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# Optimization and Intelligent Control in Hybrid Renewable Energy Systems Incorporating Solar and Biomass

Arpita Johri<sup>1,2,\*</sup>, Varnita Verma<sup>3</sup> and Mainak Basu<sup>1,\*</sup>

<sup>1</sup>School of Engineering Sciences, G.D. Goenka University, Gurgaon (Haryana), 122001, India

<sup>2</sup>Department of Electronics & Communication Engineering, ABES Engineering College, Ghaziabad, 201001, India

<sup>3</sup>School of Interdisciplinary Research Engineering, Indian Institute of Technology, New Delhi, 110016, India

\*Corresponding Authors: Arpita Johri. Email: arpita.johri@abes.ac.in; Mainak Basu. Email: mainak.basu@gdu.org

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**ABSTRACT:** The globe faces an urgent need to close the energy demand-supply gap. Addressing this difficulty requires constructing a Hybrid Renewable Energy System (HRES), which has proven to be the most appropriate solution. HRES allows for integrating two or more renewable energy resources, successfully addressing the issue of intermittent availability of non-conventional energy resources. Optimization is critical for improving the HRES's performance parameters during implementation. This study focuses on HRES using solar and biomass as renewable energy supplies and appropriate energy storage technologies. However, energy fluctuations present a problem with the power quality of HRES. To address this issue, the research paper introduces the Generalized Dynamic Progressive Neural Fuzzy Controller (GDPNFC), which regulates power flow within the proposed HRES. Furthermore, a unique approach called Enhanced Multi-Objective Monarch Butterfly Optimization (EMMBO) is used to optimize technical parameters. The simulation tool used in the research work is HOMER (Hybrid Optimization of Multiple Energy Resources)-PRO, and the system's power quality is assessed using MATLAB 2016. The research paper concludes with comparing the performance of existing systems to the proposed system in terms of power loss and Total Harmonic Distortion (THD). It was established that the proposed technique involving EMMBO outperformed existing methods in technical optimization.

**KEYWORDS:** Hybrid renewable energy sources (HRES); multi-objective optimization; generalized dynamic progressive neural fuzzy controller (GDPNFC); pre-feasibility analysis; total harmonic distortion (THD); enhanced multi-objective monarch butterfly optimization (EMMBO)

## 1 Introduction

Over the past few decades, the conventional energy sources derived from fossil fuels have played a crucial role as major energy resources [1]. Recently, however, there has been a notable shift towards non-conventional energy sources, encompassing solar, geothermal, tidal, wind, biomass, and hydropower. This transition is driven by their positive attributes such as environmental sustainability, cost-effectiveness, and natural abundance [2,3]. However, small-scale power generation and transmission are challenging in rural areas. In recent years, hybrid energy systems have been popular to produce power from more generating stations such as PV arrays with wind turbines, wind-diesel, and biomass plants with solar panels [4–6].

In Hybrid Renewable Energy Systems (HRES), optimization plays a crucial role in the development of an economically viable and secure generation system. The challenge with hybrid energy systems lies in the



need for backup due to the intermittent nature of renewable energy resources. To address this intermittency, integrating a Renewable Energy System (RES) is proposed. An examination of the feasibility and cost of incorporating biomass, wind, hydrogen cells etc. with solar cells is conducted to fulfil the energy demands of rural areas, utilizing Hybrid Optimization techniques [7–10]. Additionally, the consideration of resources and load is vital in the design of HRES. In a hybrid solar-biomass system [11,12] employing the Artificial Bee Colony (ABC) algorithm [13], Grey Wolf Optimization Scheme [14]. As a result, various controller approaches, such as PI controller, Fuzzy Logic, Artificial Neural Network (ANN), PID controllers [15] with Firefly-Pattern Search and fuzzy gain scheduling algorithms [16], are implemented to manage the unstable voltage situation in the grid-connected to renewable resources. The HRES may be a grid-connected system or a standalone system.

A standalone system with sufficient storage for power fluctuation is considered a microgrid [17]. To improve the power quality and reduction of reactive power in the peak season, the concept of microgrid and controllers are implemented for the HRES system [18]. Designing an off-grid system requires storage to feed power for an extended period during the interruption and apply batteries for such support [19]. Furthermore, due to the oversizing of the system, the generated costs are higher. Therefore, the Life cycle cost (LCC) of HRES is essential to assess the positive outcomes of using RES [20]. Besides, power quality issues [21,22] are present in any power system in varying quantum, which generally occurs in a distribution system. Harmonic currents create heating in electrical cables, leading to premature aging and overstressing electrical insulation, leading to deteriorated power quality, which will change the consecutive development of future grids [23]. Therefore, an effective control technique is required to reduce these HRES challenges.

In this paper, solar and biomass are often preferred over other renewable resources in the proposed hybrid renewable energy systems for several key reasons:

- *Availability and Flexibility:*

**Solar:** Solar energy is abundant and widely available across the globe, especially in areas with a high number of sunny days. It also offers flexibility, as it can be harnessed in various ways, from large-scale solar farms to smaller rooftop installations.

**Biomass:** Biomass is a flexible resource that can be sourced locally from organic materials like agricultural waste, wood, or even algae. It can be stored and used as fuel when needed, making it suitable for both continuous and intermittent energy production.

- *Complementary Nature:*

Solar and biomass complement each other well in hybrid systems. Solar energy is intermittent, as it only generates power during the day and is affected by weather conditions. Biomass, on the other hand, can provide a stable, continuous power supply, helping to balance out the variability of solar energy and ensuring a more reliable energy system.

- *Energy Storage:*

**Biomass:** Unlike some other renewables, biomass can be stored for long periods and used on demand. This makes it easier to manage the energy supply and smooth out periods of low solar energy generation, like at night or during cloudy weather.

**Solar:** While solar energy typically needs to be paired with storage solutions like batteries to manage intermittency, hybrid systems often combine solar with biomass to reduce reliance on large-scale storage systems.

- *Low Environmental Impact (When Managed Sustainably):*

Solar energy has a very low environmental impact once operational, as it produces no emissions during energy generation.

Biomass, when sustainably sourced, can be carbon-neutral (or even carbon-negative, depending on the feedstock) and can help reduce waste by converting organic materials that would otherwise decompose in landfills and lead to various diseases and land pollution.

- *Economic and Technological Advancements:*

Solar energy technology has seen significant cost reductions over the past decade, making it more economically viable in a wide range of applications.

Biomass technologies, while slightly more expensive than solar, are still competitive when compared to fossil fuels and provide additional benefits such as waste reduction and local job creation.

- *Scalability:*

Both solar and biomass systems can be scaled from small to large applications, making them versatile for different geographic areas and energy needs, from rural villages to urban areas.

Because of these factors, combining solar and biomass in hybrid systems creates a more reliable, sustainable, and cost-effective renewable energy solution that addresses the intermittent challenges of each resource when used alone.

The proposed work concentrated on firstly developing robust HRES that considers a wide range of operational conditions, including varying solar irradiance and biomass fuel availability. Secondly, a multi-objective optimization in system design has been proposed and the technical parameters have been investigated using dynamic fuzzy controller.

The organization of this paper is as follows: [Section 2](#) discusses the related work, and [Section 3](#) has the system descriptions along with the models. Then, [Section 4](#) has a detailed problem statement, and [Section 5](#) explains the proposed intelligent control and multi-objective optimization. Finally, the results and discussion are explained along with the comparison in [Section 6](#), and discussions are concluded in [Section 7](#). The above-mentioned sections are followed by Acknowledgement, Funding Statement, Author Contributions, Availability of Data and Materials, Conflicts of Interest and References.

## 2 Related Work

Reliability issues arise with renewable energy resources in various climatic conditions due to their intermittent nature [24–26]. To address these challenges, Li et al. [27] suggested the development of a hybrid system to ensure a dependable energy supply, considering the Loss of Power Supply Probability (LPSP) and aiming to minimize the Net Present Cost (NPC) of the system. The sizing of the model can be optimized using algorithms such as the ABC Algorithm, Firefly Algorithm (FA), Flower Pollination Algorithm (FPA), and Harmony Search (HS) algorithm. Simulation results indicate that the Firefly Algorithm outperforms other algorithms, exhibiting the best performance and the shortest execution time.

The availability and utilizations of renewable energy resources vary significantly based on geographical locations. Consequently, optimizing the model size becomes a crucial principle in the development of an economically optimized and efficient Hybrid Renewable Energy System (HRES). In addressing this need, Murugaperumal et al. [28] introduced a study focused on the techno-economic aspects and the attainability of optimal design for a HRES whose purpose is to fulfill the energy requirements of rural areas. Various load growth forecasting schemes are capable of conducting load forecast assessments, and a system operating strategies analyzer was employed in the final phase of the design.

Optimizing the size and cost of the system holds substantial importance in the development of a HRES [29–32]. Considering this, Elkadeem et al. [33] have discussed design approaches for both developing and optimizing the performance of a Hybrid Renewable Energy System (HRES), while considering grid connectivity.

A strategy was introduced by Congguang Zhang et al. [34] for the development of a HRES having solar-biomass energy supply system. It incorporated an evaluation of its thermodynamic features and feasibility. The economic aspect is examined through life cycle cost (LCC) analysis, considering a simple payback (SPB). Additionally, the optimization of thermodynamic performance is accomplished using the Genetic Algorithm.

The load frequency control (LFC) of Hybrid Renewable Energy Systems (HRES) plays a pivotal role in achieving stable system performance, particularly in the face of disturbances that can lead to frequency fluctuations. Addressing this challenge, Hasanein et al. [35] introduced the Salp Swarm Algorithm (SSA) for the optimal load frequency control of HRES. The SSA-PID controller effectively manages the system under diverse conditions, including variations in renewable energy resources, unreliability, and step load perturbations. Moreover, the SSA-PID controller improves the dynamic response of the proposed system.

Some of the important works have been included in the following [Table 1](#).

**Table 1:** Few important research works

S. No.	Author(s)	Technique used	Objectives	Advantages	Disadvantages
(1)	Dar et al. [36]	Structural breaks cointegration analysis	Assess the relationship between fossil fuel consumption and renewable energy generation in India.	Supports evidence-based policymaking; emphasizes the benefits of transitioning to renewables.	Potential complexities in policy implementation; challenges in changing consumer habits.
(2)	Farghali et al. [37]	Review of RES integration consequences	Evaluate the social, environmental, and economic impacts of integrating renewable energy sources.	<ol style="list-style-type: none"> <li>Hybrid energy systems have been improving reliability and resilience against climate change impacts.</li> <li>Solar, wind, and hydroelectric combinations had been increasing power generation while reducing environmental impacts significantly.</li> <li>Renewable energy hybrid systems had been aligning with government policies, contributing to job creation and cost reduction.</li> </ol>	<ol style="list-style-type: none"> <li>The lack of standardized methods for evaluating energy complementarity has been complicating the assessment of system performance.</li> <li>Large or poorly designed hybrid systems have been resulting in high installation costs.</li> <li>The need for thorough technical and financial evaluations before implementation has been underscored due to the complexity of these systems.</li> </ol>

(Continued)

**Table 1 (continued)**

S. No.	Author(s)	Technique used	Objectives	Advantages	Disadvantages
(3)	Jafarnejad et al. [38]	Renewable energy–water–environment (REWE) nexus analysis	To explore interconnections between renewable energy, water resources, and environmental sustainability.	<ol style="list-style-type: none"> <li>1. The study had been identifying key knowledge gaps in the REWE nexus, helping to develop solutions to support sustainable development.</li> <li>2. California had been leading the way in the adoption of renewable energy technologies, promoting both environmental and economic benefits.</li> <li>3. The development of new technologies and practices has been enabling the management of both energy and water demand in a sustainable manner.</li> </ol>	<ol style="list-style-type: none"> <li>1. The complex nature of the REWE nexus has made it challenging to manage both energy and water demands while maintaining environmental health.</li> <li>2. Some of the proposed technologies, such as cooling systems for thermoelectric plants, have been requiring significant investments and innovation.</li> <li>3. End-of-life renewable energy waste management had been an overlooked issue that needed more attention.</li> </ol>
(4)	Siren Pritchett [39]	Focused on integrating Green Software Engineering (GSE) principles with renewable energy systems to optimize their performance through energy-efficient software development, data analytics, and real-time monitoring.	To explore how sustainable software practices can enhance the efficiency and sustainability of renewable energy systems.	<ol style="list-style-type: none"> <li>1. The study has been improving operational efficiency of renewable energy systems using predictive maintenance and real-time monitoring.</li> <li>2. It had been reducing the environmental impact of energy systems by integrating GSE principles into software design.</li> <li>3. The integration of financial incentives and regulatory frameworks has been encouraging the development of sustainable software.</li> </ol>	<ol style="list-style-type: none"> <li>1. The integration of GSE has been requiring significant investment in new technologies and software development.</li> <li>2. Limited collaboration between stakeholders has been hindering the widespread adoption of GSE practices in renewable energy sectors.</li> <li>3. Real-time monitoring systems needed ongoing maintenance and updates to ensure effectiveness.</li> </ol>

(Continued)

Table 1 (continued)

S. No.	Author(s)	Technique used	Objectives	Advantages	Disadvantages
(5)	Hanief Jasmin and Akhtar Saleem [40]	Integrated predictive scaling, uncertainty quantification, generative models, and reinforcement learning (RL) to optimize resource management and enhance the adaptability of autonomous AI systems in cloud computing.	To optimize cloud computing operations by efficiently managing resources, accounting for uncertainties, and adapting to dynamic workloads.	<ol style="list-style-type: none"> <li>1. The combination of predictive scaling and RL had been enabling proactive adjustments and continuous optimization, enhancing cloud system performance.</li> <li>2. The integration of UQ had been ensuring that unpredictable fluctuations were managed effectively, improving decision-making.</li> <li>3. Generative models had been simulating various scenarios to prepare the system for rare or extreme workload patterns.</li> </ol>	<ol style="list-style-type: none"> <li>1. The need for continuous data generation and simulation has been requiring significant computational resources.</li> <li>2. The dependency on real-time learning had been introducing challenges in managing adaptation and optimization, especially during initial stages of implementation.</li> <li>3. The integration of multiple techniques has been introducing complexity, potentially affecting system stability during transition phases.</li> </ol>
(6)	Lam Hong Yin et al. [41]	IoT-based weather monitoring system	To develop a system for accurate solar energy forecasting by monitoring environmental conditions.	<ol style="list-style-type: none"> <li>1. The system provided precise and reliable data on environmental parameters, improving solar forecasting.</li> <li>2. The integration with Google Sheets enabled real-time data access and online logging for rapid decision-making.</li> <li>3. The system had been validated against established PVSyst models, confirming its high accuracy and reliability.</li> </ol>	<ol style="list-style-type: none"> <li>1. The reliance on an IoT-based platform had required stable internet connectivity for real-time data access.</li> <li>2. The system had been limited by the availability of the sensors used for specific environmental parameters.</li> <li>3. Scaling the system for wider application has introduced challenges in data storage and management.</li> </ol>
(7)	Oluwatoyosi Bamisile et al. [42]	Optimization techniques for HRES and ESS	To integrate energy storage systems with hybrid renewable energy systems (HRES) using optimization techniques.	<ol style="list-style-type: none"> <li>1. Hybrid optimization techniques had combined strengths from various approaches, improving system reliability and efficiency.</li> <li>2. Capacity and CO2 emissions constraints have been effectively incorporated to design practical and environmentally friendly systems.</li> <li>3. The study successfully addressed the intermittency and variability of renewable energy, enhancing the consistency of the energy supply.</li> </ol>	<ol style="list-style-type: none"> <li>1. The optimization techniques faced challenges in handling complex system configurations and operational strategies.</li> <li>2. Managing the life time and efficiency of energy storage systems (ESS) has remained a critical area for improvement.</li> <li>3. Large-scale deployment of these systems has introduced scalability and integration challenges.</li> </ol>

(Continued)

Table 1 (continued)

S. No.	Author(s)	Technique used	Objectives	Advantages	Disadvantages
(8)	Bade et al. [43]	Co-located utility-scale wind-solar-based hybrid power plants	To explore sizing methodologies, optimization techniques, and energy management and control strategies for co-located wind-solar HPPs.	<ol style="list-style-type: none"> <li>1. Meta-heuristic algorithms have been widely used for sizing, offering effective solutions for hybrid systems.</li> <li>2. Hybrid approaches combining multiple optimization techniques had resulted in global best configurations.</li> <li>3. Centralized and distributed control strategies have shown effectiveness in optimizing performance and improving system reliability.</li> </ol>	<ol style="list-style-type: none"> <li>1. No single optimization approach outperformed all problem types, limiting the ability to generalize solutions.</li> <li>2. The need for more comparative studies has been emphasized due to the limited number of relevant studies.</li> <li>3. Complex objective spaces and inherent uncertainty posed challenges in optimization and energy management.</li> </ol>
(9)	Espitia et al. [44]	Solar energy applications in greenhouses	To analyze the integration of solar energy in protected agriculture, particularly in greenhouses, through bibliometric and technical review.	<ol style="list-style-type: none"> <li>1. Has provided insights into hybrid systems combining solar technologies with other resources for improved energy efficiency.</li> <li>2. Has emphasized advancements in artificial intelligence for climate control, improving crop sustainability.</li> <li>3. Has highlighted the significance of energy storage and desalination technologies for sustainable greenhouse operation.</li> </ol>	<ol style="list-style-type: none"> <li>1. Has identified challenges in economic and operational feasibility, such as efficient moisture and CO2 management.</li> <li>2. The widespread implementation of solar technologies has been hindered by the lack of local and regional studies under diverse climatic conditions.</li> <li>3. Has pointed out the need for more exploration into passive systems and photovoltaic cells in greenhouse applications.</li> </ol>

### 3 System Description

The system consists of a Solar PV array, biomass generator, battery storage bank, power converter, and various dissimilar loads.

#### 3.1 Solar PV Array

The energy from solar radiation is converted into DC using photovoltaic (PV) array. In a concentrated solar power system, the sunlight is collected by mirrors, lenses, and tracking systems. PV arrays employ photovoltaic material for converting solar energy into electrical current. Electronic power converters convert the DC to AC. Parallel or serial connections of PV arrays are made through this inverter according to the required applications.

The voltage and current characteristics of solar PV array [45] can be expressed in Eq. (1):

$$I_{PV} = I_p - I_{dsc} \left[ \left( \frac{\exp q^* (V_{PV} + I_{PV} R_s^*)}{n^* \vartheta T} \right) - 1 \right] \quad (1)$$

where  $I_p$  is the photocurrent,  $I_{PV}$  is the solar PV cell current in A,  $R_s^*$  is the series resistance in  $\Omega$ ,  $I_{dsc}$  is the saturation current of the diode,  $V_{PV}$  is the solar PV voltage in V,  $q^*$  is the electron charge,  $n^*$  is the number of solar PV module,  $\vartheta$  is represented as the constant and  $T$  is denoted as the temperature.

The output power of solar PV array [46] can be obtained by Eq. (2):

$$P'_{PV} = P_{STC}^{PV} DF \left( \frac{I_{PV} R^*}{I_{PV} R_{STC}^*} \right) [1 + \eta_p (T - T_{STC})] \quad (2)$$

where  $P_{STC}^{PV}$  is the solar power under Standard Test Condition (STC),  $T_{STC}$  is the temperature of solar PV cell beneath STC condition at  $25^{\circ}C$ ,  $\eta_p$  is the coefficient of the power and  $R_{STC}^*$  is the series resistance in STC condition.

### 3.2 Biomass System Model

Biomass electricity generation can be done via either a biochemical method, such as anaerobic digestion or fermentation, or a thermo-chemical procedure such as gasification, direct combustion, or pyrolysis. The output power of the Biomass system [47] can be calibrated using the Eq. (3):

$$E_{BG} = 365 \times 24 \times \text{capacity factor} \quad (3)$$

$$P_{BG} = \frac{BG_{av} \times CV \times \eta \times 1000}{365 \times 24 \times o} \quad (4)$$

where  $P_{BG}$  is the biomass rating,  $CV$  represents the calorific value,  $\eta$  is the biomass generator's conversion efficiency, and  $o$  is the operating hour per day.

### 3.3 Battery Bank Storage System

In a Hybrid Renewable Energy System (HRES), various types of storage systems are considered to enhance reliability, stability, and efficiency of power generation, especially when integrating renewable sources like solar, wind, and hydropower [48]. Here are the main types of storage systems and their specific roles in HRES:

#### ➤ Batteries (Lithium-Ion, Lead-Acid, etc.)

**Role:** Battery storage is essential for providing short-term energy storage, especially in off-grid systems or during periods of low generation. It stores excess energy produced by renewable sources and supplies it when demand exceeds production (e.g., during cloudy or windless days).

**Key Benefits:** Quick response time, high energy density, flexible sizing and scalability

**Use Case:** Commonly used in both residential and commercial systems, as well as in grid stabilization applications.

#### ➤ Pumped Hydro Storage

**Role:** Used for long-term energy storage, pumped hydro storage involves pumping water to a higher elevation during times of excess power generation and releasing it to generate electricity when demand is high or renewable generation is low.

**Key Benefits:** Large-scale energy storage, High efficiency and long discharge duration, Proven and reliable technology

**Use Case:** Typically used in large-scale power plants to provide grid stability and balance intermittent renewable sources.

➤ *Compressed Air Energy Storage (CAES)*

**Role:** Compressed air energy storage stores excess electricity by compressing air and storing it in underground caverns or tanks. The air is released, heated, and used to drive turbines to generate electricity when needed.

**Key Benefits:** Can store large amounts of energy and long discharge times

**Use Case:** Used in large-scale systems for grid-level stabilization, typically in regions with appropriate geological conditions.

➤ *Flywheel Energy Storage*

**Role:** Flywheels store energy by spinning a rotor at high speed and release it when needed. They are typically used for short-term storage to provide rapid bursts of power.

**Key Benefits:** Fast response time, High cycling capabilities (can charge/discharge many times) and lower maintenance compared to batteries

**Use Case:** Ideal for frequency regulation and stabilizing the grid in HRES.

➤ *Thermal Energy Storage (TES)*

**Role:** Thermal energy storage systems store energy in the form of heat, typically using materials like molten salt, water, or phase-change materials. When excess renewable energy is available, heat is stored and later converted back into electricity using a heat engine or used directly for heating applications.

**Key Benefits:** Long duration storage can be used for both electricity generation and heating

**Use Case:** Commonly integrated into concentrated solar power (CSP) plants but can also be used in residential and industrial applications.

➤ *Hydrogen Storage*

**Role:** Hydrogen can be produced through electrolysis using excess renewable energy, stored, and later used in fuel cells or combustion engines to generate electricity when needed.

**Key Benefits:** High energy density and long-duration storage, can be stored and transported easily

**Use Case:** Used in both grid and off-grid HRES, particularly for long-term energy storage and transportation fuel.

➤ *Supercapacitors (Ultracapacitors)*

**Role:** Supercapacitors are used for storing energy in the form of an electric field. They provide high power output for short durations and are useful for balancing energy fluctuations in the system.

**Key Benefits:** Very fast charge/discharge cycles, excellent for short-term power balancing and frequency regulation

**Use Case:** Typically integrated with other storage technologies to support short-term balancing of renewable output.

*Integration of Storage Systems in HRES:*

- **Grid Stabilization:** Energy storage systems like batteries, pumped hydro, and CAES help to smooth out the intermittency of renewable energy sources and ensure a steady power supply to the grid.
- **Load Management:** Storage systems are used to manage demand-side variations by storing energy during off-peak times and discharging during peak demand, reducing the reliance on fossil fuel-based backup generation.

- **Renewable Penetration:** By utilizing energy storage, HRES can support higher levels of renewable energy integration, enabling more consistent and reliable power even when renewable generation fluctuates.

Each type of storage system plays a distinct role depending on the scale of the HRES, the energy demand profile, and the specific characteristics of the renewable energy sources used. In some cases, a combination of storage technologies may be used to balance the different needs of the system. The storage systems are required to compensate and balance the generated energy with the consumed energy within the system.

The capacity of battery storage bank at  $t'$  hour in charging condition can be given in Eq. (5):

$$E_B^*(t') = E_B^*(t' - 1) + (E_{ERG}^*(t') \times \eta_{0C} \times \eta_{CE}) \quad (5)$$

where  $\eta_{0C}$  and  $\eta_{CE}$  are the charge controlling and battery charging efficiency, and  $E_{ERG}^*$  is the excess energy.

In discharging conditions, the battery storage bank capacity at an  $t'$  hour can be calibrated by the Eq. (6):

$$E_B^*(t') = (1 - \omega) \times E_B^*(t' - 1) - \left[ \frac{E_{NL}^*(t')}{\eta_{0CE} \times \eta_{DCE}} \right] \quad (6)$$

$$E_{NL}^*(t') = E_{ac}^*(t') + (E_{dc}^*(t') \times \eta_{0CE}) \quad (7)$$

$$E_{ac}^*(t') = P_{BMS}(t') \times \Delta t' \quad (8)$$

$$E_{dc}^*(t') = P_{PVS}(t') \times \Delta t' \quad (9)$$

where  $\omega$  is the discharge value,  $\eta_{0CE}$  and  $\eta_{DCE}$  are the battery discharging and converter efficiency.

### 3.4 Power Converter

The power converter is a bidirectional operation connected between the DC and AC buses. Based on the power flow, it works as an inverter when the power is transferred from the PV array to the AC load, and as a rectifier to transfer the power from the biomass generator to the charging battery bank. Moreover, the converter is modeled based on its rated capacity and efficiency, which are assumed to be constant throughout its operating range. The inverter size depends on the demand of the load at peak periods  $P^*(t)$ . The power rating of the inverter  $P_{inv}^*$  [49] is expressed in Eq. (10):

$$P_{inv}^* = \frac{P^*(t)}{\eta} \quad (10)$$

where  $P^*(t)$  is the demand of the load at peak periods and  $\eta$  is represented as the system's efficiency.

## 4 Problem Statement

The primary goal of this research is to reduce the proposed system's total cost, power loss, and harmonic distortion. The primary decision variables are biomass, solar PV cell, and battery rating and sizing.

### 4.1 Objective Function

PV arrays, biomass generator and battery bank have been selected for the optimized configuration of the proposed HRES. The annualized capital cost is utilized for the economic investigation of the hybrid system.

The annualized capital cost of solar PV panels, biomass gasifiers, and power inverters can be calculated using the capacity recovery factor (CRF). The annualized net present cost (NPC) [50–53] is expressed below:

$$C_{NPC}^* = \frac{C_a^*}{CRF(I, L_p)} \quad (11)$$

where  $C_a^*$  is the overall annual cost in \$/year, capital recovery factor is denoted as  $CRF$ ,  $I$  is the interest represented in %, and the project's lifetime in overall years is represented by  $L_p$ . The CRF value can be expressed below:

$$CRF(P, N^*) = \frac{P(1+P)^{N^*}}{(1+P)^{N^*-1}} \quad (12)$$

where  $P$  is the rate of interest and  $N^*$  is the number of years. Moreover, the Cost of Energy (COE) is estimated by the homer using the Eq. (13):

$$COE = \frac{C_a^*}{P_L + D_L + G_s} \quad (13)$$

where AC or DC primary load is denoted as  $P_L$  kW/h, the deferrable load is denoted as  $D_L$  kW/year, and the overall grid sales are represented  $G_s$  in kWh/year. Moreover, the harmonic distortion of the voltage waveform affects the system's power quality. It can be measured through THD of voltage [52,53] as expressed in (14):

$$THD_V = \frac{\sqrt{\sum_{m=2}^M v_m^2}}{v_1} \times 100\% \quad (14)$$

where  $i_m^2$  and  $v_m^2$  are the current and voltage which are related to the  $m$ th harmonic.

#### 4.2 Operating Constraints

For optimizing the objective function, the following constraints are utilized. Solar irradiation and temperature at a particular time in a specific region affect the outcome of PV power. The power outcome limits of the PV array are expressed below:

$$0 \leq n'_{pv} \leq n'_{pv, \max} \quad (15)$$

where  $n'_{pv}$  is the number of PV panels. The power outcome limits of biomass are expressed below:

$$0 \leq n'_{BG} \leq n'_{BG, \max} \quad (16)$$

where  $n'_{BG}$  is the number of biomass generators. The battery storage system performs crucial function in hybrid renewable systems because it stores electrical energy. The overcharging and over-discharging of the battery drastically reduces its life. To prevent the over-discharging of the battery, its operating limit constraints have been used in the simulations. At any hour  $t$ , the battery bank's capacity ( $E_{BATT}$ ) should lie between its maximum and minimum operating capacity. The related constraints used in the simulations are given by Eqs. (17) to (19):

$$E_{B \min}^* \leq E_{BATT}^* \leq E_{B \max}^* \quad (17)$$

$$E_{B\min}^* = \left( \frac{v_B^* \times p_B^* \times n_{BATT}^*}{1000} \right) \times S_{\min}^* \tag{18}$$

$$E_{B\max}^* = \left( \frac{v_B^* \times p_B^* \times n_{BATT}^*}{1000} \right) \times S_{\min}^* \tag{19}$$

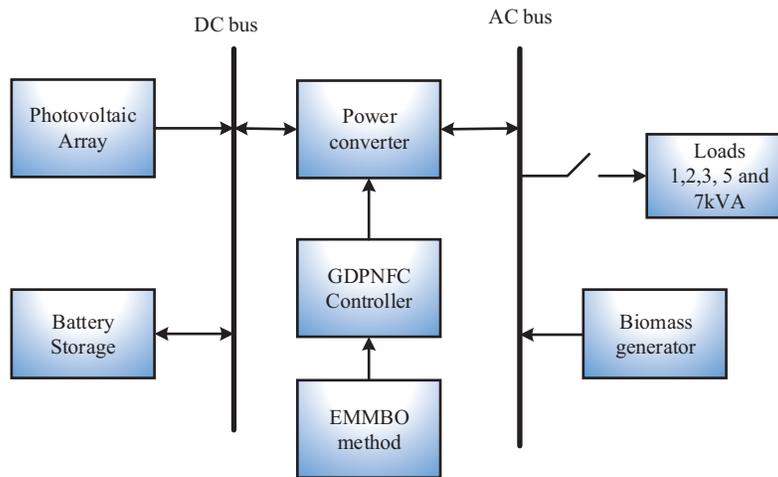
where  $E_{B\min}^*$  and  $E_{B\max}^*$  represents the minimum and maximum operating capacity of the battery storage,  $S_{\min}^*$  and  $S_{\max}^*$  are denoted as the minimum and maximum state of charge value of the battery,  $v_B^*$  is the rated voltage of the battery,  $p_B^*$  is the rated capacity of the battery in Ah, and  $n_{BATT}^*$  is the number of the battery. In the network, the total generation of power from the grid and distributed energy resources must be equal to the summation of load demand and power losses of the system [53].

$$P'_G + \sum_{k=1}^m P'_{DG} - \sum_{k=1, i=k+1}^{mn} D_{ki}^2 \cdot Y'_{ki} = \sum_{k=1}^m P'_L \tag{20}$$

where  $P'_G$  is the total power supplied through the grid,  $P'_{DG}$  is the power generation from distributed generation,  $D$  is the branch current,  $Y'$  denotes the branch impedance, and  $P'_L$  is the system load demand.

### 5 Proposed GDPNFC and EMMBO

The HRES is integrated with the grid framework, which contains PV arrays, biomass, and battery storage component. Furthermore, the units of the HRES are integrated with the grid using converters. In this research, the PV array and biomass are used for power generation to meet the 1, 2, 3, 5, and 7 kVA load demand. Furthermore, when the demand outstrips the power generation, the grid will satisfy the essential for storage. The representation of the proposed control arrangement of the HRES system is illustrated in Fig. 1.



**Figure 1:** Representation of the Proposed hybrid solar-biomass system with the control method

The Enhanced Monarch Butterfly Optimization (EMMBO) [54,55] and the Generalized Dynamic Progressive Neural Fuzzy Controller (GDPNFC) [56–58] are both innovative approaches that contribute significantly to the implemented work.

*Enhanced Monarch Butterfly Optimization (EMMBO) Novelty:*

- **Inspiration:** EMMBO is based on the Monarch Butterfly Migration behavior, an intelligent optimization technique that mimics the migration patterns of Monarch butterflies. The traditional Monarch Butterfly Optimization (MBO) algorithm is improved in EMMBO, which enhances its ability to explore and exploit the solution space more effectively.
- **Enhanced Exploration and Exploitation:** The “Enhanced” aspect in EMMBO refers to its improved mechanisms for balancing exploration (searching broadly across the solution space) and exploitation (refining the best solution found). This is done by incorporating modifications to the search strategies, possibly introducing new genetic operations or dynamic adjustments to control the search behavior.
- **Robustness:** The enhancement in EMMBO aims to overcome the limitations of standard MBO algorithms, such as slow convergence and tendency to get trapped in local optima. This improvement makes EMMBO more robust, especially in complex optimization problems.

**Contribution:**

- **Optimization Problems:** EMMBO has been particularly useful in solving complex and large-scale optimization problems, particularly in engineering, machine learning, and artificial intelligence, where traditional optimization algorithms might struggle.
- **Better Solution Quality:** By enhancing the original MBO, EMMBO often achieves better performance in terms of solution quality and computational efficiency.
- **Application Range:** EMMBO has demonstrated its ability to be applied to a wide range of real-world problems, such as power system optimization, feature selection, machine learning hyperparameter tuning, and scheduling problems.

*Generalized Dynamic Progressive Neural Fuzzy Controller (GDPNFC) Novelty:*

- **Hybrid Approach:** The GDPNFC combines the power of neural networks, fuzzy logic systems, and dynamic controllers, creating a hybrid approach that is more adaptive and capable of handling uncertain and nonlinear systems.
- **Progressive Learning:** The “progressive” aspect of the GDPNFC refers to its ability to progressively learn from its environment and adjust the control strategy over time. It learns the system’s dynamics as it operates, making it more effective in real-time control applications.
- **Dynamic Adaptation:** Unlike traditional fuzzy controllers, GDPNFC can adapt to changing system dynamics in real-time, making it suitable for complex systems that require continuous adjustment, such as in robotics, autonomous systems, and industrial control.

**Contribution:**

- **Improved Control Performance:** GDPNFC offers improved performance over traditional control systems, particularly in systems with uncertainties, nonlinearities, and dynamic changes. It provides a more robust solution for controlling complex systems.
- **Versatility:** The use of neural networks in conjunction with fuzzy logic allows GDPNFC to handle both qualitative and quantitative data. This makes it highly versatile, as it can be applied to a wide range of control problems, including those with uncertain or imprecise information.
- **Real-Time Adaptive Control:** GDPNFC is particularly beneficial for real-time applications that require continuous monitoring and adjustment, such as in robotics, process control, and autonomous vehicles. The system’s ability to learn and adapt dynamically provides a significant advantage in environments where conditions are constantly changing.

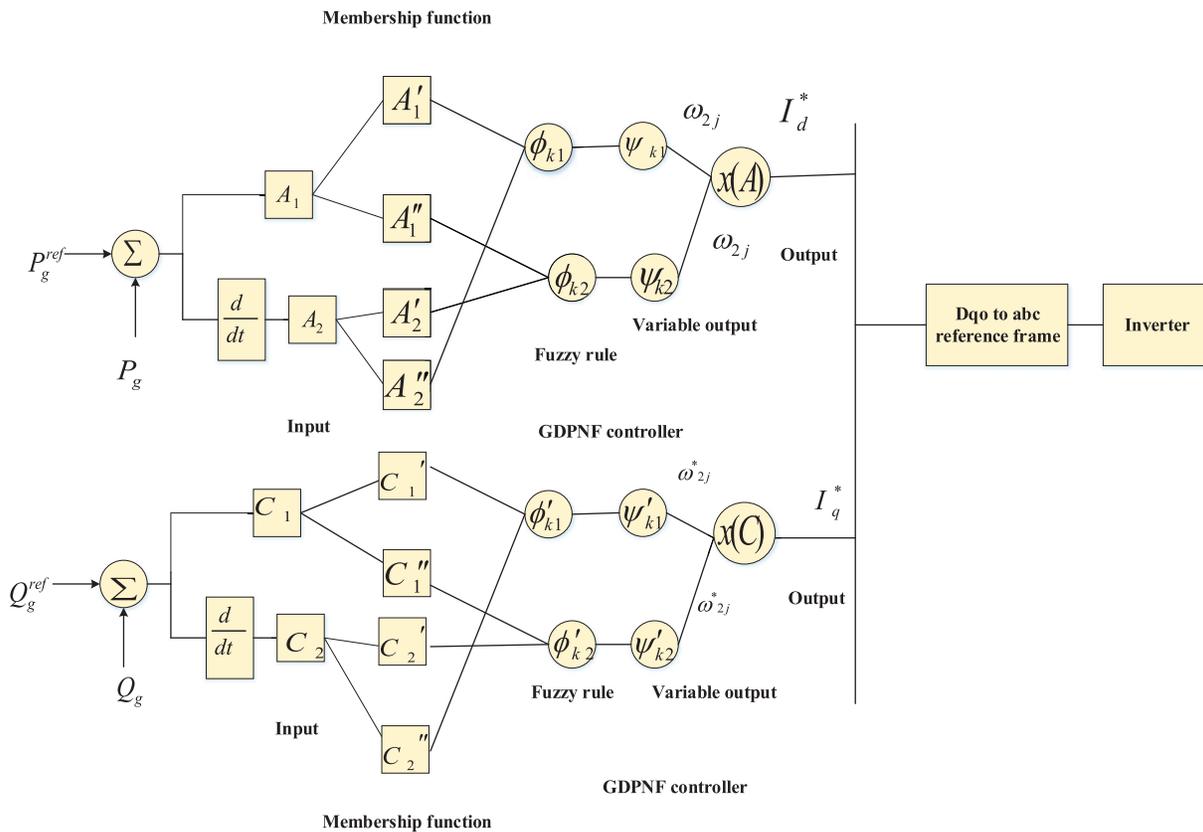
Hence, the key contribution of EMMBO lies in enhancing the Monarch Butterfly Optimization algorithm to provide more efficient solutions for complex optimization problems, improving both exploration and exploitation, and delivering higher-quality outcomes. GDPNFC, a hybrid controller combines

neural networks, fuzzy logic, and dynamic control, contributing to improved real-time adaptive control for nonlinear, uncertain, and dynamic systems. Its progressive learning capability is particularly useful for systems that evolve over time.

Both methods provide innovative solutions in their respective domains, significantly advancing the state-of-the-art in optimization and control systems.

### 5.1 Proposed GDPNFC Control Method

The GDPNFC-based intelligent control is applied to the inverter to regulate the output power delivered to the grid. In the GDPNFC-based control system, active and reactive power is the two input of the GDPNFC, illustrated in Fig. 2.



**Figure 2:** GDPNFC-based novel intelligent control method for new hybrid solar-biomass system

The active power of the GDPNFC determines the direct component of the current to be provided through an inverter [57,58]. The active power is expressed in Eq. (21):

$$P_g = V_{gd}I_{gd} + V_{gq}I_{gq} \tag{21}$$

The error between the active power stipulated via the grid  $P_g^{ref}$  and the actual active power injected through the inverter into the grid  $P_g$  is given to the input of the GDPNFC Controller, represented as  $A_i$ . The membership function (MF) in Gaussian functions is expressed in Eq. (22):

$$\mu_{ik}(A_i) = \exp\left(-\frac{(A_i - b_{ik})^2}{\omega_k^2}\right) \quad (22)$$

$$i = 1, 2, \dots, p, \quad k = 1, 2, \dots, m$$

where  $\mu_{ik}$  is the  $k$ th membership function of  $A_i$ ,  $\omega_k$  is the width of  $k$ th the Gaussian membership function  $A_i$ ,  $i$  is the number of input variables,  $m$  is the number of membership functions, and  $b_k$  is denoted as the center of  $k$ th the Gaussian membership function  $A_i$ . Similarly, in the reactive power of the GDPNF controller, the error between the reactive power stipulated via the grid  $Q_g^{ref}$  and the actual reactive power injected through the inverter into the grid  $Q_g$  is given to the input of the GDPNF Controller and denoted as  $C_i$ .

$$\mu_{ik}(C_i) = \exp\left(-\frac{(C_i - b_{ik})^2}{\omega_k^2}\right) \quad (23)$$

$$i = 1, 2, \dots, p, \quad k = 1, 2, \dots, m$$

For **IF**-part of the fuzzy rule, then the output of the  $k$ th rule for active power is expressed below:

$$\phi_k = \exp\left(-\frac{\sum_{i=1}^p (A_i - b_{ik})^2}{\omega_k^2}\right) = \exp\left[-\frac{\|A - b_k\|}{\omega_k^2}\right] \quad k = 1, 2, \dots, m \quad (24)$$

where  $A = A_1, A_2, \dots, A_p$ . The number of variables is equal to the fuzzy rules. The equation represents the output of the  $m$  variable (Eq. (25)):

$$\psi_k = \frac{\phi_k}{\sum_{j=1}^p \phi_j} = \frac{\exp\left[-\frac{\|A - b_k\|}{\omega_k^2}\right]}{\sum_{j=1}^m \exp\left[-\frac{\|A - b_j\|}{\omega_j^2}\right]} \quad k = 1, 2, \dots, m \quad (25)$$

The summation of the active power output is expressed in Eq. (26):

$$x(A) = \sum_{j=1}^p \omega_{2j} \cdot \psi_j = \frac{\sum_{j=1}^p \omega_{2j} \exp\left[-\frac{\|A - b_k\|}{\omega_k^2}\right]}{\sum_{j=1}^p \exp\left[-\frac{\|A - b_j\|}{\omega_j^2}\right]} \quad (26)$$

where  $\omega_{2j}$  is the weight of each rule, and  $x$  is denoted as the output variable value. Similarly, the summation of the reactive power output is illustrated in the Eq. (27):

$$x(C) = \frac{\sum_{j=1}^p \omega_{2j} \exp\left[-\frac{\|C - b_k\|}{\omega_k^2}\right]}{\sum_{j=1}^p \exp\left[-\frac{\|C - b_j\|}{\omega_j^2}\right]} \quad (27)$$

If  $\|E_i\| > k_{e^*}$ , then the error criterion is denoted in Eq. (28):

$$\|E_i\| = \|y_i - x_i\| \quad (28)$$

where  $y_i$  represented as the desired output and  $x_i$  is the GDPNFC output. The equation calculates the distance between the input  $A_i$  and the centre  $b_k$  in the Eq. (29):

$$D_i(k) = \|A_i - b_k\| \quad k = 1, 2, \dots, m \quad (29)$$

If  $d_{\min}^* > k_{d^*}$ , the  $d_{\min}^*$  value can be determined using the Eq. (30):

$$d_{\min}^* = \arg \min(D_i(k)) \quad (30)$$

where  $k_{d^*}$  is the accommodation boundary radius. The hierarchical learning method gradually reduces the accommodation boundaries' effective radius and the given error. More specifically, the selected  $k_{e^*}$  and  $k_{d^*}$  constants are given in Eqs. (31) and (32):

$$k_{e^*} = \max(PE_{\max} \times \alpha^i, PE_{\min}) \quad (31)$$

$$k_{d^*} = \max(L_{\max} \times \delta^i, L_{\min}) \quad (32)$$

where  $PE_{\max}$  is the predefined maximum error,  $PE_{\min}$  is denoted as the accuracy of GDPNFC output,  $\alpha$  and  $\delta$  are the convergence and decay constant,  $L_{\max}$  represented as the largest input space  $L_{\min}$  and the smallest length of interest. The current components are transformed from the reference frame of direct quadrature zero transformation to the ABC reference structure, which is utilized to describe the switching pulses of the inverter.

## 5.2 Proposed EMMBO for Optimization

The novel EMMBO method is proposed to optimize the unit cost of the system along with optimizing the power loss, THD, and controller performance. The flow chart of EMMBO for proposed hybrid solar and biomass system is illustrated in Fig. 3. The main aim of using the proposed controller is to improve the dynamic performance and regulate the power flow of the grid-integrated HRES.

The monarch butterfly migrates from southern Canada and the northern USA to Mexico during the autumn and summer. Therefore, the migration of the population of monarch butterflies can be separated into two groups: Land 1 and Land 2. Furthermore, the monarch butterfly migration can be simplified by the butterfly individuals living in Land 1 for four months and Land 2 for seven months. In April, the butterfly individuals in Land 2 move to Land 1, and the butterfly individuals in Land 1 move to Land 2 in September. Based on the EMMBO, the annualized cost is expressed in Eq. (33):

$$C_{i,j} = C_{p,j}^t \quad (33)$$

where  $C_{i,j}$  represents the present annualized cost  $j$ th element of  $C_i$ ,  $C_{p,j}^t$  indicates  $j$ th the element of  $C_p$  that is optimized annualized cost. The value  $P$  is randomly selected from subpopulation 1 and calculated by the Eq. (34):

$$P = rand * peri \quad (34)$$

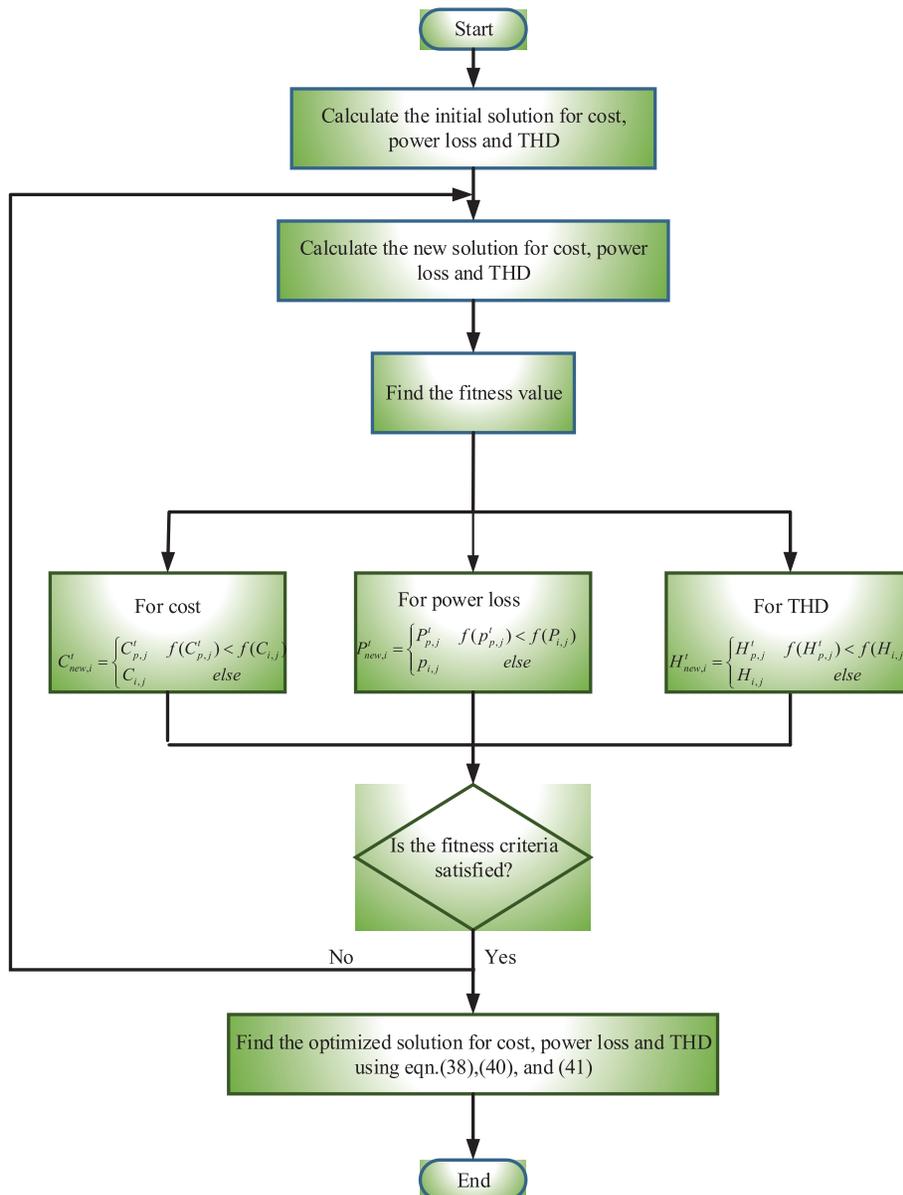
Then, they  $C_{new,i}^t$  can be computed using the greedy strategy as given by,

$$C_{new,i}^t = \begin{cases} C_{p,j}^t & f(C_{p,j}^t) < f(C_{i,j}) \\ C_{i,j} & else \end{cases} \quad (35)$$

where  $C_{new,j}^t$  represents the annualized cost. The fitness value of  $C_{p,j}^t$  and  $C_{i,j}$  is  $f(C_{p,j}^t)$  and  $f(C_{i,j})$  respectively. Similarly,  $P_{new,i}^t$  and  $H_{new,i}^t$  are calculated using greedy strategy is estimated for the power loss and harmonics, which is given by,

$$P_{new,i}^t = \begin{cases} P_{p,j}^t & f(P_{p,j}^t) < f(P_{i,j}) \\ P_{i,j} & \text{else} \end{cases} \tag{36}$$

$$H_{new,i}^t = \begin{cases} H_{p,j}^t & f(H_{p,j}^t) < f(H_{i,j}) \\ H_{i,j} & \text{else} \end{cases} \tag{37}$$



**Figure 3:** Flow chart for the EMMBO in hybrid solar and biomass system

The crossover operator is included in the butterfly adjusting operator, which is expressed in Eq. (38):

$$C_{new,j}^t = C_{p,j}^t \times (1 - C_{cr}) + C_{i,j} \times C_{cr} \quad (38)$$

Here  $C_{cr}$  is the crossover rate, which is calculated by the Eq. (39):

$$C_{cr} = 0.8 + 0.2 \times \frac{f(C_{i,j}) - f(C_{best})}{f(C_{worst}) - f(C_{best})} \quad (39)$$

where  $C_{best}$  and  $C_{worst}$  indicate the best and worst annualized cost corresponding to the fitness of  $f(C_{worst})$  and  $f(C_{best})$ , respectively. The crossover rate can lie from 0.2 to 0.8. Similarly, the power loss and total harmonics are optimized by the Eqs. (40) and (41):

$$P_{new,j}^t = P_{p,j}^t \times (1 - P_{cr}) + P_{i,j} \times P_{cr} \quad (40)$$

$$H_{new,j}^t = H_{p,j}^t \times (1 - H_{cr}) + H_{i,j} \times H_{cr} \quad (41)$$

where  $P_{new,j}^t$  and  $H_{new,j}^t$  is represented as the annualized power loss and total harmonics. Once the optimal solution is attained, the criteria stop the process until it continues till the finest solution is reached.

## 6 Result and Discussion

The proposed technologies on hybrid solar and biomass system models are implemented in HOMER pro software, and the power quality results were compared with MATLAB. In addition, the HOMER simulation software provides optimized results for the hybrid system by performing simulations based on input parameters like fuel price and costs per unit of the proposed hybrid system.

### Case Study

In this research, the National Capital Region (NCR) of India is chosen, which is located at 28.7041°N and longitude 77.1025°E that has been selected for the proposed hybrid system. The proposed hybrid solar and biomass system is validated by Homer software. The execution values are 1 kW of PV cells, 500 kW of biomass generator with 12 batteries, and 3.33 kW converter. The dissimilar loads are considered, such as 1, 2, 3, 5, and 7 kVA of load demand, which is shown in Table 2. Moreover, the simulation time step is considered for one hour and run on data for one year. The initial optimization assessment data for hybrid solar and biomass systems is detailed. Initially, the total Net Present Cost (NPC) of the hybrid solar and biomass system is \$.462,101. Then, the COE and primary investments are \$9.17/kWh and \$504,395, respectively.

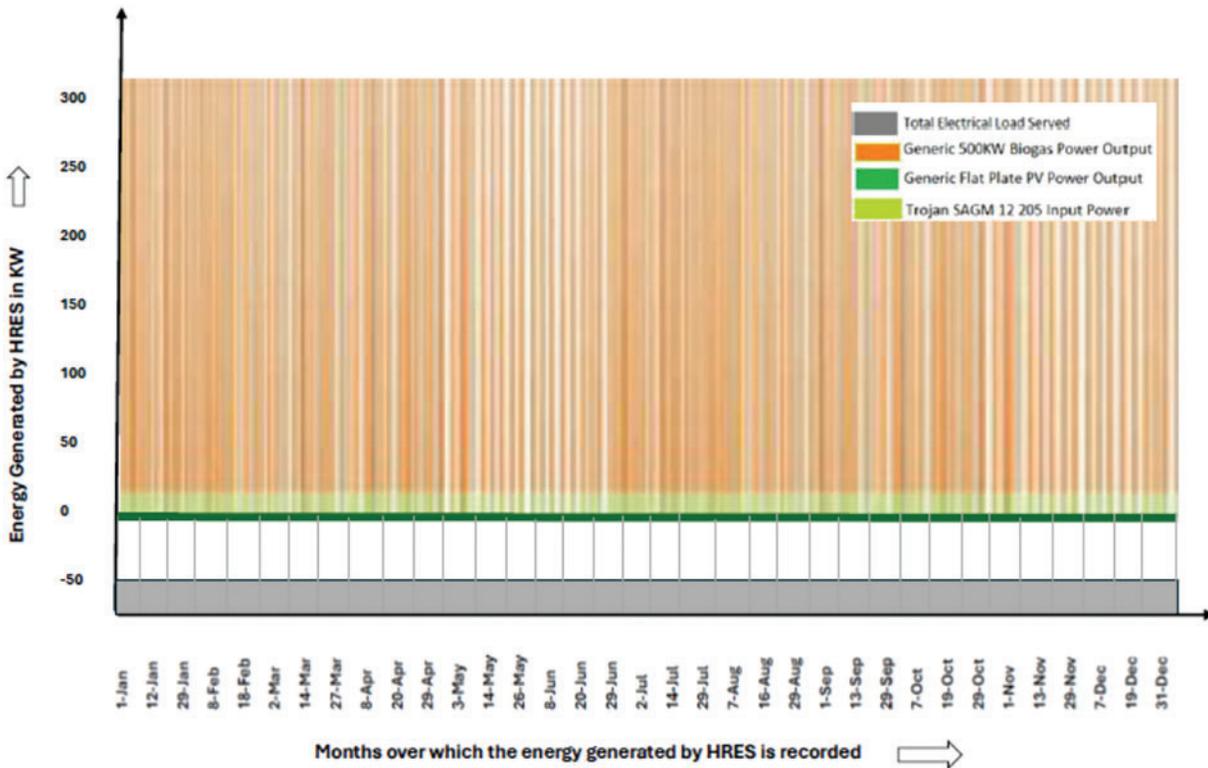
**Table 2:** Initial optimization result data for hybrid solar and biomass system

	Architecture						Cost			System			Biomass			
	PV/ Biomass/ Battery/ converter	PV (kW)	Bio (kW)	SAGM 12	Con verter (kW)	Effi ciency	Dis patch	NPC (\$)	COE (\$)	Oper ating cost (\$)	Initial cap- ital (\$)	Ren frac (%)	Total fuel (tonnes /yr)	Hours	Produc tion (kWh)	Fuel (tons)
	1.00	500	28	3.33	0	LF	462,101	9.17	-3,309	504,395	100	139	177	44250	139	88.6

Based on the electricity produced, the Biomass Generator is the big contributor to this configuration system with 73%, and another 27% of energy is generated from PV panels. The HRES has also been configured with load following dispatch strategy.

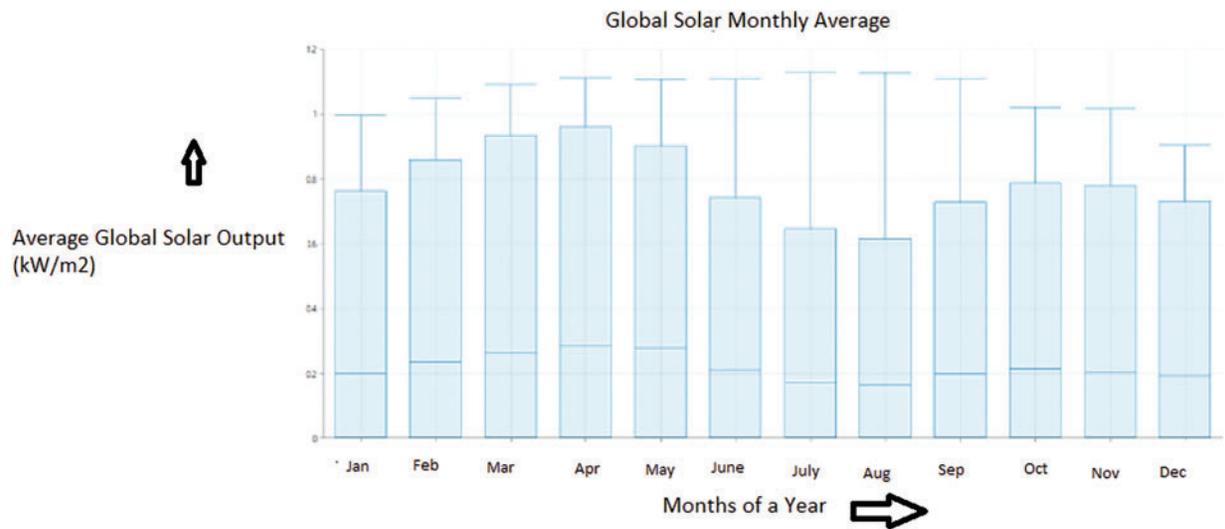
A load following dispatch strategy is when the generator runs; it produces just enough energy to meet the loads. The energy generated by HRES developed is shown in Fig. 4, where the grey color indicates the

total electrical load served, moreover the orange color denotes the power output. Besides, the green color represents the input power of the system. The average biomass power is 250 kW.



**Figure 4:** Energy generated by developed HRES

The performance of the 1 kW PV arrays for the average global period is represented in Fig. 5. The average electrical energy generated by 1 kW PV arrays over the year is 1.2 kWh/month. During the months of July and August, it produces more power compared to the other months of the year. Furthermore, April, May, and June generate 1.1 kW of power. Besides, the October and December month produces the same power at the rate of 1.01 kW. December month generates low power while compared to the other months. Before optimization, the Levelized cost of the PV arrays is 0.0311 \$/kWh. The hours of operation of solar PV panels are 4401 Hrs/yr. Moreover, the minimum and maximum power output of solar PV array is 0 and 0.985 kW, which is demonstrated in Table 3.



**Figure 5:** 1 kW PV arrays for average global

**Table 3:** Performance of PV arrays before optimization

Quantity	Value (kW/yr)	Units
Minimum output	0	kW
Maximum output	0.985	kW
PV penetration	40.2	%
Hours of operation	4401	Hrs/yr
Levelized cost	0.0311	\$/kWh

After applying the proposed intelligent control approach, the overall production of PV arrays is 1632 kWh/yr. Moreover, the most minor and most significant power output is 0.186 and 4.47 kW/d, which are demonstrated in Table 4. The average electrical energy generated by 1 kW PV arrays over the year is 1.2 kWh/month, and the rated capacity of the PV panel is 1 kW. Besides, solar PV panels obtain a capacity factor of 18.6%.

**Table 4:** Performance of PV arrays using the proposed method

Quantity	Value (kWh/yr)	Units
Rated capacity	1.00	kW
Mean output	0.186	kW
Mean output	4.47	kW/d
Capacity factor	18.6	%
Overall production	1632	kWh/yr

The Contour plot for the performance of the 1 kW PV arrays is expressed in Fig. 6. The contour plot represents solar power generation in the hours and years of the day with the rating of 1 kW. The average global solar rate of 1 kW is demonstrated in Fig. 7.

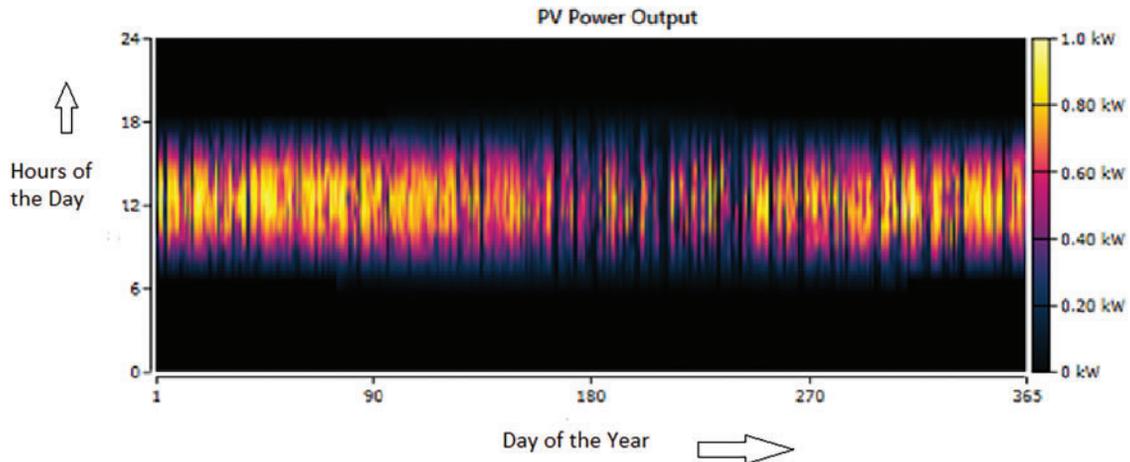


Figure 6: Contour plot for the performance of the 1 kW PV arrays

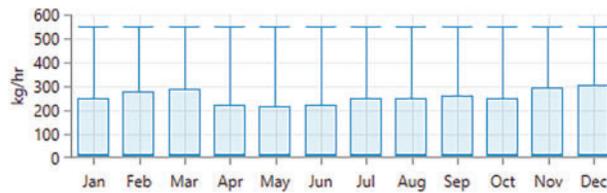


Figure 7: The performance of the 500 kW biomass

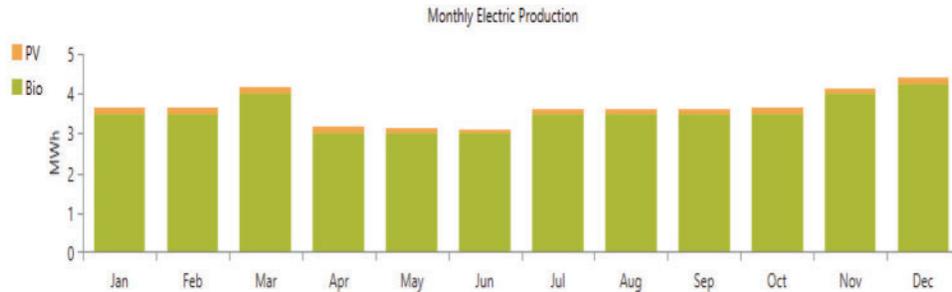
The performance of the 500 kW Biomass Generator for the HRES is shown in Fig. 7 and Table 5. The average electrical output generated per month is around 250 kW. Furthermore, January and November produced more power than the other months. For example, in June, the biomass generator generated low power at 44,250 kWh/yr.

Table 5: Performance quantity of biomass power generation

Quantity	Value	Units
Number of starts	177	Starts/year
Operational life	11.3	Yr
Capacity factor	1.01	%
Fixed generation cost	14.1	\$/hr
Electricity production	44,250	kWh/yr
Minimum electrical output	250	kW
Fuel energy consumption	139	Tons/yr
Mean electrical efficiency	29.8	%

The total amount of biomass feedstock consumed by the generator is 139 Tons/yr. As a result, the mean electrical efficiency of the system is improved by 29.8%, and the operational life is achieved as 11.3 years.

The monthly power generation using the hybrid system is detailed in Fig. 8 and Table 6. The amount of renewable fraction has attained 100% of values, and the maximum amount of renewable penetration is considered 510%.

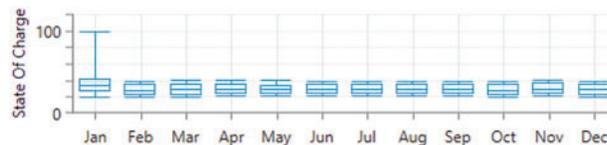


**Figure 8:** Monthly power generation using the hybrid system

**Table 6:** Monthly hybrid power generation system

Parameters		kWh/yr	%
Production	Generic flat plate PV	1632	3.72
	Generic 500 kW biogas generator	42,250	96.3
	Overall	43,882	100
Consumption	AC primary load	3927	100
	DC primary load	0	0

The performance of the 12V Trojan SAGM12 205 battery for the HRES connection is illustrated in Fig. 9. The annual throughput of the Trojan SAGM12 205 battery is around 3327 kW/hr, and storage depletion is 55.0 kW/yr. Also, total losses are reduced up to 503 kW/hr, which are illustrated in Table 7. Moreover, the nominal capacity of Trojan SAGM12 205 battery is 73.5 kWh, and the expected life is 20.5 years. Therefore, the lifetime throughput is increased to 63.983 kWh.



**Figure 9:** The Performance of the Trojan SAGM 12 205

Consequently, the proposed hybrid system is validated with different load conditions such as 1, 2, 3, 5, and 7 kVA. The cost optimization of these loads under the system incorporation is estimated. The optimization results of hybrid solar and biomass systems using homer pro is illustrated in Table 8.

**Table 7:** Performance of 12V Trojan SAGM12 205 battery

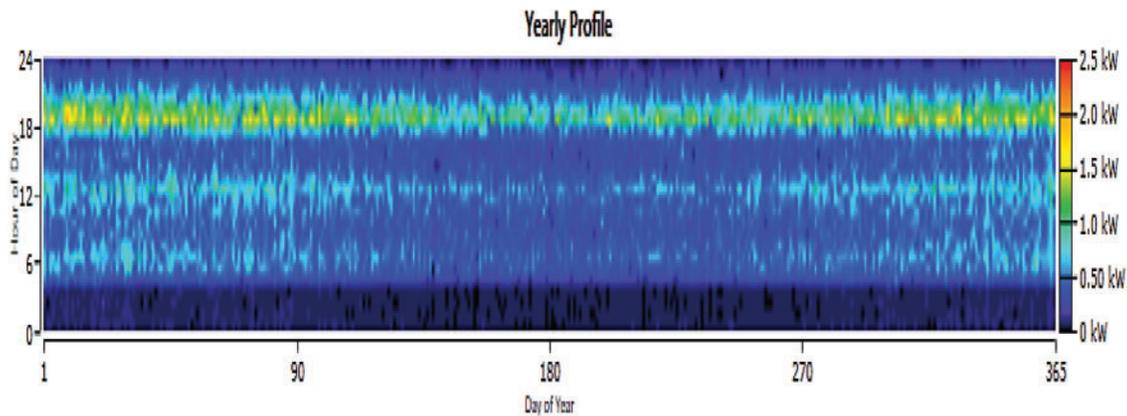
Quantity	Value (kW/yr)
Energy in	3327
Energy out	2878
Storage depletion	55.0
Losses	503
Annual throughput	3122

**Table 8:** Optimization result of hybrid solar and biomass systems with 1 kVA

Component	Capital (\$)	Replacement (\$)	O&M (\$)	Salvage (\$)	Fuel cost (\$)	Total (\$)
Generic flat plate PV	560.00	0	89.48	0.00	0.00	649.48
Converter	34,928.47	166.56	255.14	31.00	0.00	35,319.17
Trojan SAGM12 205	16,678.00	3655.15	3170.27	3586.31	0.00	19,917.11
Biomass generator	372,150.00	490.00	1080.19	50,015.09	0.00	323,215.10
Complete System	424,316.47	3821.72	4595.09	53,632.41	0.00	379,100.87

The hybrid renewable systems with 1 kW solar panels, 500 kW Biomass Generator, 12 batteries, 1 kVA load, and converter have the lowest (NPC) at \$35,319.17. The proposed GDPNFC and EMMBO approaches have been applied in the hybrid system to enhance performance and reduce costs. The optimization by HOMER shows that the HRES developed is the best and the optimal design. Moreover, the operating cost of the system is \$379,100.87 per year.

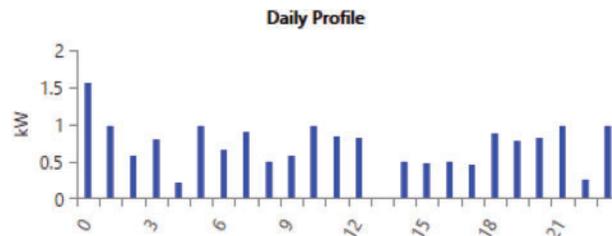
The yearly profile of the 1 kVA system is demonstrated in Fig. 10. The average 11.13 kWh/day of the scaled load is attained, and an average of 0.46 kW is achieved. The peak load is obtained as 2.32 kW and the 20%-time step. The validated time step size is 60 min.

**Figure 10:** Yearly profile of 1 kVA system

Then, the proposed system is connected with the 2 kVA load. The optimization results of hybrid solar and biomass systems with 2 kVA using homer pro are illustrated in Table 9. The daily profile of the 2 kVA system is demonstrated in Fig. 11.

**Table 9:** Optimization result of hybrid solar and biomass systems with 2 kVA

Component	Capital (\$)	Replacement (\$)	O&M (\$)	Salvage (\$)	Fuel cost (\$)	Total (\$)
Generic flat plate PV	560.00	0	89.48	0.00	0.00	649.48
Converter	28,437.5	135.61	207.73	25.24	0.00	28,755.0
Trojan SAGM12 205	18,830.00	3655.15	3579.24	46.48	0.00	22,362.86
Biomass generator	372,150.00	0	984.32	51,204	0.00	321,930.28
Complete System	419,977.50	135.61	4860.0	51,275.77	0.00	373,689.22

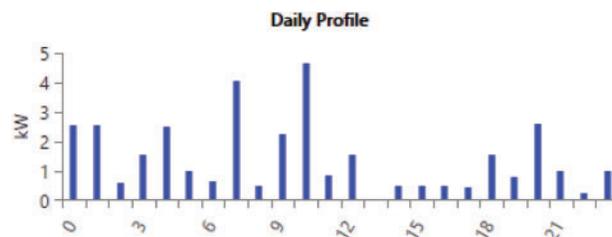
**Figure 11:** Daily profile of 2 kVA system

The average 11.13 kWh/day of the scaled load is attained, and an average of 0.46 kW is achieved. The peak load is obtained as 2.32 kW and the 20%-time step. The validated step size is 60 min, and a 0.29 load factor is taken.

Also, the proposed system is connected with the 3 kVA load and validated the performance. The optimization results of hybrid solar and biomass systems with 3 kVA using homer pro are illustrated in [Table 10](#). The daily profile of the 3 kVA system is demonstrated in [Fig. 12](#).

**Table 10:** Optimization result of hybrid solar and biomass systems with 3 kVA

Component	Capital (\$)	Replacement (\$)	O&M (\$)	Salvage (\$)	Fuel cost (\$)	Total (\$)
Generic flat plate PV	560.00	0	89.48	0.00	0.00	649.48
Converter	46,666.7	222.54	340.89	41.42	0.00	649.48
Trojan SAGM12 205	18,292.00	4372.93	3477.07	3677.78	0.00	22,464.2
Biomass generator	372,150.00	0	1003.49	50,966.25	0.00	322,187.24
Complete System	437,668.67	4595.67	4910.94	54,685.45	0.00	392,489.63

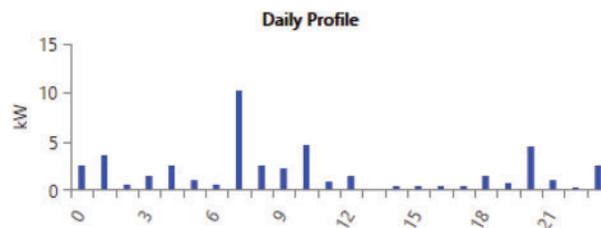
**Figure 12:** Daily profile of 3 kVA system

The average 11.13 kWh/day of the scaled load is attained, and an average of 0.46 kW is achieved. The peak load is obtained as 1.6 kW and the 20% time step. The validated time step size is 60 min and 0.19 load factor.

Similarly, the proposed system is connected with the 5 kVA load and the performance is validated. The optimization results of hybrid solar and biomass systems with 5 kVA using homer pro are illustrated in Table 11. The daily profile of the 5 kVA system is demonstrated in Fig. 13. The average 11.13 kWh/day of the scaled load is attained, and an average of 0.46 kW is achieved. The peak load is obtained as 4 kW and the 20%-time step. The validated time step size is 60 min, and the load factor is 0.12.

**Table 11:** Optimization result of hybrid solar and biomass systems with 5 kVA

Component	Capital (\$)	Replacement (\$)	O&M (\$)	Salvage (\$)	Fuel cost (\$)	Total (\$)
Generic flat plate PV	560.00	0	89.48	0.00	0.00	649.48
Converter	75,511.07	360.09	551.59	67.02	0.00	76,355.73
Trojan SAGM12 205	13,450.00	4541.11	2556.67	1639.52	0.00	18,908.26
Biomass generator	372,150.00	0.00	1323.08	47,003.09	0.00	326,469.99
Complete system	461,671.07	4901.20	4520.82	48,709.64	0.00	422,383.46

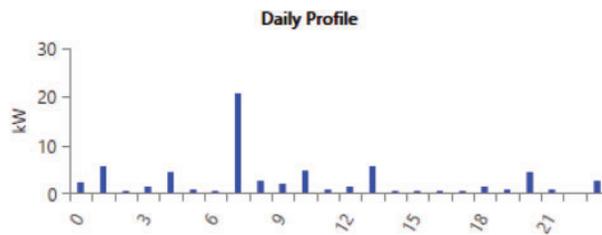


**Figure 13:** Daily profile of the 5 kVA system

Furthermore, the proposed system is connected with the 7 kVA load and validated the performance. The optimization results of hybrid solar and biomass systems with 7 kVA using homer pro are illustrated in Table 12. The daily profile of the 7 kVA system is demonstrated in Fig. 14. The average 11.13 kWh/day of the scaled load is attained, and an average of 0.46 kW is achieved. The peak load is obtained as 5.6 kW and the 20%-time step. The validated time step size is 60 min, and the load factor is 0.08.

**Table 12:** Optimization result of hybrid solar and biomass systems with 7 kVA

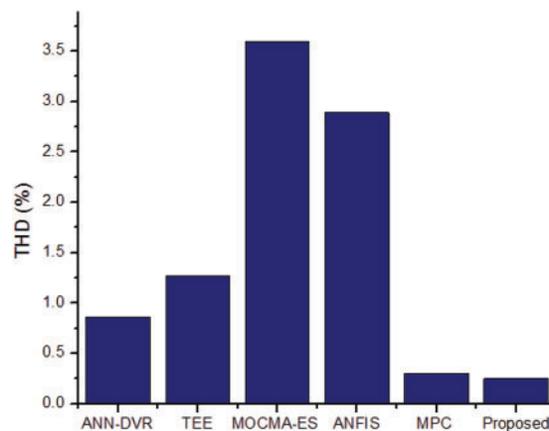
Component	Capital (\$)	Replacement (\$)	O&M (\$)	Salvage (\$)	Fuel cost (\$)	Total (\$)
Generic flat plate PV	560.00	0	89.48	0.00	0.00	649.48
Converter	116,620.49	556.13	851.89	103.51	0.00	117,924.99
Trojan SAGM12 205	15,064	4245.01	2863.47	2546.64	0.00	19,625.84
Biomass generator	372,150.00	0.00	1,131.33	49,380.00	0.00	323,900.34
Complete system	504,394.49	4801.14	4936.14,	4936.17	0.00	462,100.65



**Figure 14:** Daily profile of 7 kVA system

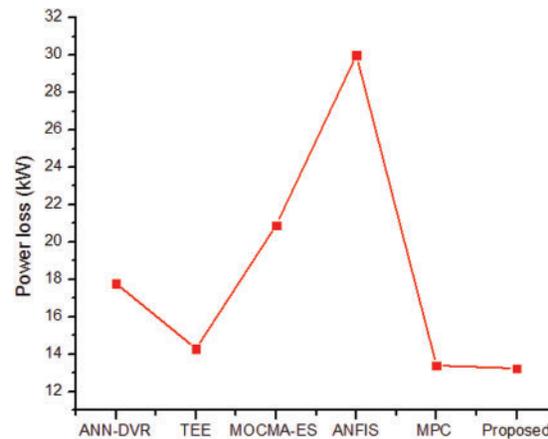
The analysis shows that biomass has a more significant initial investment than photovoltaics. Battery storage units are the same price as biomass, except that they are infinitely reusable. Batteries are significantly more expensive to maintain than solar power but are four times smaller than biomass power. When total cost is considered, which includes capital, operation and maintenance, replacement, and salvage, PV and battery storage are virtually the same. In contrast, biomass has a cost that is more than tenfold that of PV and battery storage.

The THD and power loss obtained from the proposed system are 3.289% and 13.25 kW. For validating the performance of the proposed method, the results of the hybrid system are compared with some of the conventional state-of-the-art techniques such as the Artificial Neural Network (ANN) controller of Dynamic Voltage Restorer (DVR) [30], techno-enviro-economic (TEE) [31], Multi-Objective Covariance Matrix Adaption-Evolution Strategy (MOCMA-ES) algorithm [32], adaptive neuro-fuzzy inference system (ANFIS) [33] and model predictive control (MPC) [34]. The comparison representation of the proposed method attained THD value with the existing techniques is demonstrated in Fig. 15.



**Figure 15:** Comparison of THD with the existing technique

Moreover, the proposed EMMB optimization technique in the hybrid system has reduced the power loss to 13.25 kW. Therefore, the proposed result is compared with similar existing techniques, as shown in Fig. 16.



**Figure 16:** Comparison of power loss with the existing technique

The computational time of the proposed approach has been achieved at 10 s. The reliability of the HRES was estimated using the Loss of Power Supply Probability (LPSP), expressed by the Eq. (42):

$$LPSP = \frac{\sum_{t^*=1}^{T^*} LPS^*}{\sum_{t^*=1}^{T^*} E_{load}(t^*)} \quad (42)$$

where  $LPS^*$  is the power supply loss (kW) estimated when the energy generated by the RES is lower than the load demand,  $E_{load}(t^*)$  is the power consumed by the load  $t^*$  (kW). Then, the overall comparison of the proposed with existing methods are shown in Table 13.

**Table 13:** Overall comparison of the proposed solution over conventional methods

Techniques	ANFISA [21]	TEE [55]	ANN-DVR [59]	MOCCA-ES [60]	MPC [61]	Proposed
THD	2.89	1.27	0.86	3.6	0.30	0.25
Power loss (kW)	30	14.3	17.8	20.90	13.4	13.25
LPSP	0.34	0.5	0.1	0.42	2.536	0.01

In this paper, the proposed EMMB optimization technique significantly reduced the power loss at 13.25 kW and minimized the THD value of hybrid solar and biomass systems at 0.25%. Moreover, the cost of the entire system is significantly diminished and improves the system's performance. In addition, this proves that the proposed system is more reliable than the other existing system.

## 7 Conclusion and Future Scope

The optimal design of hybrid solar and biomass systems is the power system's most challenging and significant issue. In this paper, the GDPNFC has been proposed to regulate the power supply of the proposed hybrid system. Subsequently, the power loss, THD, and cost of the hybrid solar and biomass system were reduced using the EMMB optimization technique. Finally, Homer software implemented the proposed

hybrid solar and biomass system. From the simulation, the outcome shows that the NPC for the hybrid solar and biomass system attains \$462,101.

Moreover, the harmonics distortion range was attained within the limit of 5%. Besides, the power loss and THD of the proposed approach were compared with other existing approaches, indicating that the proposed technique reduces the power loss and THD of the hybrid solar and biomass system. Therefore, it can be concluded that the proposed system is more reliable and cost-effective for providing sustainable energy per the demand scenario.

In the future work, an analysis of the environmental benefits and cost implications of implementing the proposed system would make the study more holistic and relevant for policymaking. Moreover, the potential benefits of integrating additional renewable sources could be explored.

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**Author Contributions:** This section provides a clear description of the roles and contributions made by each author in the development and completion of this research. Arpita Johri: She conceptualized the study and formulated the research framework. She has played a pivotal role in designing the methodology, overseeing the data collection process, and ensuring adherence to ethical standards. Additionally, she performed the statistical analysis and contributed to the interpretation of results. The initial draft of the manuscript was prepared by herself, who also handled the manuscript revisions based on reviewers' comments. Varnita Verma: She contributed significantly to the data collection and management. They were responsible for conducting literature reviews and assisting in the development of research methodology. Varnita Verma also provided critical insights during the data analysis phase and reviewed the manuscript for intellectual content and technical accuracy. Her efforts ensured the inclusion of relevant academic references and proper citation of sources. Mainak Basu supported the study by validating the research methodology and ensuring accuracy in the experimental procedures. He has contributed to refining the research questions and provided expert insights during the result interpretation. Mainak Basu was actively involved in proofreading the manuscript for coherence and clarity and assisted in formatting it according to the target journal's guidelines. All authors have read and approved the final manuscript and agree to be accountable for all aspects of the work to ensure its accuracy and integrity. This collaborative effort reflects the complementary expertise and shared responsibility of all authors in achieving the research objectives. All authors reviewed the results and approved the final version of the manuscript.

**Availability of Data and Materials:** The data has been collected using HOMER Pro software by providing the geographical location of the site—the National Capital Region (NCR) of India, which is located at 28.7041°N and longitude 77.1025°E that has been selected for the proposed hybrid system. Software Availability: Homer Pro Software, MATLAB 2016.

**Ethics Approval:** This study was conducted in compliance with ethical standards and received approval from Dr. Mainak Basu, under the capacity of research Supervisor at the G. D. Goenka University, Gurugram, Haryana, India. The ethical approval process ensured that the study adhered to the principles outlined as per the guidelines of G. D. Goenka University, Gurugram, Haryana, India. This study did not involve human participants, animal subjects, or any biological materials. It was purely technical and based on simulations conducted using computational tools and software. The research adhered to ethical principles relevant to technical and simulation-based studies, including

ensuring the accuracy and integrity of data, transparency in methodology, and proper acknowledgment of all references and resources used. No sensitive or confidential information was involved, and no potential conflicts of interest arose during the study. The research followed standard practices to ensure reproducibility, reliability, and adherence to ethical research conduct in technical disciplines. If additional information on ethical considerations or compliance is required, the authors are prepared to provide further details.

**Conflicts of Interest:** The authors wish to draw attention to the following facts which may be considered as potential conflicts of interest and to significant financial contributions to this work. They wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome. It is confirmed that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. It is further confirmed that the order of authors listed in the manuscript has been approved. The authors confirm that the due consideration has been given to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing the authors confirm that they have followed the regulations of the respective institutions concerning intellectual property. It is confirmed that any aspect of the work covered in this manuscript that has involved either experimental animals or human patients has been conducted with the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript.

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