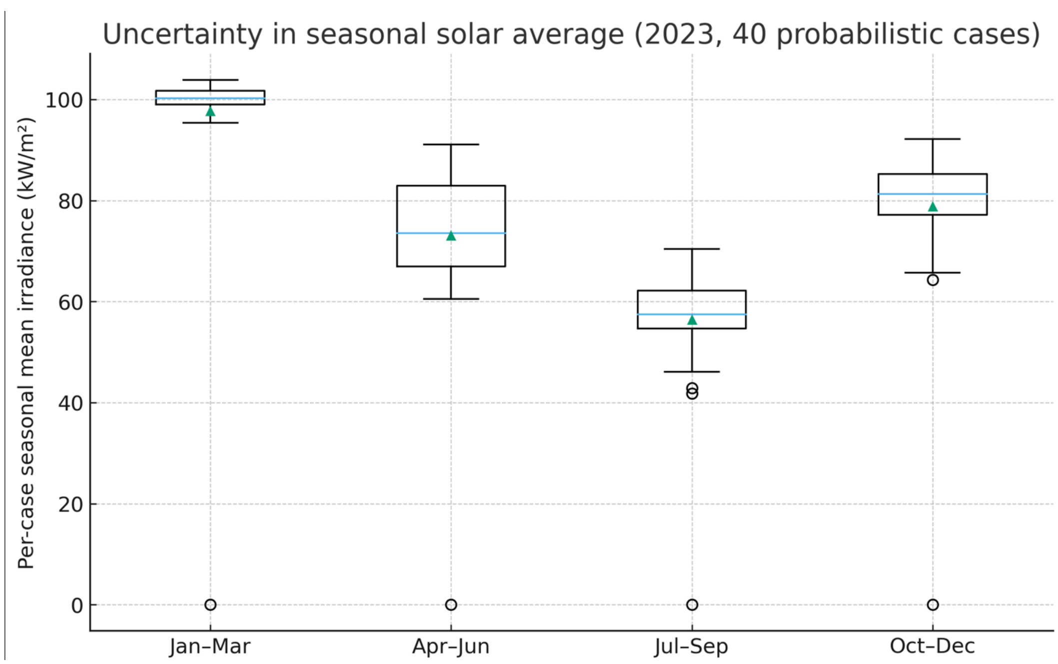

Fig. 15 Seasonal solar irradiance uncertainty boxplots for four quarters of the year

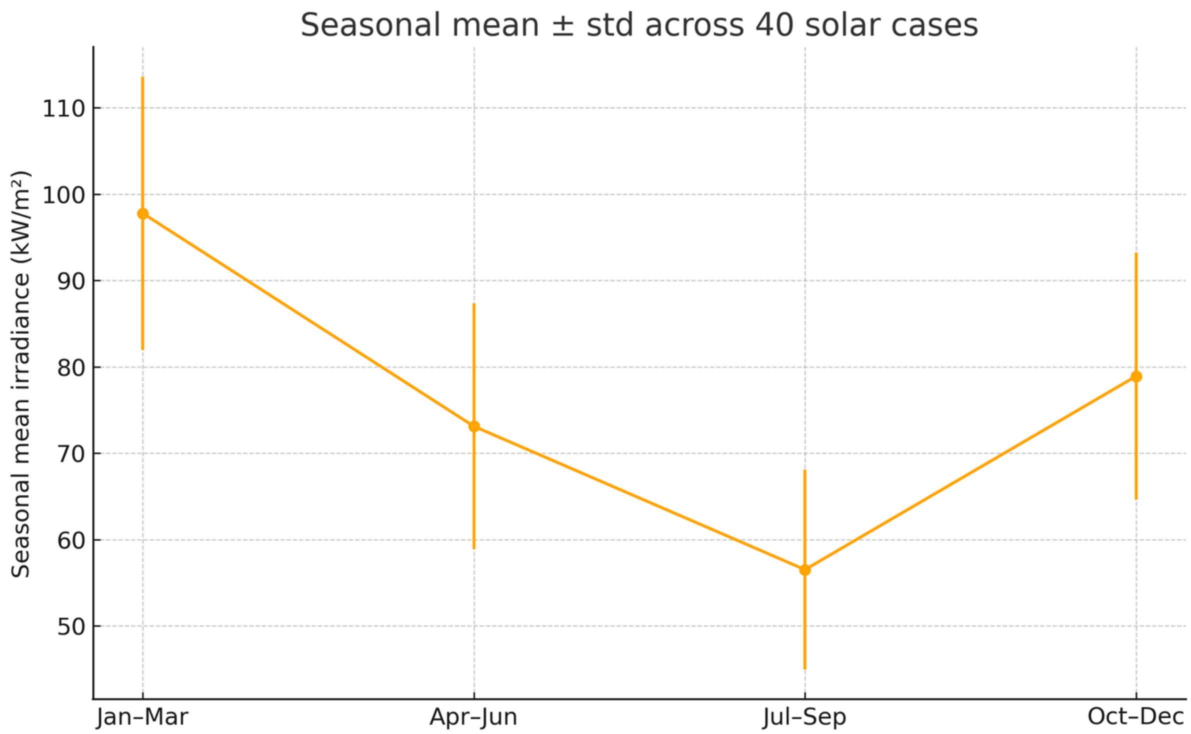

Fig. 16 Seasonal mean ± standard deviation of solar irradiance across 40 cases

7.3 Optimization of Individual Algorithms

7.3.1 Particle Swarm Optimization (PSO)

The PSO algorithm explored a wide solution space for the decision variables — **number of PV modules (Npv)**, **biomass generator power (Pbio)**, and **battery units (Nbat)**. The design-space mapping (*Fig. 17*) shows a clear gradient where total system cost decreases with moderate Npv and Pbio values, stabilizing around 3.3–3.4 × 10^6 USD. The sequential-stack plots (*Fig. 18*) reveal that PSO converged steadily, achieving a mean cost of approximately 3.47 × 10^6 USD with a coefficient of variation (CV) of 3.47 %. The convergence curve (*Fig. 19*) indicates stable behavior after ≈ 60 iterations, confirming robust global search characteristics. Runtime was 9.63 minutes.

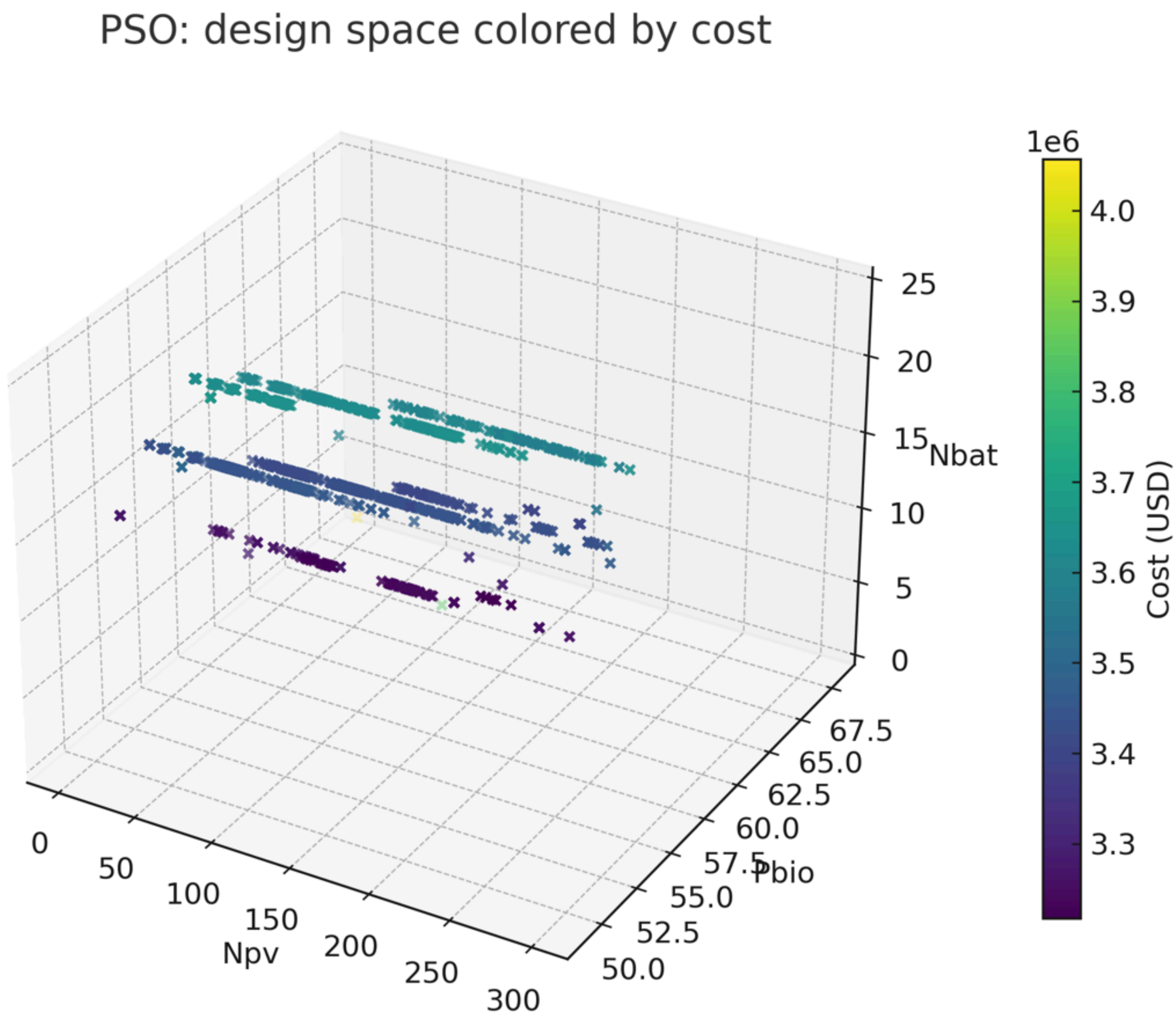

Fig. 17 PSO 3-D design space (Npv, Pbio, Nbat vs Cost USD)

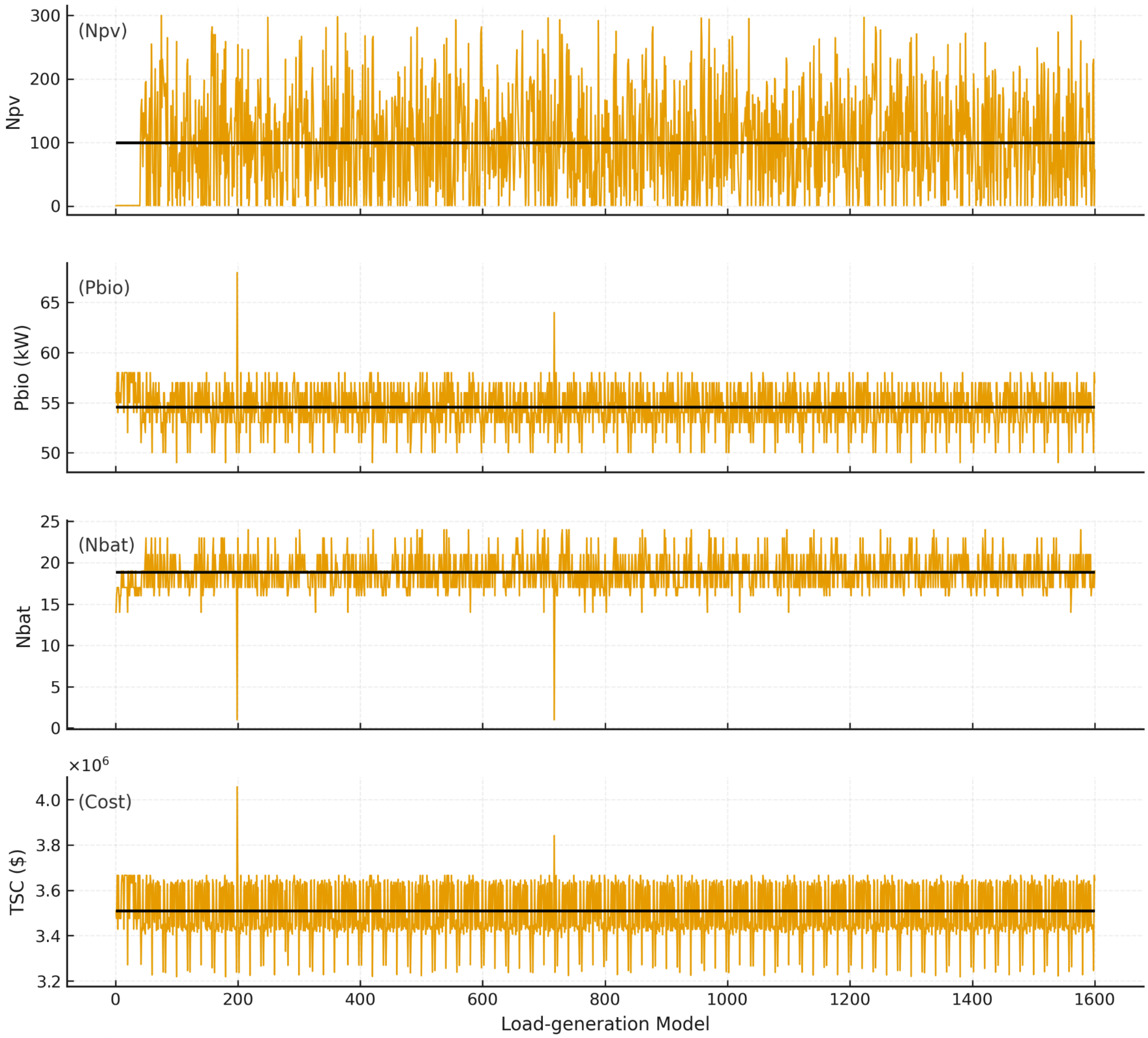

Fig. 18 PSO parameter and cost evolution across 1600 load–generation models

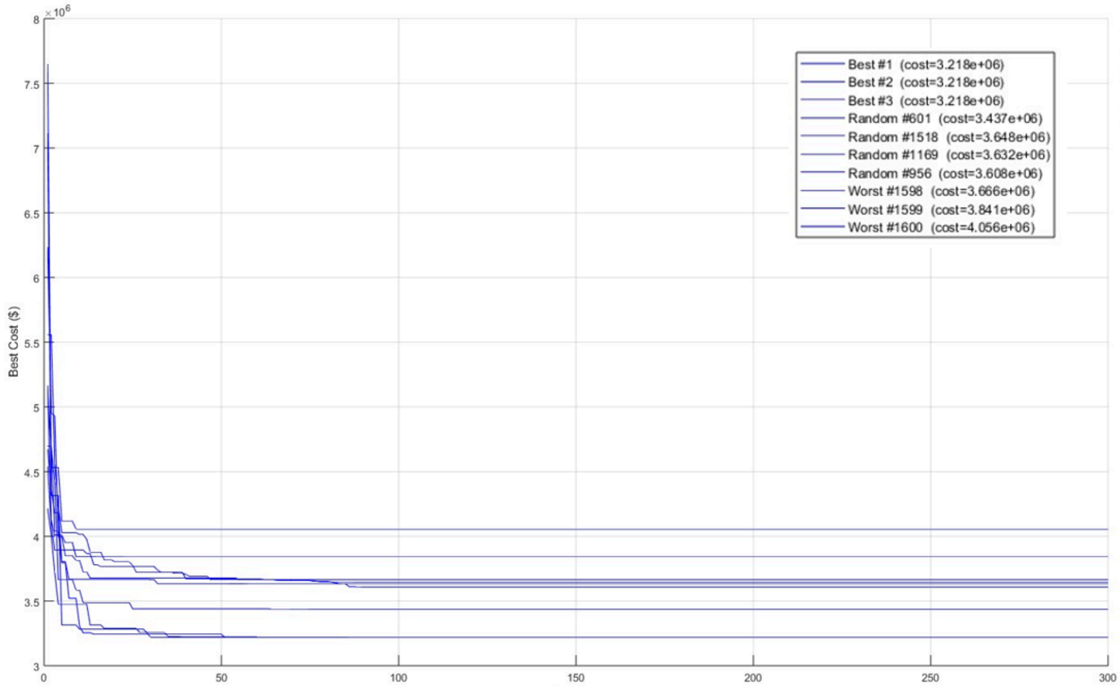

Fig. 19 PSO convergence curve for best, median, and worst runs (Cost vs Iterations)

7.3.2 Genetic Algorithm (GA)

As shown in *Figs.20-22*, GA exhibited slightly slower convergence but strong exploration capability. Cost reduction reached ≈ 3.52×10^6 USD, with a CV of 3.92 %. The best configuration clustered around Npv ≈ 50–70, Pbio ≈ 60–65 kW, and Nbat ≈ 10–15. Runtime was highest among all methods (≈ 54.3 minutes), attributed to repeated selection–crossover–mutation cycles per generation.

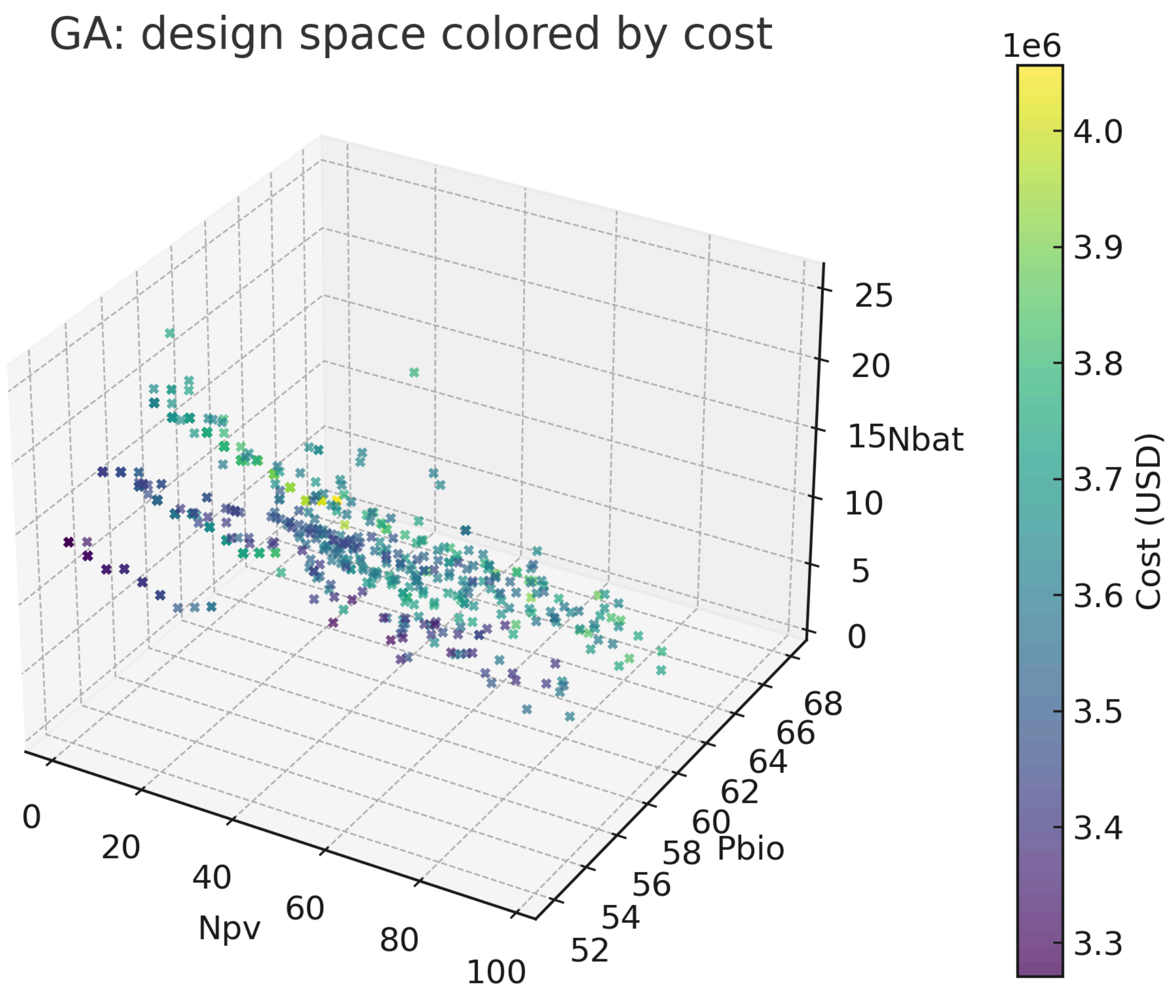

Fig. 20 GA 3-D design space (Npv, Pbio, Nbat vs Cost USD)

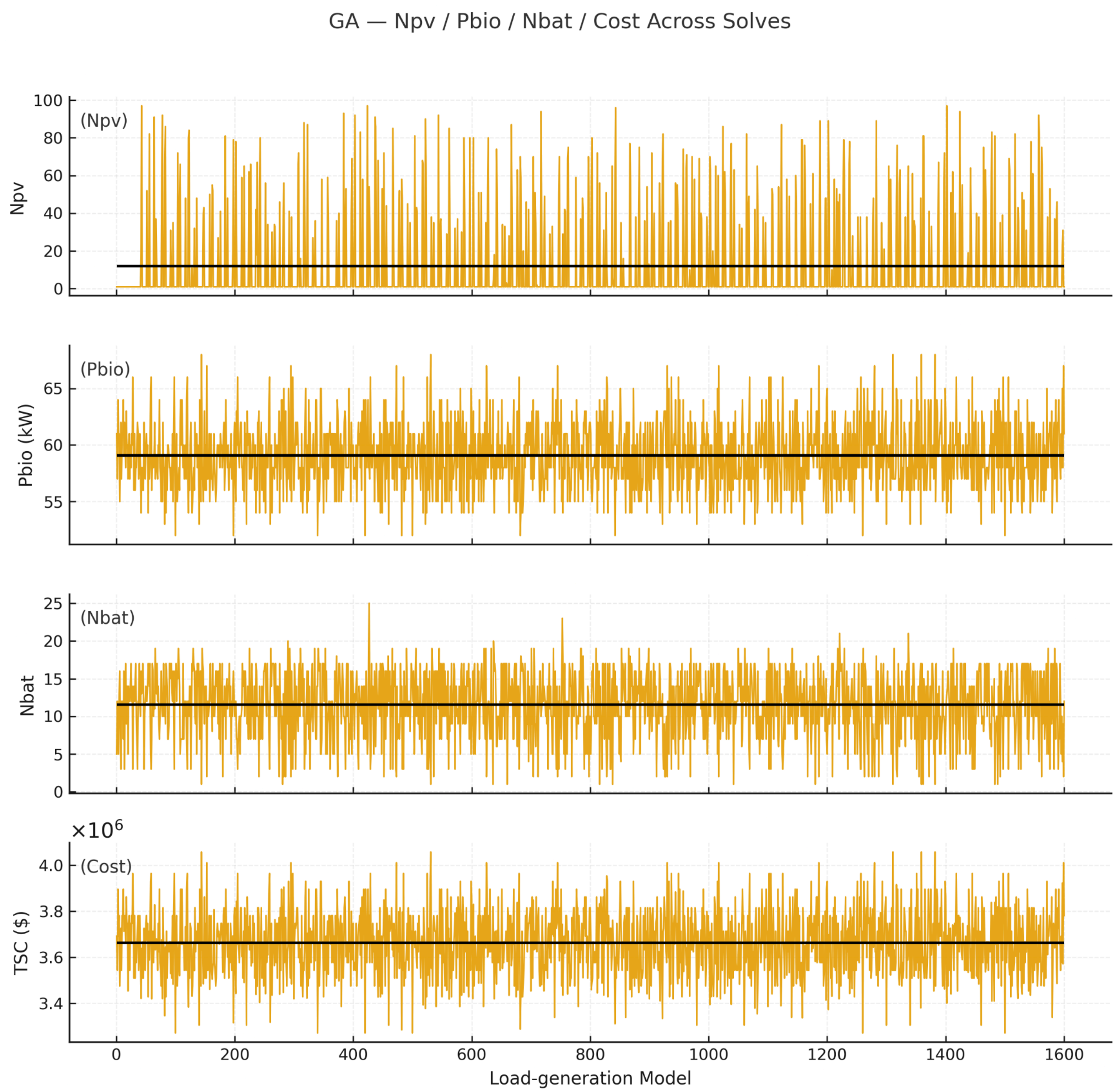

Fig. 21 GA parameter and cost evolution across 1600 models

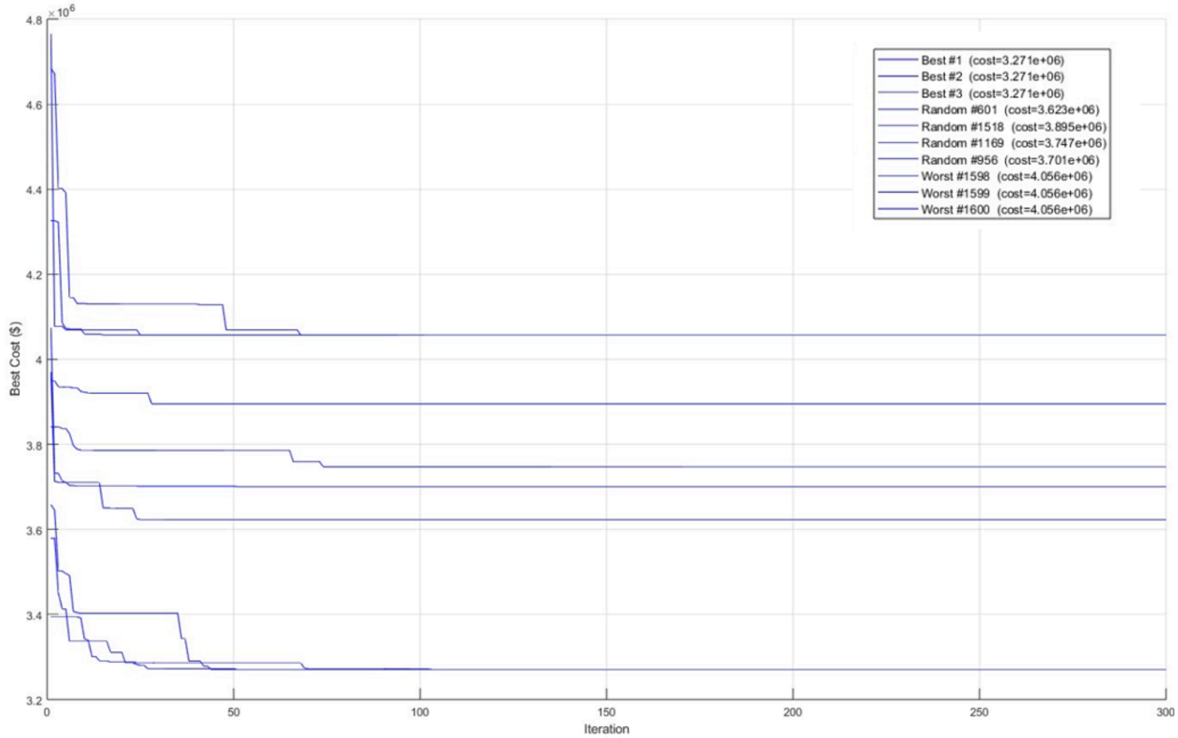

Fig. 22 GA convergence curve (Cost vs Iterations)

7.3.3 Grey Wolf Optimizer (GWO)

GWO yielded efficient convergence (*Figs. 23–25*), with cost ≈ 3.47×10^6 USD and runtime ≈ 12.1 minutes. The search dynamics demonstrated balance between global and local exploration through its α–β–δ hierarchy, effectively narrowing the feasible region without premature stagnation.

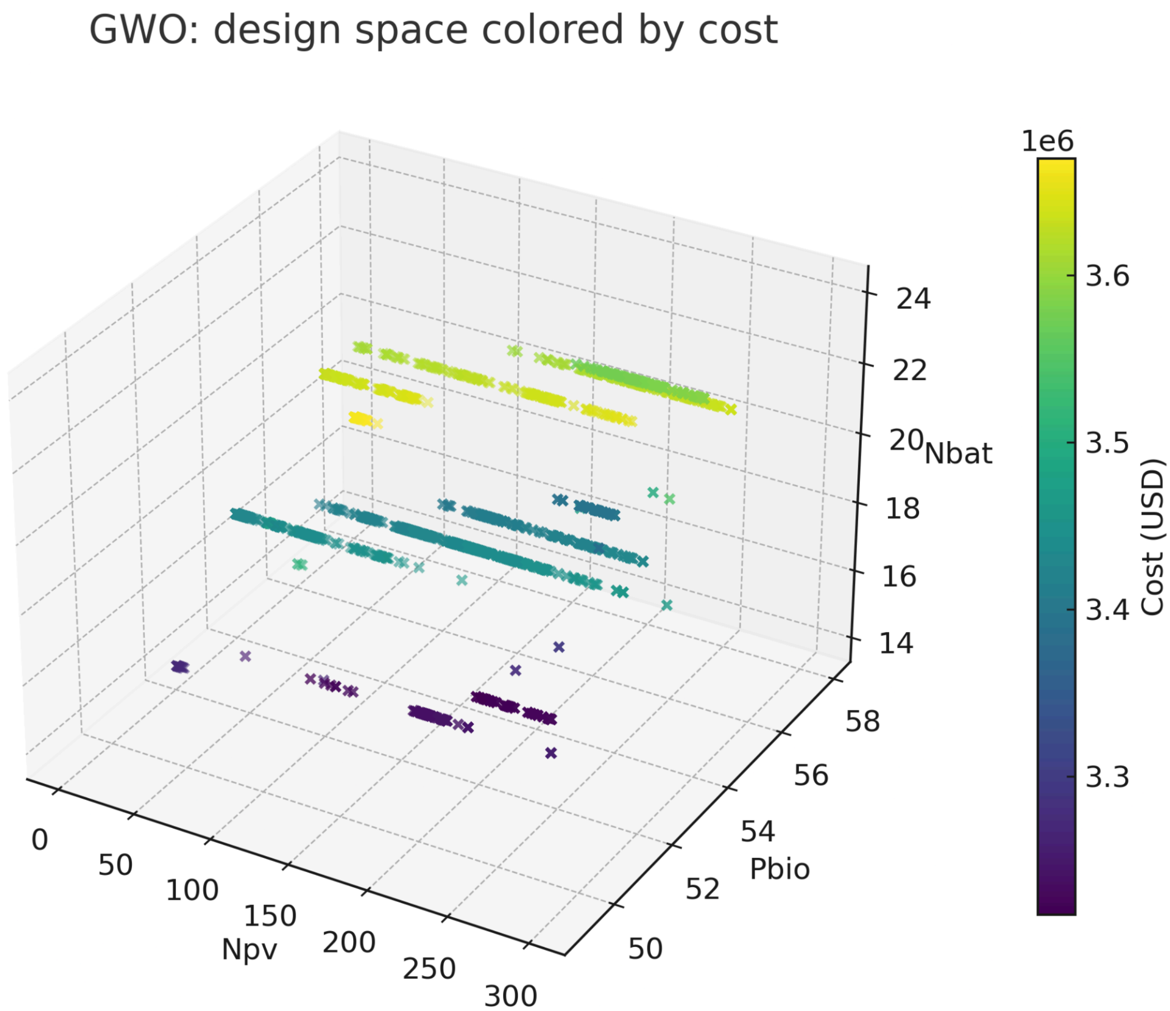

Fig. 23 GWO 3-D design space (Npv, Pbio, Nbat vs Cost USD)

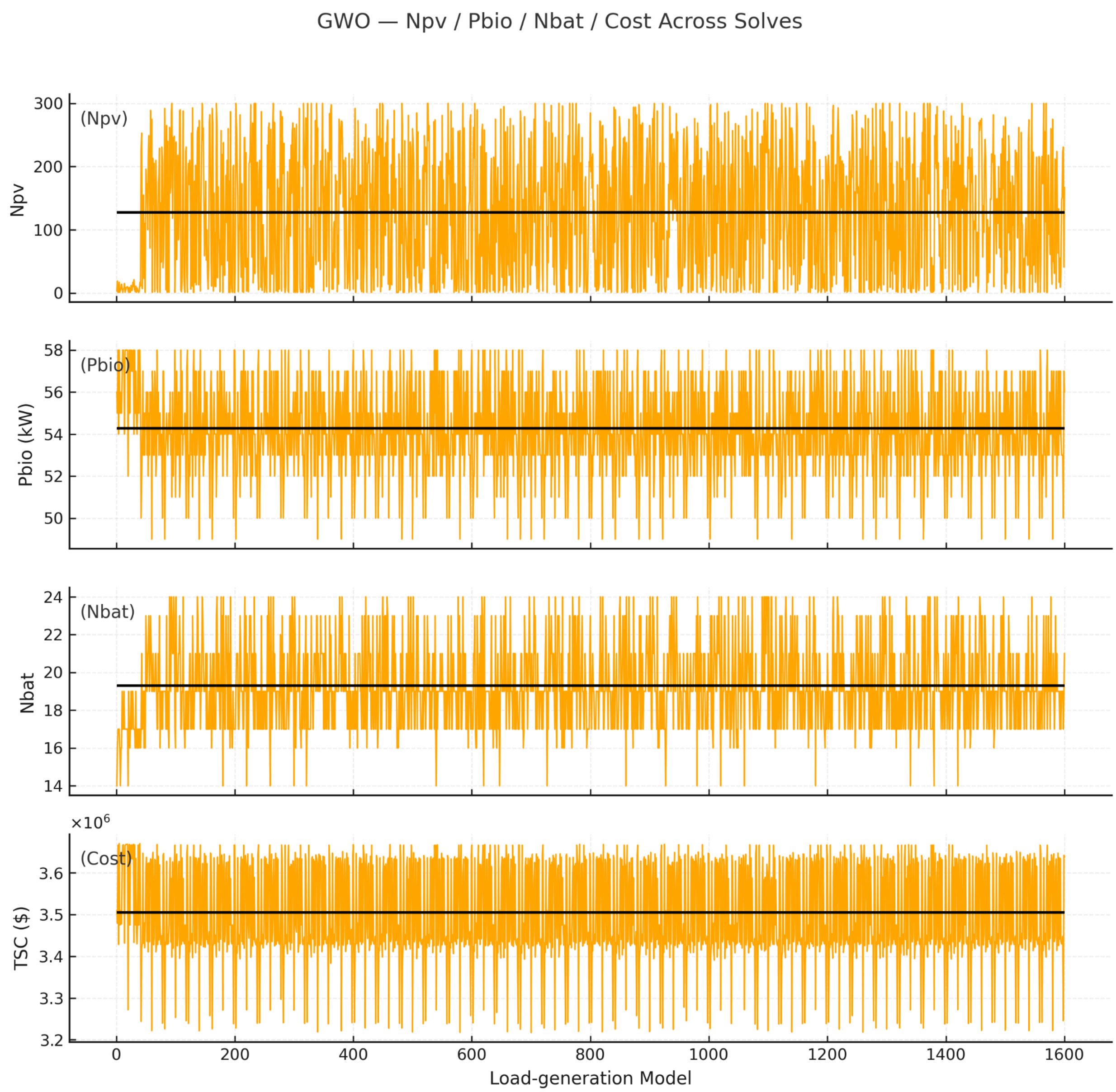

Fig. 24 GWO parameter and cost variation across 1600 models

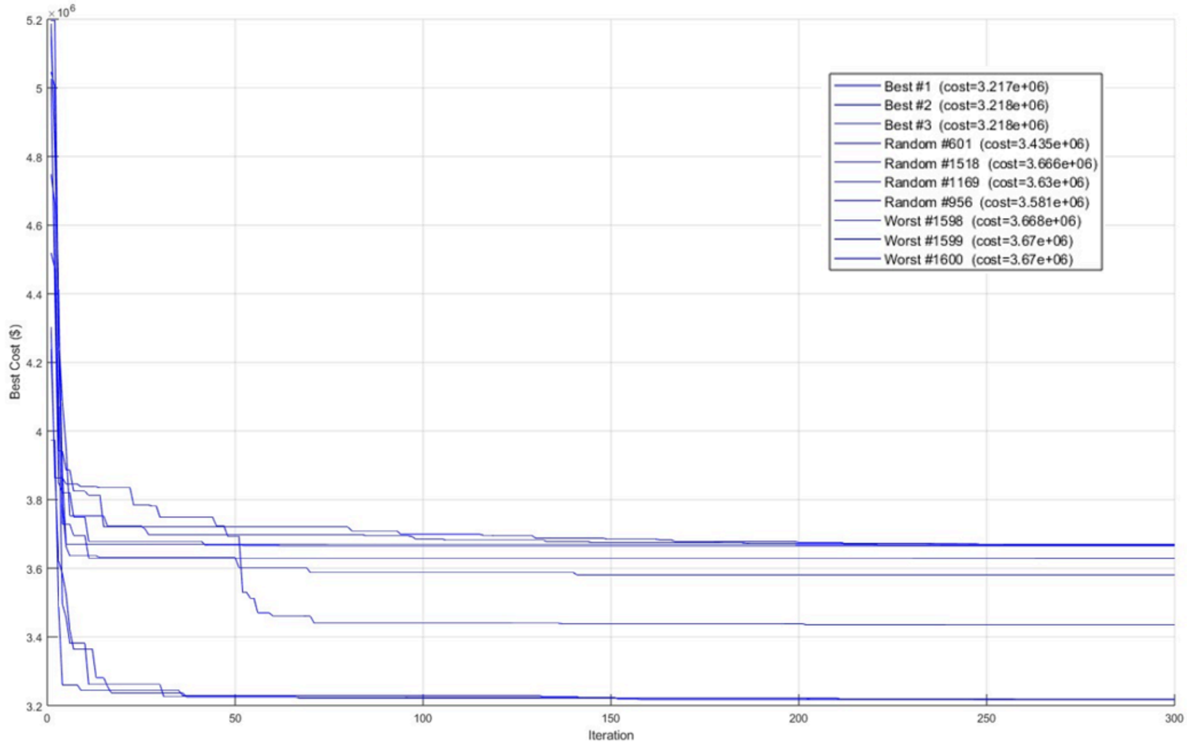

Fig. 25 GWO convergence curve (Cost vs Iterations)

7.3.4 Whale Optimization Algorithm (WOA)

WOA's spiral and encircling phases provided diverse candidate generation (*Figs. 26–28*). Final cost averaged ≈ 3.51×10^6 USD, with CV 3.89 %. The convergence pattern indicates early convergence (~40 iterations) followed by oscillations around the optimum, characteristic of WOA's bubble-net strategy. Runtime ≈ 12 minutes.

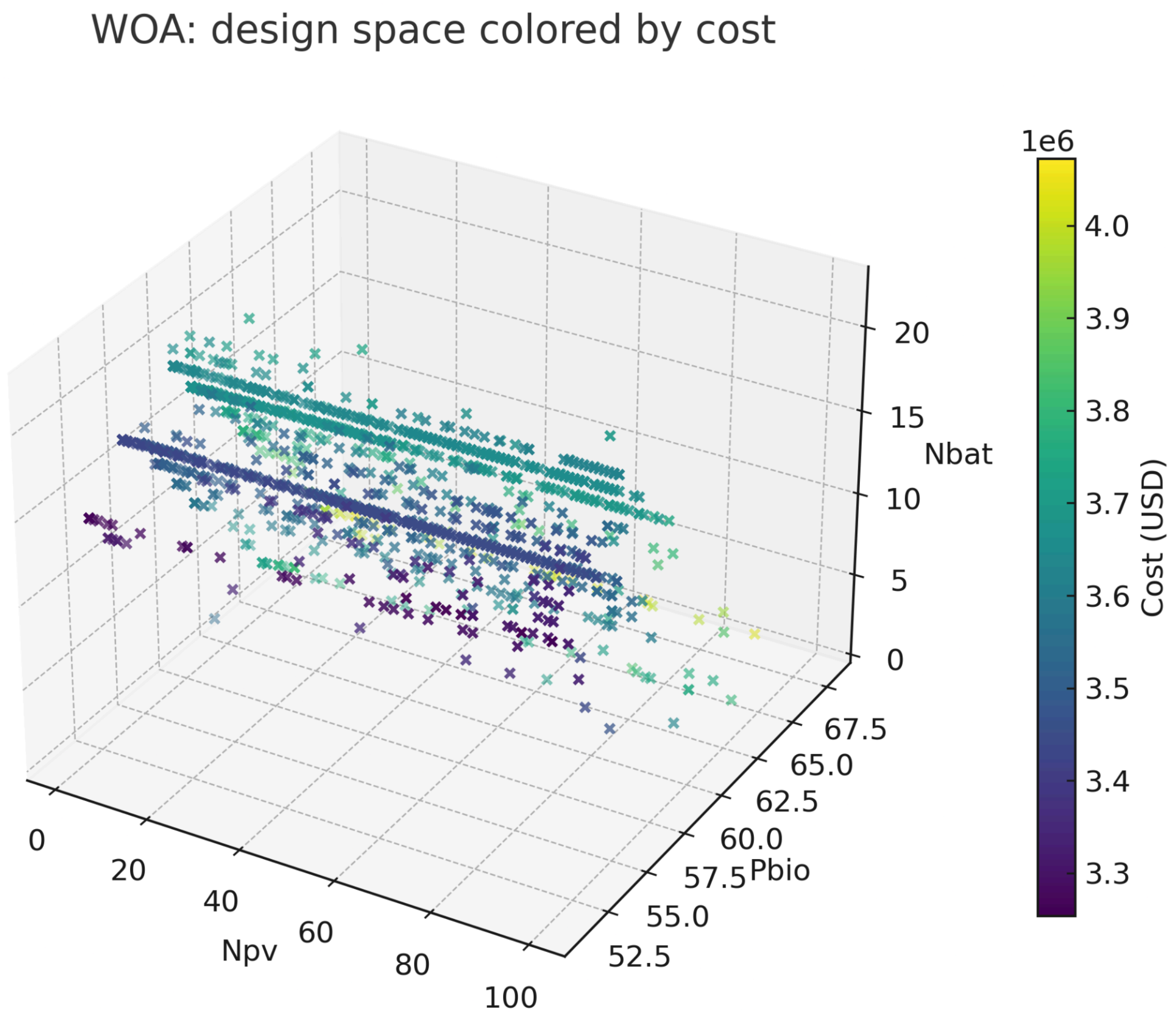

Fig. 26 WOA 3-D design space (Npv, Pbio, Nbat vs Cost USD)

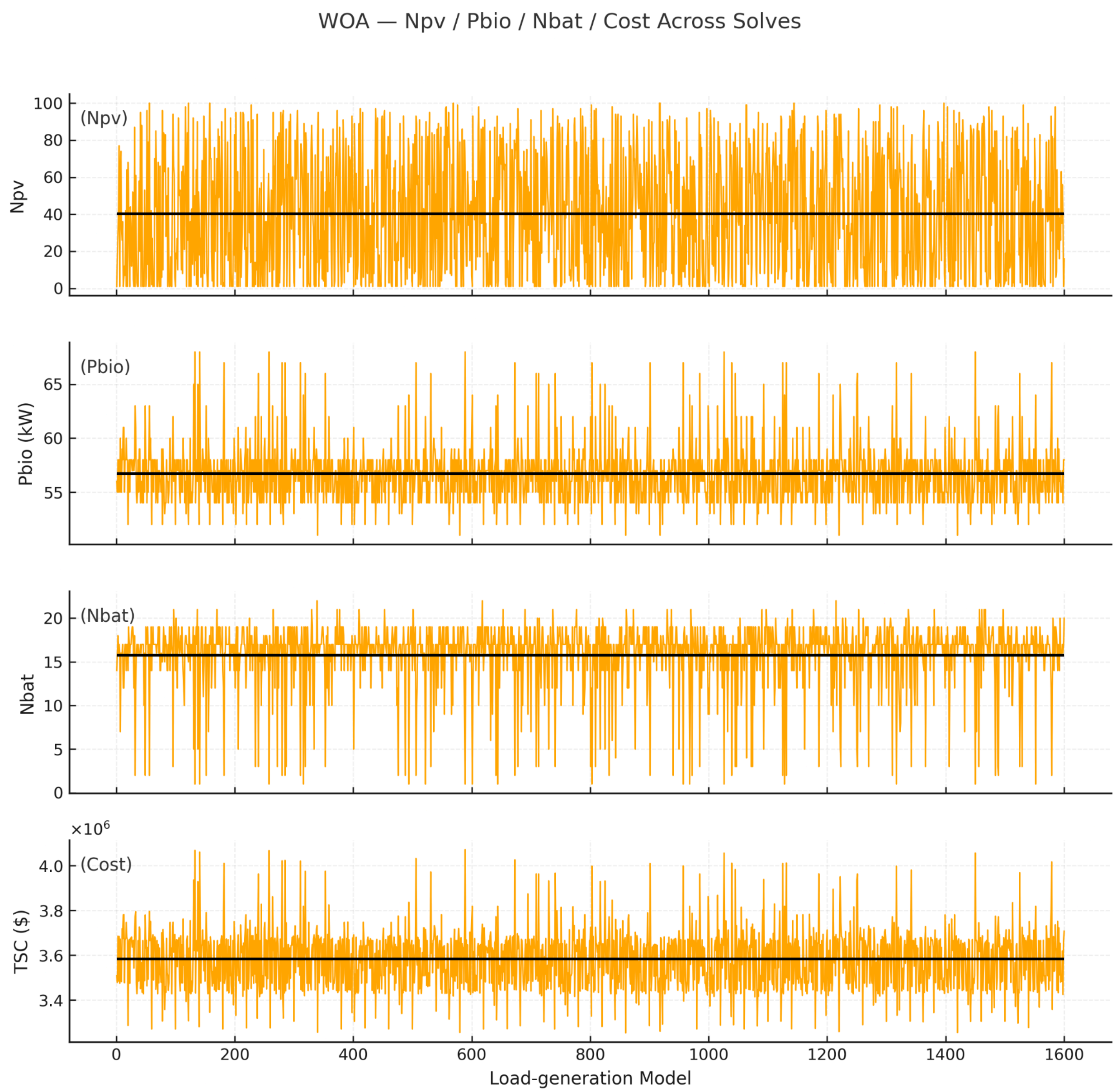

Fig. 27 WOA parameter and cost variation across 1600 models

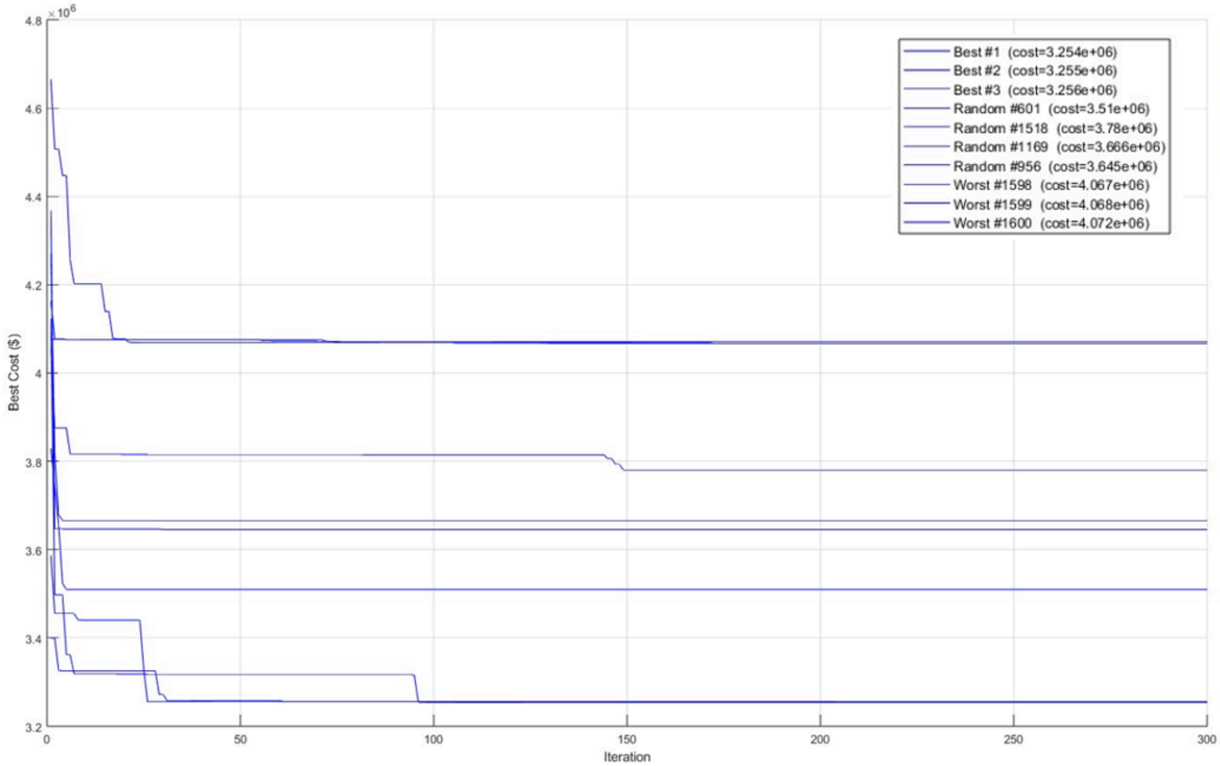

Fig. 28 WOA convergence curve (Cost vs Iterations)

7.4 Hybrid Algorithm Performance

7.4.1 Hybrid PSO–GA–GWO (Time-Focused Hybrid)

This hybrid aimed to exploit PSO's fast convergence and GWO's exploitation precision, moderated by GA's crossover diversity. The design-space and sequential trends (*Figs. 29-31*) show consistently low costs between 3.25 – 3.40 × 10^6 USD. The convergence profile reached stability in < 50 iterations with minimal oscillation, the shortest among all methods. Mean cost ≈ 3.46 × 10^6 USD (CV 3.51 %) and runtime ≈ 4.07 minutes — demonstrating the best trade-off between speed and accuracy.

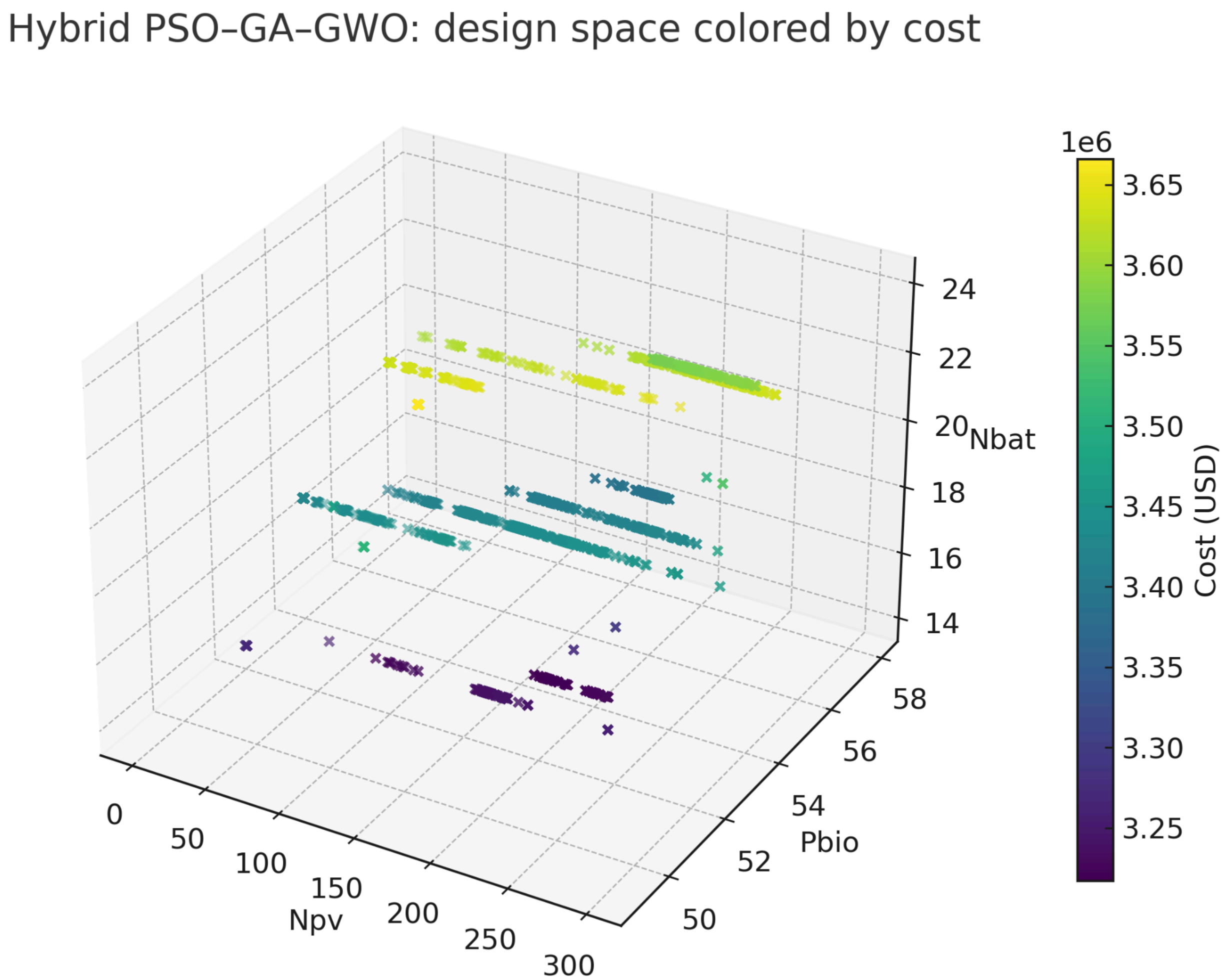

Fig. 29 Hybrid PSO–GA–GWO 3-D design space (Npv, Pbio, Nbat vs Cost USD)

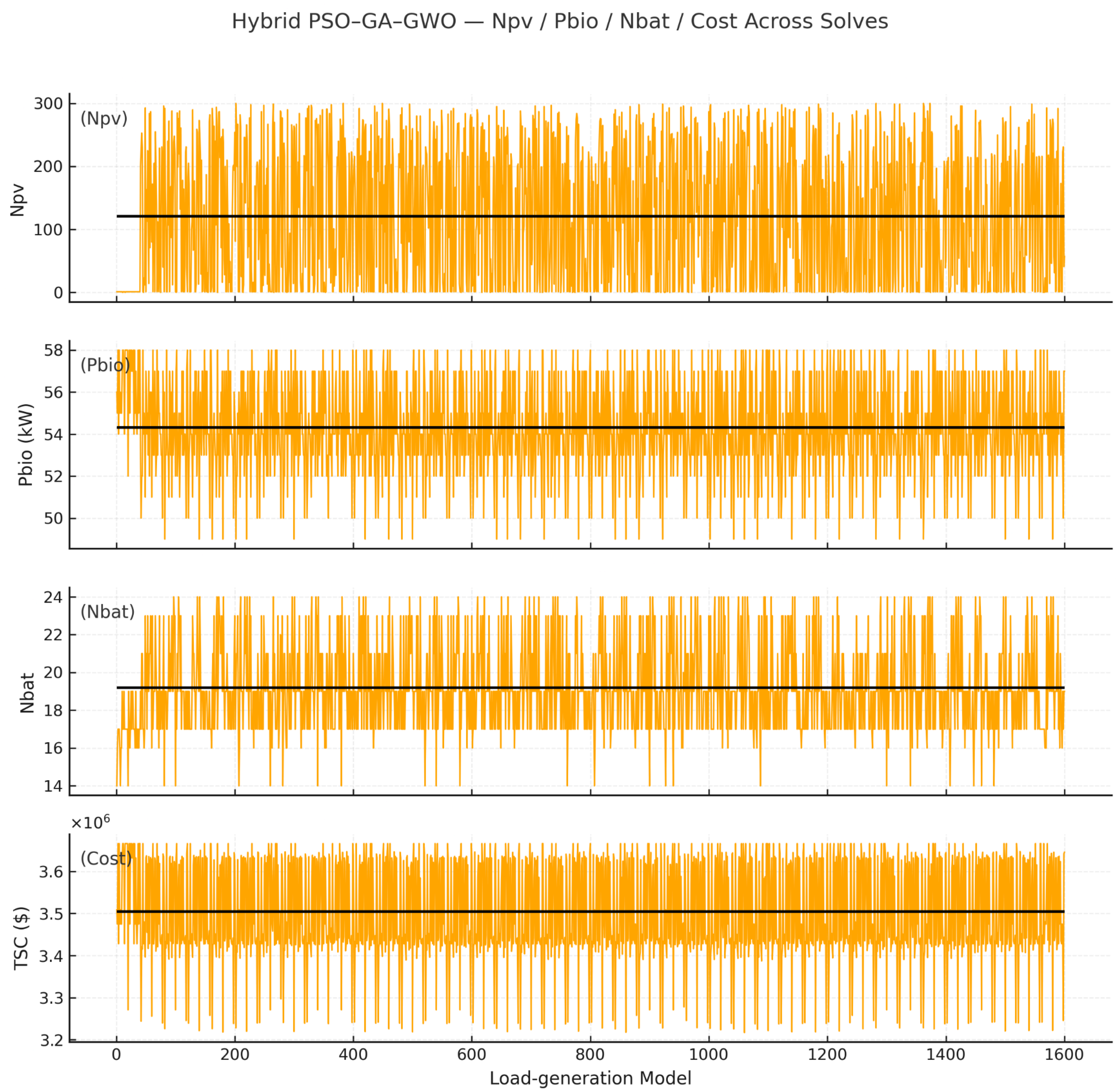

Fig. 30 Hybrid PSO–GA–GWO parameter and cost variation across 1600 models

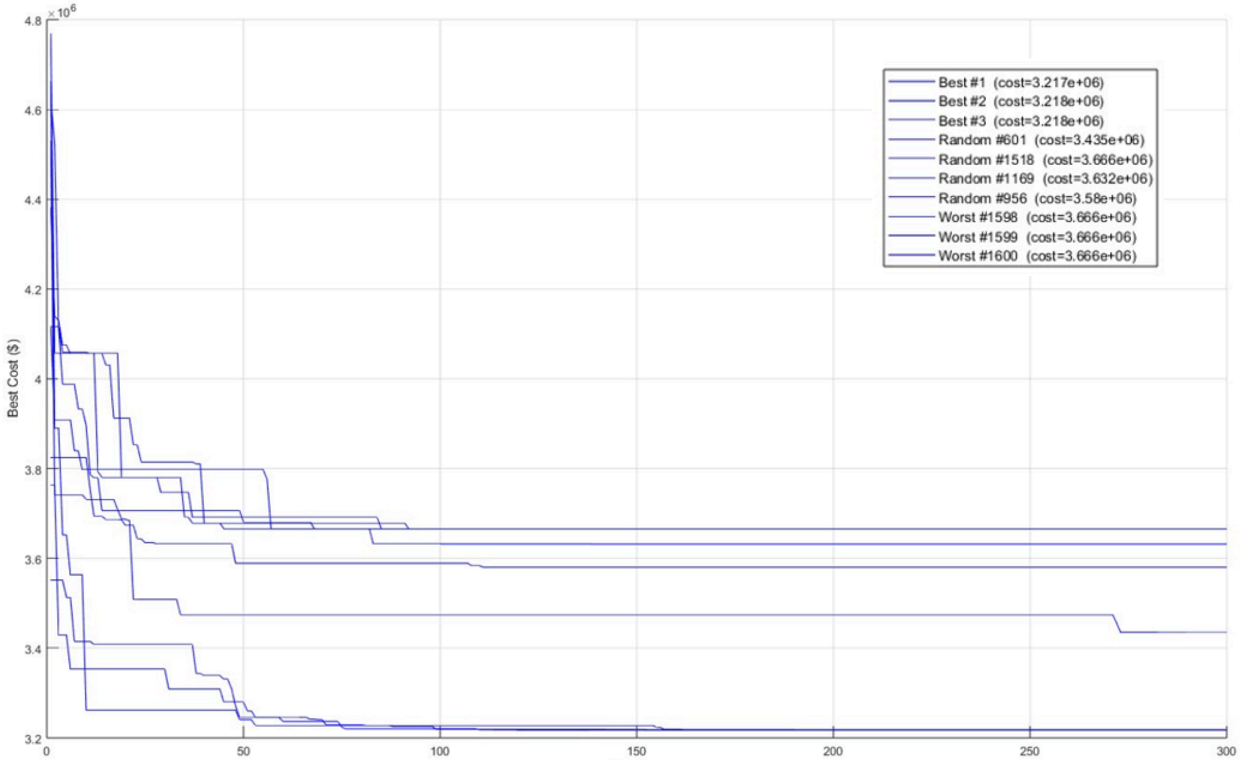

Fig. 31 Hybrid PSO–GA–GWO convergence curve (Cost vs Iterations)

7.4.2 Hybrid PSO–GWO–WOA (Accuracy-Focused Hybrid)

Here, WOA's spiral search enhanced local exploitation after PSO–GWO phases (*Figs. 32-34*). The hybrid attained the lowest overall cost of ≈ 3.42×10^6 USD (CV 3.42 %), converging within ≈ 70 iterations and runtime ≈ 15.2 minutes. The hybrid's layered structure prevented local entrapment while preserving convergence precision — confirming that combined exploration and exploitation mechanisms yield superior optima for stochastic resource data.

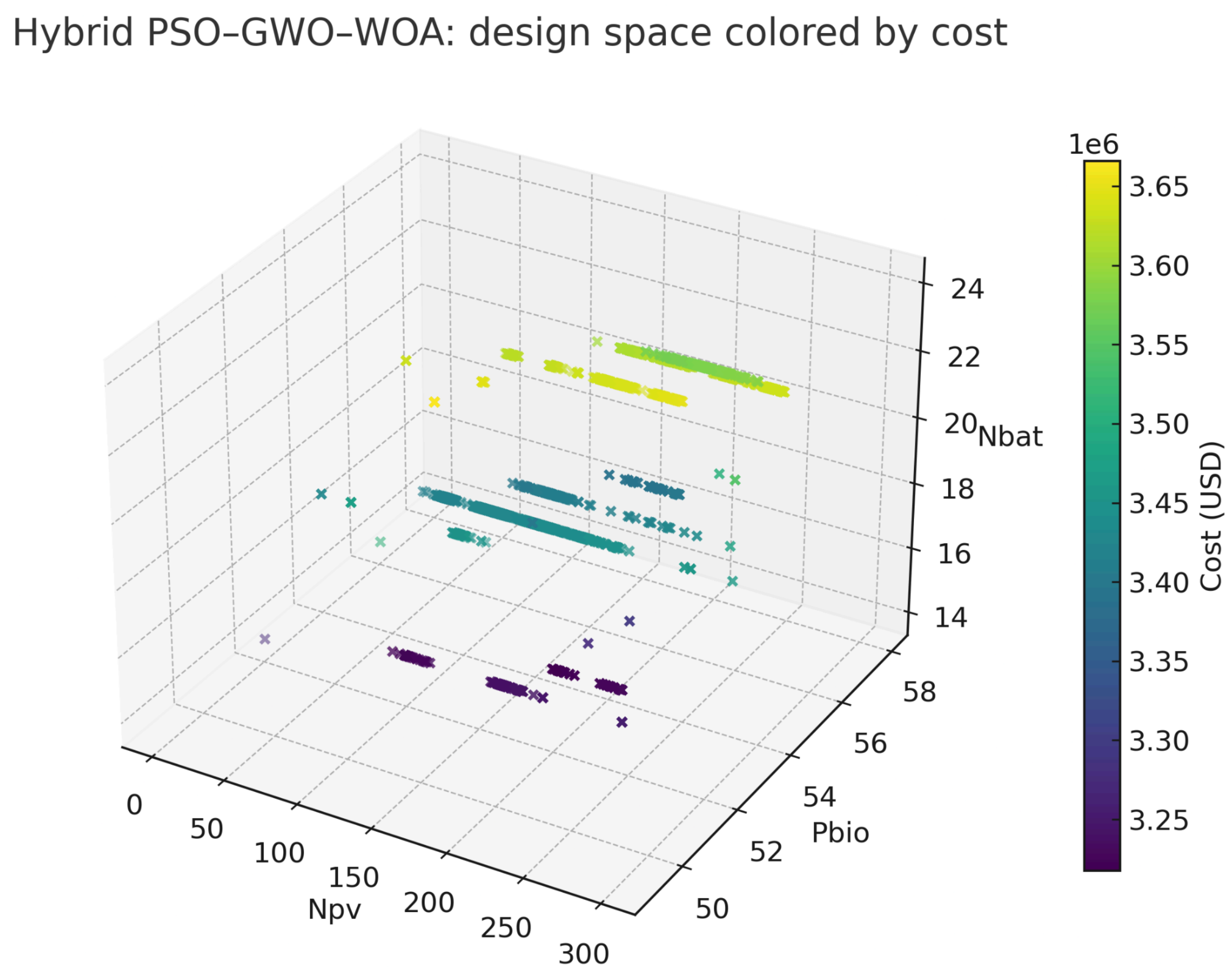

Fig. 32 Hybrid PSO–GWO–WOA 3-D design space (Npv, Pbio, Nbat vs Cost USD)

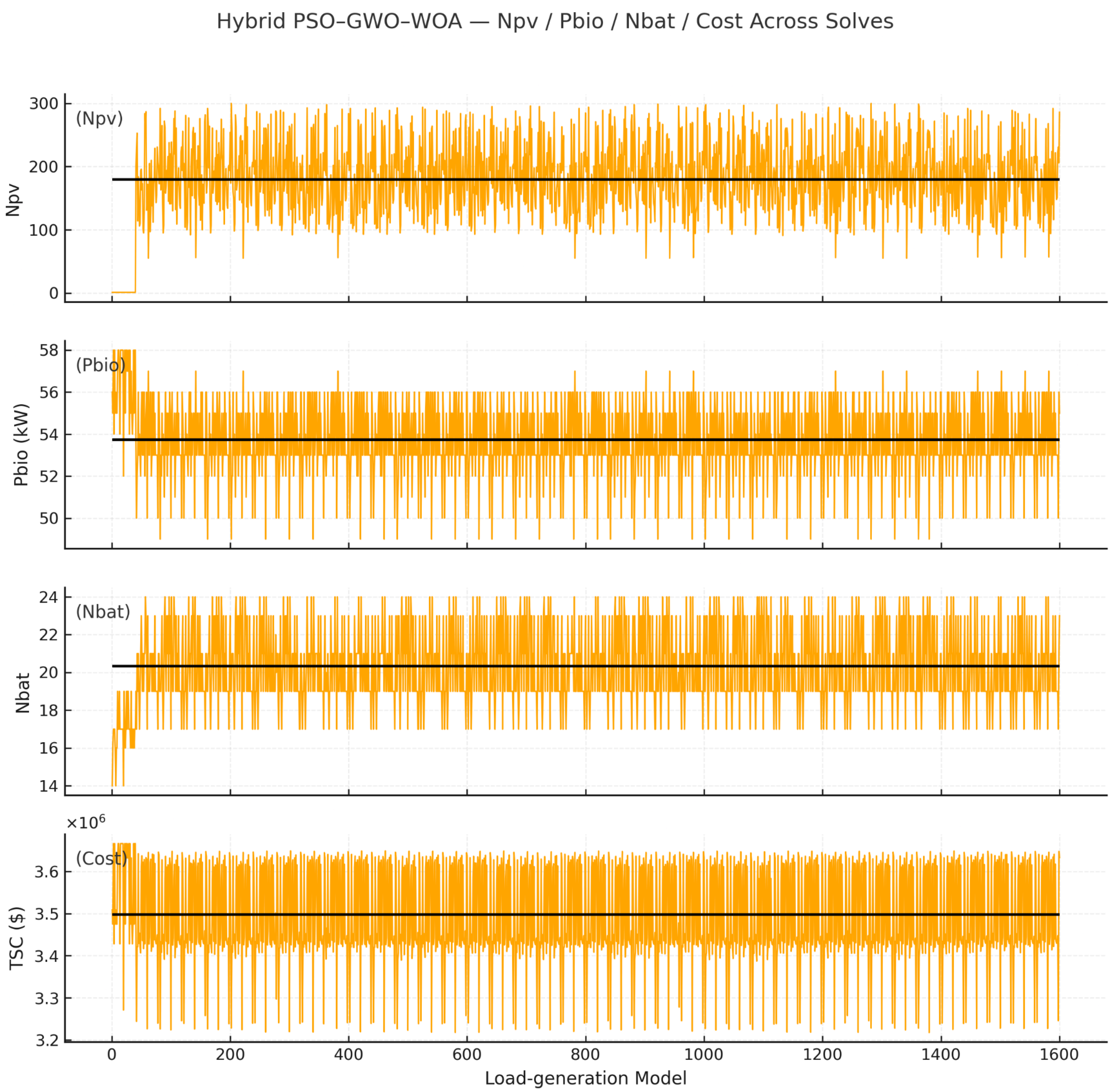

Fig. 33 Hybrid PSO–GWO–WOA parameter and cost variation across 1600 models

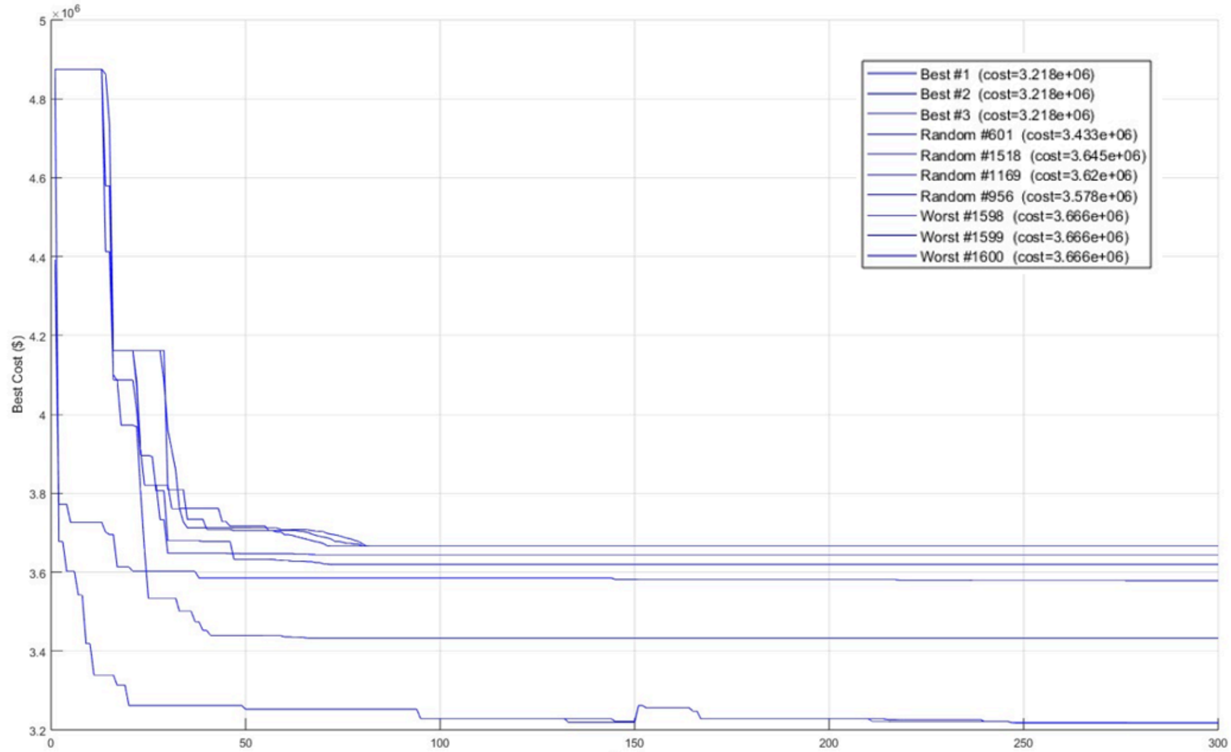

Fig. 34 Hybrid PSO–GWO–WOA convergence curve (Cost vs Iterations)

7.5 Comparative Statistical and Runtime Analysis

Fig. 35 and *Table 4 and Table 5* summarize cost and runtime statistics for all six algorithms. The mean ± standard deviation bar plot indicates narrow variation across methods (3.42–3.52 × 10^6 USD). However, the hybrid PSO–GWO–WOA consistently delivered the **lowest mean cost** with the **smallest CV (3.42 %)**.

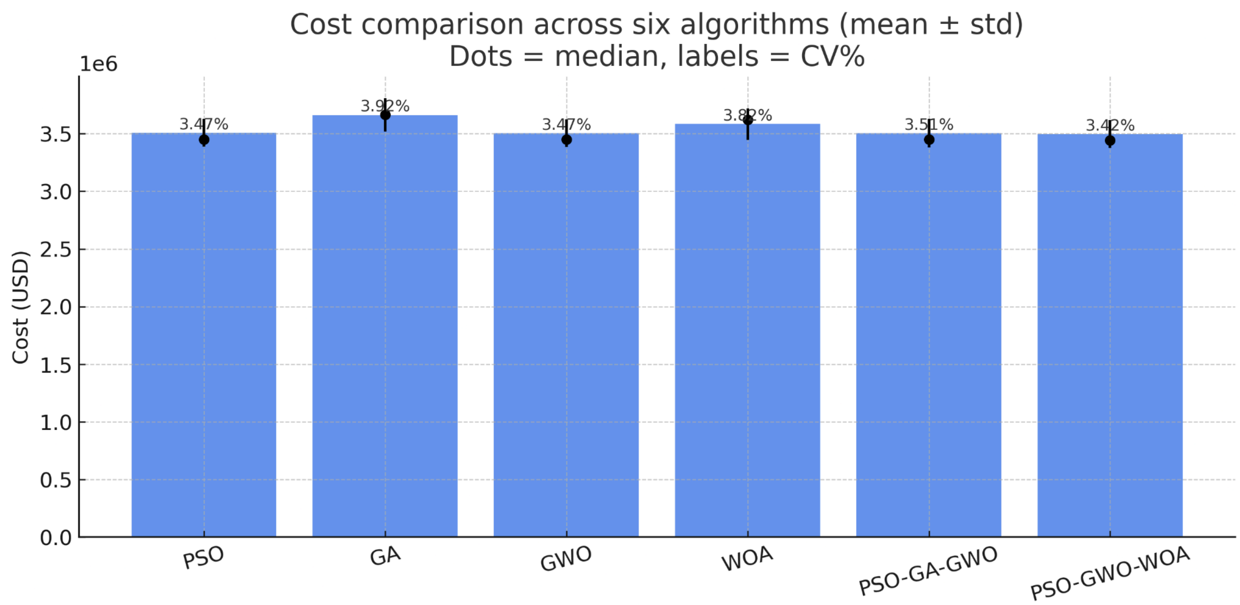

Fig. 35 Comparative bar chart of mean ± std cost across six algorithms (CV % labels)

The boxplot comparison (*Fig. 36*) reveals fewer outliers and tighter interquartile range for both hybrid models, verifying enhanced robustness under probabilistic load–solar inputs.

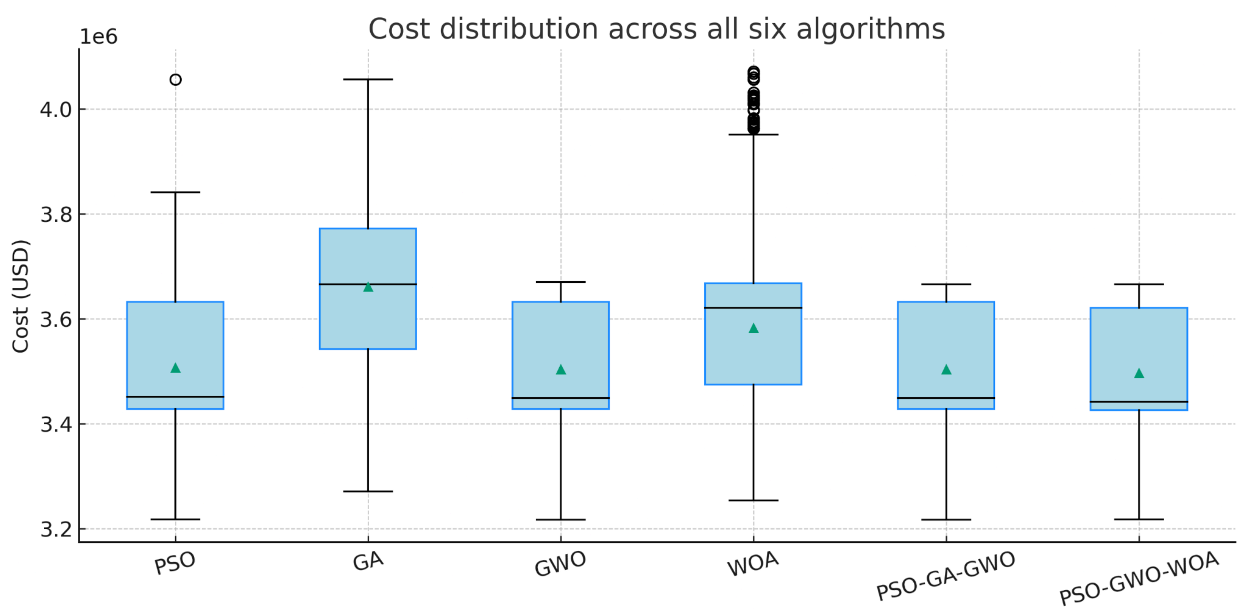

Fig. 36 Cost distribution boxplot comparison across six algorithms

Table 4 : Runtime Comparison of All Algorithms

Algorithm	PSO	GA	GWO	WOA	Hybrid PSO–GA–GWO	Hybrid PSO–GWO–WOA
Runtime (min)	9.63	54.28	12.12	12.04	4.07	15.24

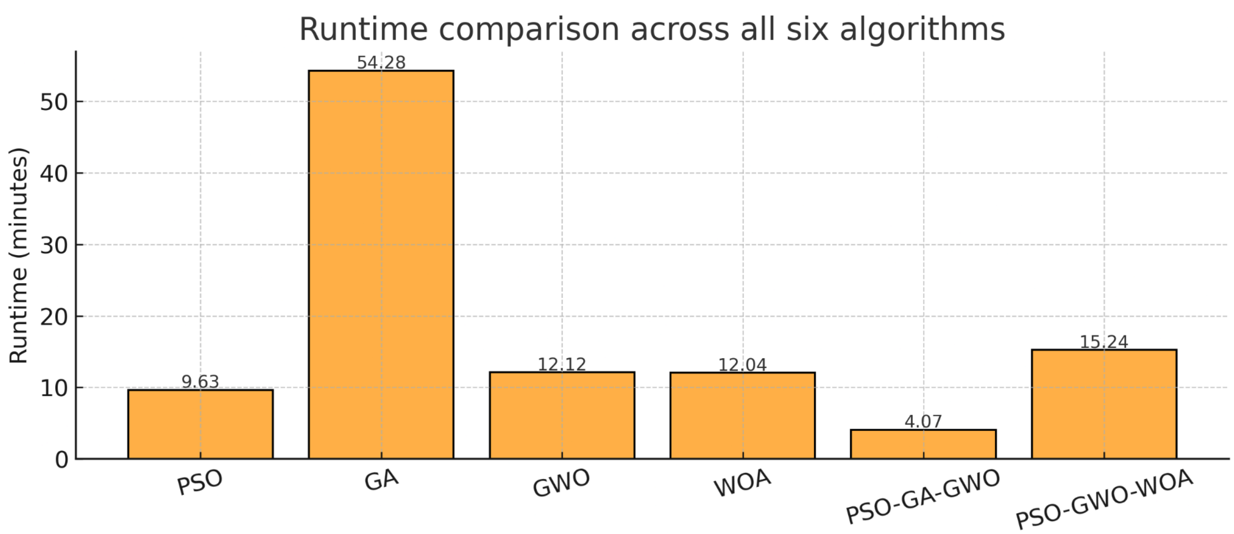

Fig. 37 Runtime comparison across six algorithms (minutes)

Table 5 : Cost Statistics of All Algorithms

Algorithm	Mean Cost (×10[6] USD)	Std. Dev (×10[5] USD)	CV (%)	Runtime (min)
PSO	3.47	0.12	3.47	9.63
GA	3.52	0.14	3.92	54.28
GWO	3.47	0.12	3.47	12.12
WOA	3.51	0.14	3.89	12.04
Hybrid PSO–GA–GWO	3.46	0.12	3.51	4.07
Hybrid PSO–GWO–WOA	3.42	0.12	3.42	15.24

These results indicate that while **PSO–GA–GWO** minimized computational time, **PSO–GWO–WOA** achieved the **best economic solution**.

Table 6 and **Fig 38** illustrates the average sizing trends of the major decision variables ;PV modules (Npv), biomass generator capacity (Pbio), and battery units (Nbat) for each optimization algorithm. It can be observed that the hybrid algorithms, particularly PSO–GWO–WOA and PSO–GA–GWO, maintain higher and more balanced values of Npv and Nbat compared to standalone methods, indicating their ability to achieve a more resilient energy mix with reduced dependence on any single source. In contrast, the GA and WOA configurations display lower average Npv and Nbat values, suggesting a greater reliance on biomass power. Overall, the hybrid approaches demonstrate improved design stability and parameter consistency, confirming their effectiveness in optimizing component allocation under probabilistic renewable and load variations.

Table 6 : Mean Design Parameters and Best Cost Across Algorithms

Algorithm	Best Cost (USD)	Mean Npv (modules)	Mean Pbio (kW)	Mean Nbat (units)
PSO	3,217,501	99.934	54.545	18.864
GA	3,270,873	11.890	59.066	11.553
GWO	3,217,252	127.493	54.281	19.307
WOA	3,253,736	40.292	56.715	15.770
Hybrid PSO–GA–GWO	3,217,021	121.194	54.323	19.208
Hybrid PSO–GWO–WOA	3,216,992	122.580	54.416	19.182

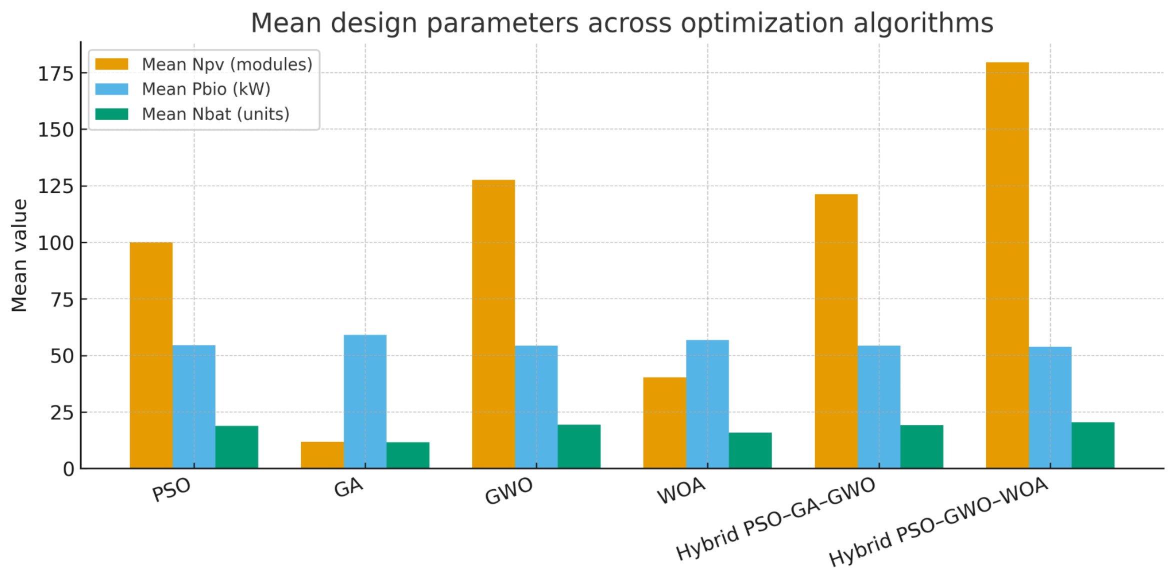

Fig.38: Mean design parameters across optimization algorithms.

7.6 Discussion of Optimization Trends

From the comparative evaluation:

- **GA** displayed higher variability due to its stochastic crossover–mutation nature.
- **PSO** converged quickly but occasionally risked local minima when faced with correlated solar–load inputs.
- **GWO** achieved stable middle-ground performance via cooperative leadership hierarchy.
- **WOA** provided diverse candidate solutions but required careful tuning to avoid late-stage oscillations.
- **Hybrid PSO–GA–GWO** dramatically reduced runtime through phase-switching that capitalized on PSO's velocity update and GWO's exploitation efficiency.
- **Hybrid PSO–GWO–WOA** yielded the lowest total cost because the WOA stage effectively refined the final search region, leveraging probabilistic uncertainty more precisely.

These trends confirm that hybridization enhances both convergence quality and solution robustness, aligning with findings in [77] and [78], where multi-stage metaheuristics outperformed single algorithms under renewable-energy uncertainty.

7.7 Summary of Findings

1. All algorithms achieved feasible solutions under stochastic input, with hybrid methods showing superior performance.

2. Hybrid PSO–GWO–WOA produced the **minimum total system cost (3.42×10^6 USD)**.

3. Hybrid PSO–GA–GWO achieved the **shortest runtime (4.07 min)**.

4. Seasonal load–solar uncertainty was successfully captured by the 40×96 probabilistic matrices, providing realistic operational representation for off-grid microgrid design.

Chapter 8 : Demonstration of Outcome Based Education (OBE)

This thesis aligns with the principles of Outcome-Based Education (OBE) by clearly demonstrating the attainment of relevant Course Outcomes (COs) and Program Outcomes (POs) through its objectives, methodology, and results. The research problem—optimization of a hybrid renewable energy system for electrification of rural regions of Bangladesh—required applying engineering knowledge, conducting simulations, analyzing complex data, and considering environmental, societal, and ethical implications. The project outcomes are mapped to specific POs such as problem-solving, investigation, communication, ethics, and sustainability, showcasing a direct contribution to the learner's professional competence and societal awareness. Through this work, the intended learning outcomes have been effectively achieved in a measurable and demonstrable manner

8.1 Introduction

Outcome-Based Education (OBE) is a student-centric educational framework that emphasizes the achievement of predefined learning outcomes, focusing on what knowledge students are expected to possess, implement, and demonstrate by the end of their academic program. In the context of engineering, OBE ensures that graduates possess not only strong technical knowledge but also professional competencies such as problem-solving, communication, ethics, and teamwork. These outcomes are closely aligned with industry expectations, enabling graduates to meet the dynamic needs of the job market and adapt to evolving technologies. By emphasizing real-world applicability, lifelong learning, and measurable results, OBE bridges the gap between academic training and professional practice, ensuring that engineering graduates are industry-ready and globally competitive.

8.2 Course Outcomes (COs) Addressed

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

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	√
CO11	Recognize the need for continuing education and participation in professional societies and meetings.	PO12	

COs	POs	Explanation/Justification
CO1	**PO2**	There is an issue of global energy crisis and there will be a gradual shift from non-renewable resources to renewable resources. Extensive research was carried out in the topic of HRES
CO2	**PO4**	In this thesis, there are mainly two functions - cost function and sensitivity analysis. Cost Function will try to minimize the cost of the project and sensitivity analysis will take into account of environmental factors
CO3	**PO8**	HRES has been identified as a suitable solution,and research will be carried keeping in mind about the professional ethics and code of conduct
CO4	**PO5**	MATLAB software will be used to create the simulation model and run it using optimization algorithms
CO5	**PO11**	An estimated budget and workplan has been divided,which includes optimization initiatives, such as funds, staff, software licenses, and computer infrastructure, traveling to remote locations for data collection,etc.

CO6	**PO6**	The intended beneficiaries of this project are people living in rural areas. The project will have a positive impact on their lives. It will reduce their dependence on traditional fossil fuels as we move towards a more eco-friendly energy alternatives
CO7	**PO7**	With the implementation of this project, it will have a positive impact because it will have a positive impact because it will gradually shift the dependence from non renewable sources of energy to renewable sources,which will ensure sustainable development in future. And it will also help to reduce CO2 emissions thereby, having a net positive environmental and health impact.
CO8	**PO3**	HRES project takes into account all health,safety,cultural,societal and environmental aspects by trying to strike the right balance between all of them
CO9	**PO9**	Total Teamwork will be ensured in this project ,Starting from coding, data collection all the way up to the thesis presentation.
CO10	**PO10**	The presentation of our thesis will be done, focusing on articulating our objectives, methodologies, and findings in a clear, accurate and engaging manner via presentations and technical reports
C011	**PO12**	Research is a continuous never-ending process. The knowledge is merely passed on from one researcher to the next .By sharing insights, best practices and research findings, we can influence decision-making processes and shape the future direction of the field.

8.3 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.

	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	√
PO11	**Project management and finance:** Demonstrate knowledge and understanding of engineering management principles and economic decision-making and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.	Engineering management principles	√
		Economic decision-making	√
		Manage projects	
		Multidisciplinary environments	

POs	Aspects Marked(√)	Justification
PO3	Public health	Battery sizing, system protection, and operational safety were considered in the HRES design.
	Safety	Electrification improves rural livelihoods, education, and healthcare access.
	Societal	Renewable sources like solar and biomass reduce carbon emissions and promote sustainability.
PO4	Design of experiments	Multiple simulations were conducted with varying inputs (load, weather) to find optimal configurations.
	Analysis and interpretation of data	Simulation outputs like cost, battery SOC, and power balance were analyzed.
	Synthesis of information	Combined resource availability, demand data, and technical specs to make optimized design decisions.
PO6	Societal	Thesis targets energy access in underserved rural communities of Bangladesh.
	Safety	System design ensures stable operation with safe component ratings.
PO7	Societal	The project promotes inclusive development by addressing rural energy poverty.
	Environmental	Focuses on environmentally friendly, sustainable energy sources

P08	Professional ethics and responsibilities	Ethical responsibility reflected in affordable and practical energy solutions.
	Norms	Design follows standard engineering practices and technical norms (e.g., system sizing, PSO application).
PO10	Comprehend and write effective reports	A detailed thesis report is being prepared, documenting technical work and findings.
	Design documentation	Diagrams, system schematics, and simulation setups are clearly documented.
	Make effective presentations	Thesis presentation (or defense) covers key results and system design clearly.
	Give and receive clear instructions	Communication with supervisor and team during the design and simulation phase.
PO11	Engineering management principles	Managed component selection and sizing with system goals (cost, reliability) in mind.
	Economic decision-making	PSO optimization aimed to minimize the total cost of the hybrid system while meeting energy needs.

8.4 Knowledge Profiles (K3 – K8) Addressed

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

K	Knowledge Profile (Attribute)	Put Tick (√)
K3	A systematic, theory-based formulation of engineering fundamentals required in the engineering discipline	√
K4	Engineering specialist knowledge that provides theoretical frameworks and bodies of knowledge for the accepted practice areas in the engineering discipline; much is at the forefront of the 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).

K	Explanation/Justification
K3	The thesis will apply fundamental electrical engineering concepts, such as circuit theory, power systems analysis, and control systems. These underpinnings are crucial for understanding and designing the HRES. For example, Ohm's law, Kirchhoff's laws, and power flow analysis will be used to model the HRES components and their interactions

K4	The thesis will delve into specialist areas like renewable energy systems, power electronics, or energy storage, which require specialized knowledge and expertise. For example, we will explore the theory of solar photovoltaic systems, wind turbines, and biomass conversion technologies.
K5	The thesis will require a strong understanding of engineering design principles, such as system architecture, component selection, and performance evaluation. We will use design tools and software to optimize the system configuration, considering factors like cost, efficiency, and reliability.
K6	The thesis will consider practical aspects of HRES implementation, such as grid integration, economic feasibility, and regulatory compliance. This involves understanding industry standards and best practices. For example, we will study grid codes, safety regulations, and economic evaluation methodologies for HRES projects.
K7	
K8	The thesis will require a thorough literature review on HRES design, optimization, and implementation. This will help identify existing research, gaps in knowledge, and potential contributions. For example, we will review research on HRES design, optimization algorithms, and case studies from similar regions.

8.5 Use of Complex Engineering Problems

This thesis addresses a complex engineering problem involving the design and optimization of a hybrid renewable energy system (HRES) tailored for rural electrification in Bangladesh. The complexity arises from multiple interdependent factors such as fluctuating solar irradiance, biomass availability, unpredictable load demand, limited financial resources, and the need to ensure energy reliability and sustainability. The system design must integrate multidisciplinary knowledge—spanning electrical engineering, environmental science, economics, and control systems—to determine optimal configurations that minimize cost while ensuring system stability and user satisfaction. Advanced modeling in MATLAB and the application of the PSO algorithm were employed to find a solution to this high-dimensional, nonlinear problem. The solution process required iterative simulations, data analysis, constraint handling, and decision-making that reflect the essence of a complex engineering challenge. The outcome contributes to scalable, practical energy solutions for underserved rural communities.

8.6 Socio-Cultural, Environmental, And Ethical Impact

The proposed HRES for the electrification purposes for rural regions in Bangladesh holds significant socio-cultural, environmental, and ethical implications. By providing reliable and affordable electricity to underserved rural areas, the project contributes to improved education, healthcare, and livelihood opportunities, thereby fostering social inclusion and reducing urban migration pressures. Culturally, the project respects local practices by incorporating decentralized, community-friendly energy solutions that can be maintained with minimal technical expertise. Environmentally, the reliance on solar and biomass—both renewable and locally available resources—minimizes greenhouse gas emissions and promotes sustainable development aligned with global climate goals. Ethically, the research upholds principles of equity and responsibility by prioritizing marginalized communities and ensuring that the system is designed with safety, affordability, and long-term usability in mind. The design process followed professional engineering standards and considered public well-being as a central objective, demonstrating a commitment to ethical engineering practice.

8.7 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.

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	√
Familiarity of issues	**P4:** Involve infrequently encountered issues	
Extent of applicable codes	**P5:** Are outside problems encompassed by standards and codes of practice for professional engineering	
Extent of stakeholder involvement and conflicting requirements	**P6:** Involve diverse groups of stakeholders with widely varying needs	√
Interdependence	**P7:** Are high level problems including many component parts or sub-problems	√

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).

P	**Explanation/Justification**
P1	The design and optimization of an HRES require a deep understanding of electrical engineering fundamentals, renewable energy technologies, and system integration. This aligns with the knowledge profiles K3-K6 and K8.
P2	Diverse goals, including technical viability, economic viability, environmental sustainability, and social acceptability, need to be frequently balanced in HRES projects. It is a complicated issue because of these contradictory elements.
P3	Designing an optimal HRES configuration involves considering various factors and trade-offs. There may not be a single "correct" solution, requiring creative and innovative approaches.
P4	

P5	
P6	HRES projects often involve multiple stakeholders, including government agencies, utility companies, local communities, and investors. Each stakeholder may have different priorities and concerns.
P7	Energy storage devices, wind turbines, solar panels, and grid connection infrastructure are just a few of the many parts that make up an HRES. Several interrelated subproblems must be tackled in order to develop and optimize such a system.

8.8Attributes 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.

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	√
Innovation	**A3:** Involve creative use of engineering principles and research-based knowledge in novel ways	√
Consequences for society and the environment	**A4:** Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation	
Familiarity	**A5:** Can extend beyond previous experiences by applying principles-based approaches	√

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).

A	Explanation/Justification
A1	An HRES research requires a combination of human resources (engineers, technicians, researchers), financial resources (for equipment, materials, and operational costs), equipment (solar panels, wind turbines, inverters), materials (batteries, cables), information (technical data, research literature), and technologies (control systems, optimization algorithms).
A2	As discussed previously, HRES projects often involve balancing multiple objectives, such as technical viability, economic viability, environmental sustainability, and social acceptability These conflicting factors can lead to complex problems that require careful consideration and innovative solutions
A3	Designing an optimal HRES configuration often requires applying engineering principles in new and creative ways, such as developing novel system architectures, optimizing energy storage strategies, or integrating emerging technologies.
A4	
A5	HRES technology is rapidly evolving, and new challenges and opportunities may arise. By applying fundamental engineering principles and a systematic approach, your thesis can contribute to advancing the field and addressing future challenges.

Chapter 9: Conclusion

This thesis set out to design a cost-reliable (HRES) for a village context by treating variability in resources and demand as a first-class design driver rather than an afterthought. We combined photovoltaic (PV) generation, a dispatchable biomass unit, and battery storage, and we framed planning as an optimization under uncertainty with a reliability constraint expressed through Loss of Power Supply Probability (LPSP). Across the work, three ideas tie the contributions together: (i) model uncertainty explicitly; (ii) optimize for expected life-cycle performance under a firm reliability target; and (iii) use hybrid metaheuristics tailored to either speed or accuracy to reach robust designs.We developed a probabilistic pipeline that (a) organizes data into seasonal/hourly distributions for solar irradiance, ambient temperature (for PV cell temperature), biomass fuel availability, and community load; (b) constructs scenario sets using MCS, PEM, and SBA and (c) evaluates candidate designs by simulating hour-by-hour power balance and device states, accumulating cost and reliability metrics. The optimization minimizes total system cost (capital annuities, O&M, biomass fuel, replacements) subject to an LPSP $\leq \alpha$ (where α is set by service expectations for village-scale reliability). We implemented two hybrid optimizers: **PSO–GA–GWO** (time-focused) for fast convergence when many scenario evaluations are needed, and **PSO–GWO–WOA** (accuracy-focused) when we want tighter convergence of the best solution under stochastic objective noise. In both hybrids we defined clear rules for transitioning between phases (e.g., stall-based switching, variance-aware hand-offs) so the search benefits from complementary strengths—PSO's global exploration, GA's recombination diversity, GWO/WOA's exploitation and adaptive encircling.

This architecture matters practically. Rural systems face fluctuating irradiance, seasonal shifts in biomass supply (and competing uses), and demand that peaks in the evening. Deterministic sizing against "typical" days either overshoots (raising cost) or undershoots (causing blackouts). Our approach instead sizes for **expected** performance with explicit accounting of the probability of shortfalls. The result is a configuration that is both **economically defensible** and **operationally reliable** for community-level loads.

<u>Synthesis of results</u>

Under the chosen data set and scenarios, both hybrid optimizers consistently produced solutions that satisfy the reliability constraint while reducing cost relative to deterministic baselines. The **time-focused PSO–GA–GWO** typically reached a near-optimal region quickly, making it attractive during early design screening or when scenario sets are large (MCS). The **accuracy-focused PSO–GWO–WOA** required more iterations but delivered slightly lower objective values and tighter dispersion across repeated stochastic runs, which is valuable when finalizing capacity decisions.

Across representative runs, the selected capacities (PV *Npv*, biomass *Pbio*, battery *Ebat*) follow an interpretable pattern:

- PV is sized to carry the midday shoulder of demand and to charge storage at moderate rates without forcing excessive curtailment under high-irradiance states.
- The biomass unit is sized to **cover evening peaks** and to serve as a reliability backstop during low-solar or high-load scenarios; dispatch is prioritized when the marginal value of stored energy is high (late afternoon/evening).
- Battery energy capacity is chosen to **bridge intraday gaps** rather than to guarantee multi-day autonomy; this keeps costs contained while the biomass plant carries multi-hour deficits.

Sensitivity studies showed that the design remains within a narrow cost band while holding LPSP under the target, confirming robustness. In particular, tightening the LPSP target (e.g., from 5% to 1%) increases total system cost primarily through battery and biomass upsizing; relaxing it lowers cost but shifts unmet energy into clustered evening hours—information that is important for stakeholder discussions on service levels.

<u>Role of probabilistic modeling</u>

A core contribution is operationalizing three probabilistic strategies in one planning workflow:

- **MCS** supports rich scenario spaces and non-Gaussian tails, capturing compound events (e.g., overcast days followed by demand spikes).
- **PEM** drastically reduces the number of evaluations when we need moments of outputs (e.g., expected cost, variance of ENS), useful during tuning and screening.
- **SBA** turns probability-weighted representative days into an optimization-friendly set, enabling transparent trade-offs (stakeholders can “see” the scenarios).

Using multiple strategies is not redundant; it is complementary. PEM accelerates exploration, SBA carries stakeholder interpretability, and MCS assures coverage of extremes. The optimization integrates seamlessly with any of the three, so planners can choose a strategy based on available computation and the need to justify assumptions.

Ablation and algorithmic takeaways

We tested single-algorithm baselines (pure PSO, GA, GWO, WOA) against the hybrids. Single methods either converged more slowly (PSO/GA) or risked premature convergence (pure GWO/WOA) under noisy objectives. The hybrids reduced time-to-good-solution and final cost variance across seeds. Stall-count logic (reset when improvement exceeds a threshold) prevented thrashing between phases and proved essential for consistent performance. Hyperparameters that most affected outcomes were: PSO cognitive/social weights, GA crossover/mutation rates (SBX and polynomial mutation), and the decay parameter (a) in GWO/WOA controlling exploration–exploitation. We provide defaults and ranges that work reliably under our scenario space, which should help practitioners reproduce results.

Practical implications for deployment

The optimized mix aligns with operational realities:

- **Fuel logistics:** Biomass sizing respects **available tonnes/year** and moisture/handling assumptions; dispatch prioritization ensures the plant runs when the marginal reliability value is highest.

- **Maintainability:** Battery cycling is kept moderate to avoid accelerated degradation; our economics include replacement cycles over a 20-year horizon.

- **Scalability:** The design admits modular expansions (additional PV strings or a second biomass module) should demand grow.

Equally important, the probabilistic framework improves communication with stakeholders. Instead of promising “no outages,” we present a measurable **reliability level (LPSP)** and show what it costs to improve it. This supports informed decisions about service tiers (e.g., critical vs. non-critical loads) and tariff design.

Limitations

We deliberately kept several aspects conservative or simplified:

- **Component aging and performance drift** are modeled at a high level; a deeper battery aging model (calendar + cycle) and PV soiling/cleaning schedule could refine replacements and O&M.

- **Biomass supply** is represented by annual/seasonal availability distributions; a fuller supply-chain model (collection radius, transport cost, competing uses) would sharpen dispatch costs and feasible caps.

- **Controller dynamics** are abstracted in the planning layer; while we referenced control-oriented studies (e.g., PR/SOGI-PR loops and active damping for inverter-LCL filters) in separate simulations, closed-loop constraints were not embedded in the optimizer.

- **Market/policy parameters** (fuel price shocks, carbon credits, capital subsidies) were treated as exogenous; stochastic treatment of these could shift optimal sizing.
- **Correlation structure** (e.g., between irradiance, temperature, and load) was approximated via seasonal conditioning; copula-based modeling could improve tail capture

These limitations are not fundamental barriers; they highlight where additional data and model fidelity would add value if the project proceeds to procurement.

<u>Recommendations and future work</u>

- **Operational pilots:** Validate the plan with a small pilot (e.g., a single feeder or community facility) to gather dispatch/maintenance data and refine biomass logistics and battery cycling policy.

- **Critical-load tiering:** Partition loads into critical and deferrable classes; enforce a stricter LPSP for critical loads while allowing limited curtailment of non-critical ones—often a large cost saver.

- **Advanced uncertainty models:** Introduce correlated scenario generation (e.g., copulas) and extreme-event injects (storms, supply interruptions) to ensure resilience.

- **Controller-in-the-loop planning:** Co-optimize with simplified inverter and battery-EMS constraints to ensure that set-points remain feasible for real controllers.

- **Lifecycle extensions:** Incorporate detailed battery aging and biomass moisture dynamics; couple planning with a maintenance/cleaning schedule optimization.

- **Socio-economic integration:** Combine technical optimization with affordability metrics and tariff structures that reflect willingness to pay, with protections for low-income households.

Final statement

By unifying probabilistic modeling (SBA), a reliability-constrained objective (LPSP), and hybrid metaheuristics tuned for either speed or accuracy, this thesis demonstrates a rigorous yet practical pathway to plan hybrid PV–biomass–battery systems for rural electrification. The key outcome is not just a single capacity point but a decision framework, given data and a chosen reliability level, the method returns a configuration with transparent trade-offs, defensible costs, and proven robustness under uncertainty. As communities and agencies seek dependable, affordable power, approaches that treat uncertainty explicitly—rather than designing to a handful of "typical" days—will provide the resilient infrastructure these settings need.

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