Impact of Wind Speed Profiles on Hybrid Solar-Wind System: An Optimization and Machine Learning Investigation

[1]Bhoopendra Patel [2]Dr. H. N. Suresh
Department Of Mechanical Engineering
Swami Vivekanand University, Sagar, Madhya Pradesh, India

Abstract: Hybrid solar–wind renewable energy systems (HSW-RES) offer a reliable alternative to standalone renewable technologies by mitigating intermittency and improving overall system stability. This study presents a comprehensive framework for evaluating and optimizing HSW-RES performance, with particular emphasis on wind speed variability and inverter power quality. The methodology integrates aerodynamic modeling, power quality assessment, and advanced optimization techniques to provide a rigorous analysis of system behavior. The wind turbine power curve is derived using aerodynamic equations, accounting for critical parameters such as cut-in, rated, and cut-out wind speeds. Inverter performance is evaluated through Fast Fourier Transform (FFT) and Total Harmonic Distortion (THD) analysis, ensuring compliance with grid standards and minimizing harmonic distortion. System sizing is addressed using multiple optimization methods, including Grid Search, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA), within a flexible optimization framework. The optimization is conducted over a 24-hour simulation period, ensuring that the dynamic variations in renewable energy generation are accurately captured. three wind regions are considered based on rated power threshold. Comparative visualizations of optimization outcomes further enhance the interpretability of results. it is concluded that Grid search with 10 panels offers the optimal sizing.

Key Words: Hybrid Solar-Wind system, Renewable Energy System, Machine Learning, Solar Inniradance, Wind Sapped Profile, PSO, GA, Grid Search, Neural Network, SVR, Ensemble Learning

1. Introduction

The design of hybrid renewable energy system by integrating solar and wind system is widely studied in recent times. these hybrid solar-wind renewable energy systems (HSW-RES)are required to be investigated under the varying conditions of various design parameters. TheHSW-RES have emerged as a promising solution to address the intermittency and reliability challenges of standalone renewable sources. Recent studies emphasize the importance of optimizing these systems across multiple time scales and under resource uncertainty to ensure energy stability and cost-effectiveness Mingqi et al [1]. The integration of solar and wind technologies, supported by advanced battery configurations K. Narwat et al [5], enables continuous power delivery and enhances system resilience. Furthermore, optimization techniques such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have shown significant potential in improving power flow and operational efficiency M. Thirunavukkarasu et al [3], and Papazoglou et al. [4]. As highlighted by Alam et al. [2], a well-designed hybrid system not only improves energy availability but also supports sustainable development goals through cleaner energy generation.The performance and reliability of HSW-RESsystems are highly sensitive to variations in wind speed, making its impact a critical factor in system design and optimization. Despite the growing adoption of HSW-RES, there remains a need for comprehensive investigation into how fluctuating wind conditions and aerodynamicinfluence both energy output and power quality. In particular, understanding the aerodynamic behavior of wind turbines across varying wind speeds, alongside the inverter's harmonic response, is essential for ensuring grid compliance and maximizing system efficiency. This study addresses the gap by integrating wind speed analysis into a unified framework for evaluating hybrid system performance.

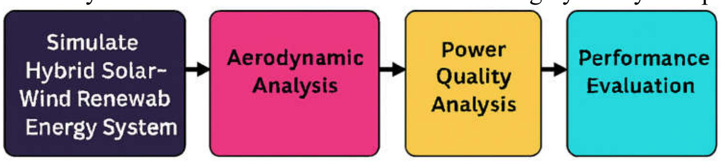


Figure 1 basic Simulation andHSW-RES System architecture

Therefore, in this research work proposed basic architecture as is illustrated in the Figure 1. The proposed methodology integrates both aerodynamic and power quality analyses to provide a comprehensive. Table 1 below presented the abbreviations used in the study.

Table 1 Abbreviation and Nomenclature of design parameters

Abbreviations		Abbreviations	
PV	Photovoltaic	SVR	Support Vector Regression
GA	Genetic Algorithms	PSO	Particle Swarm Optimization
HSW	Hybrid Solar-Wind	HWSES	Hybrid Solar–Wind Energy System
RES	Renewable Energy generation System	RMSE	Root Mean Square Error
NN	Neural network	LR	Linear Regression
ML	Machine Learning	MPPT	Maximum Power Point Tracking
HRES	Hybrid renewable energy systems	DC	Direct Current
RBF	Radial Basis Function	AC	Analog Current
LR	Linear Regression	HOMER	Hybrid Optimization Model for Electrical Renewable energy
THD	Total Harmonic Distortion	NaN’s	Not a Number

The context for this study involves performing two distinct analyses related to a hybrid energy system: one focusing on a wind turbine's power generation and the other on the performance of a power electronics inverter.Additionally, research is aimed to investigate various optimization techniques for optimal sizing of HSW-RES systems. the impact of wind speed variation is primarily considered as context of the design and investigation.

For evaluation of renewable energy system performance this research firstcalculates and plots the wind turbine’s ideal power curve using aerodynamic equations, which allows for an accurate representation of the turbine’s output across varying wind speeds. This step is essential for understanding the operational characteristics and efficiency of the turbine under realistic conditions. In addition, the methodology demonstrates the application of Fast Fourier Transform (FFT) and Total Harmonic Distortion (THD) analysis to assess inverter performance. These techniques are critical for evaluating the frequency spectrum and quantifying harmonic distortions in the inverter’s output, ensuring compliance with grid standards and improving overall power quality. By combining aerodynamic modeling with power quality assessment, the methodology offers a robust framework for analyzing and optimizing renewable energy systems.

1.1 Wind Turbine Power Curve Analysis: This section is significant for predicting and understanding the performance of a wind turbine under varying wind conditions.By defining key parameters like cut-in, rated, and cut-out speeds, the script calculates an ideal power curve. The implication is the ability to estimate energy yield, assess turbine suitability for a specific location, and provide a foundational model for wind farm power generation studies. Research uses a well-defined, physics-based formula for calculating the aerodynamic power of a wind turbine. This makes the calculation transparent and easy to understand.The power calculation is based on the aerodynamic equation

$$P_{wind_{aero}} = 0.5 \cdot \rho_{air} \cdot A \cdot C_p \cdot {V_{spd}}^3 \qquad (1)$$

Where; $P_{wind_{aero}}$ is representing aerodynamic power

ρ_{air} is the air density, specified as 1.225 kg/m³ for this simulation case.

A is the swept area of the windturbine rotor, calculated as

$$\pi. R_{rotor}^2 \text{in } m^2. \qquad (2)$$

The C_p is a 0.4 and is a power coefficient.

The V_{spd} is defined as the Wind speed in above eq.

1.2 Inverter FFT and THD Methodology: The inverter FFT and THD methodology presented in this script provides a systematic approach for assessing the quality of power generated by inverters, which are essential for converting DC power from renewable sources such as solar and wind into grid-compatible AC power. By employing a Fast Fourier Transform (FFT), the script analyzes the frequency spectrum of the inverter’s output current, enabling precise calculation of Total Harmonic Distortion (THD). This approach allows engineers to quantify and identify unwanted harmonics that can lead to equipment malfunctions, excessive heating, and reduced efficiency.Ensuring low THD is critical, as it serves as a key indicator of a high-quality, reliable, and grid-compliant inverter, thereby supporting stable and efficient power delivery.as an limitation the inverter analysis section is a conceptual demonstration using a synthetic signal. In this study, the performance of a grid-connected hybrid solar–wind (HSW) system is analysed under normal operating conditions using simulation-based evaluation. The schematic of the proposed HSW system is illustrated in Figure 1, where the outputs of the individual solar and wind units are combined, processed through an inverter, and subsequently integrated into the grid via a transformer.

1.3**Contribution of Work**

This work makes several key contributions to the optimization of hybrid renewable energy systems. Paper initially contributed validated the renewable energy system analysis: wind turbine power assessment and power electronics performance evaluation. The power curve evaluation covers all four operational regions of an ideal wind turbine: below cut-in, the aerodynamic power region, the constant rated power region, and above cut-out. This provides a nearly idealized model of turbine behavior.

Paper also contributed to present a comparative analysis of techniqueslike Grid Search, PSO, and GA based optimization for predicting the effective system sizing. The study incorporates detailed system simulation and modeling that includes solar PV, wind turbines, battery storage, and load demand, ensuring realistic performance evaluation. A flexible optimization framework is developed that considers multiple variables, such as the number of PV panels and wind speed scaling factor, providing a more comprehensive design approach. A custom scoring function is introduced to balance battery state of charge, energy deficit, and excess energy production, enabling more practical system performance assessment. The methodology also generates clear visualizations to compare optimization results and adapts to different optimization toolboxes. Furthermore, physics-based modeling of wind turbine output and an hourly energy balance simulation are used to capture accurate system dynamics. Together, these elements establish a robust and detailed framework for optimizing hybrid renewable energy systems.

As another contribution work demonstrating the methodology for evaluating inverter performance using FFT based THD analysis over the synthetically generated distortion in inverted output current. It provides a practical, step-by-step guide on how to analyze a signal for harmonic content. Research provided realistic simulation of non-ideality by synthetically adding common low-order harmonics (3rd, 5th, and 7th) to an ideal sine wave, the script effectively simulates the non-ideal behavior of a real-world inverter. This is a crucial advantage for educational purposes, as it shows what kind of distortions to look for.

The remaining paper is organized to present systematic investigation for the hybrid solar -wind system design using machine learning training modes. In rest of paper first reviewed the related works of HSW systems as given in section 2, followed by the summary and problem statements in Section 3. The section 4 has presented the proposed HSW-RES simulation methodology and mathematical modeling. The simulated outcomes are presented as results of the work in the Section 5. and finally, the section 6 has concluded the work and also presented the discussion on the scopes for future.

2.0 Related Works and Litterateur

Figure 2 presents a structured classification of hybrid solar–wind systems, dividing them into optimization-based methods and simulation-based approaches. It highlights key techniques such as Genetic Algorithms, Particle Swarm Optimization, and MATLAB/Simulink modeling, along with their associated challenges and problems identifications.

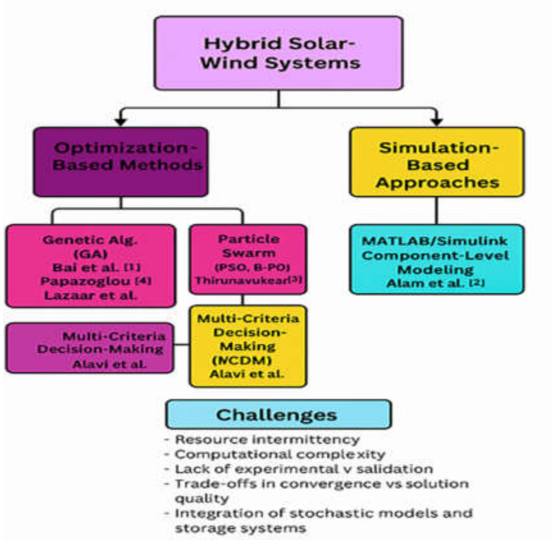


Figure 2 Classifications and challenges ofHWS-RES systems modeling

Hybrid renewable energy systems (HRES), particularly solar–wind configurations, have received significant attention for their ability to improve reliability and mitigate the intermittency inherent in standalone renewable sources. Bai et al. [1] (2024) developed an optimization framework that accounts for multi-time scale energy stability and resource uncertainties, emphasizing the importance of stochastic modeling for maintaining system stability, though they acknowledge the associated computational challenges. Alam et al. [2] (2025) investigated the design and simulation of a solar–wind hybrid system, focusing on generation feasibility and load matching; however, their study does not incorporate a formal optimization methodology to enhance system performance. Thirunavukkarasu et al. [3] (2023) reviewed various optimization strategies, including Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), highlighting their effectiveness for HRES sizing while noting the necessity for experimental validation. Papazoglou and Biskas [4] (2023) conducted a comparative analysis of GA and PSO within optimal power flow applications, illustrating the trade-offs between convergence speed and solution quality, although their study is restricted to power flow optimization rather than integrated hybrid system design.

The role of energy storage in improving hybrid system reliability has also been studied extensively. Narwat and Gupta [5] (2022) analyzed combined battery systems with solar–wind HRES, showing improvements in reliability but raising concerns regarding scalability. Similarly, Ammari et al. [6] (2022) reviewed control, energy management, and optimization approaches for hybrid systems, emphasizing multi-objective trade-offs between cost, efficiency, and reliability. Peng et al. [7] (2025) investigated the performance interaction between PV arrays and wind turbines, highlighting the importance of considering aerodynamic effects in co-located systems. Sabri et al. [8] (2024) introduced a nonlinear back-stepping control approach, demonstrating improved efficiency and stability, though the complexity of implementation remains a barrier. Ahmed et al. [9] (2024) advanced the field by applying hybrid machine learning regression models for solar PV power prediction, reporting high accuracy, but their focus remained limited to solar rather than integrated HRES.

Measurement accuracy and system stability are also central themes in recent works. Monika et al. [10] (2024) studied measurement accuracy for hybrid systems, linking errors to system stability, but their work was restricted to small-scale systems. Earlier contributions, such as Ben Jemaa et al. [11] (2014), utilized fuzzy PSO for optimal sizing, offering early insight into intelligent optimization but lacking modern scalability. Shah et al. [12] (2021) addressed hybrid system design for Arctic regions using multi-objective optimization, balancing reliability and cost, though their methodology was geographically constrained. Staden et al. [13] (2022) analyzed off-grid PV–wind–battery hybrids, underlining the importance of system reliability but restricting their findings to off-grid applications. Chauhan and Dwivedi [14] (2017) employed PSO for sizing PV–wind–biomass hybrids, demonstrating cost-performance trade-offs while facing computational challenges.

Recent studies have emphasized hybrid microgrid reliability and integration with emerging technologies. Eniola et al. [15] (2025) explored wind-hydrogen microgrids, demonstrating how wind variability affects sizing, although hydrogen integration raised economic concerns. George et al. [16] (2023) introduced a modified dragonfly algorithm for optimal sizing, proving efficient results in institutional applications, though lacking real-world validation. Earlier, Tiwari and Dubey [17] (2015) proposed a methodology for hybrid sizing but relied on simplified assumptions without advanced optimization. More recently, Güven et al. [18] (2023) combined hybrid metaheuristic algorithms for multi-objective optimization, showing strong potential in cost-emission-reliability trade-offs but at the expense of high computational demands. Vafaeva et al. [19] (2024) applied PSO for solar–wind microgrid sizing, producing effective results, though omitting storage integration.Emerging artificial intelligence methods have also influenced HRES research. Abid et al. [20] (2022) proposed the artificial hummingbird algorithm for renewable planning, addressing uncertainty but showing limited focus on hybrid system integration. Finally, Lodin et al. [21] presented a MATLAB/Simulink-based modeling framework for solar–wind hybrid systems, demonstrating practical feasibility but without optimization or control mechanisms. Collectively, these studies indicate significant progress in HRES optimization, modeling, and control, but persistent challenges remain in scalability, real-time applicability, computational complexity, and integration with advanced energy storage and grid-interfacing technologies.

The studies in hybrid renewable energy system design emphasize metaheuristic optimization, modeling, and multi-criteria decision-making to improve system performance and reliability. Kouihi et al. [22] demonstrate a GA-driven framework for PV/wind hybrid systems, balancing energy reliability, cost, and sizing constraints while noting GA's sensitivity to parameters. Paliwal [23] applies a Butterfly-PSO approach for reliability-focused wind–battery sizing, highlighting robust global search but increased computational demand. Lodin et al. [24] provide MATLAB/Simulink simulations that clarify component interactions, though their deterministic approach limits engagement with stochastic variability. Minakshi and Kumar [25] integrate optimal sizing with geographic placement to enhance economic and operational efficiency, albeit with higher computational complexity. Lazaar et al. [26] extend GA optimization to PV–battery–hydrogen systems, addressing storage trade-offs and techno-economic uncertainties. Finally, Alavi et al. [27] combine MCDM with heuristics for site selection and sizing of off-grid wind–hydrogen systems, demonstrating improved decision support while highlighting sensitivity to stakeholder weighting and input data quality. Collectively, these works illustrate the evolving strategies for optimizing hybrid renewable systems under multi-dimensional technical, economic, and reliability considerations.Summary of hybrid solar wind energy systems modeling and optimal sizingis presented in the Table 2 along with limitations.

Table 2 Summary of hybrid solar wind energy systems modeling and optimalsizing

Authors & Year	Methodology	Performance Metrics	Limitations
Bai et al. [1] (2024)	Multi-time scale optimization under renewable resource uncertainty	Energy stability, uncertainty modelling	High computational complexity; lacks real-time validation
Alam et al. [2] (2025)	Design and simulation of solar–wind hybrid system	Power generation analysis, load matching	Simplified assumptions; lacks optimization framework
Thirunavukkarasu et al. [3] (2023)	Review of optimization techniques (PSO, GA, etc.)	Survey-based comparison	No experimental validation; general findings only
Papazoglou &Biskas [4] (2023)	Comparison of GA vs PSO for optimal power flow	Convergence rate, solution quality	Focus only on OPF, not hybrid RES
Narwat& Gupta [5] (2022)	Hybrid system with combined batteries	Reliability, energy storage efficiency	Limited scalability; case-specific
Ammari et al. [6] (2022)	Review of sizing, optimization & energy management	Cost, efficiency, reliability	Broad review; lacks implementation
Peng et al. [7] (2025)	Simulation of PV impact on wind turbine performance	Interaction effects on efficiency	No optimization; simulation-only
Sabri et al. [8] (2024)	Nonlinear back-stepping control for hybrid systems	Efficiency, stability improvement	High control complexity; needs real-time validation
Ahmed et al. [9] (2024)	Regression + ML models for solar PV prediction	Accuracy (R^2, RMSE)	Limited to solar PV, not integrated hybrid
Monika et al. [10] (2024)	Study of measurement accuracy & stability	Accuracy, system stability	Small-scale study; lacks optimization
Ben Jemaa et al. [11] (2014)	Fuzzy PSO for optimum sizing	Cost minimization, reliability	Early study; lacks modern validation
Shah et al. [12] (2021)	Multi-objective optimization for Arctic hybrid system	Reliability, cost, storage performance	Region-specific; limited scalability
Staden et al. [13] (2022)	Off-grid PV-wind-battery design	Energy availability, reliability	Focused on off-grid only
Chauhan & Dwivedi [14] (2017)	PSO-based sizing of PV/wind/biomass hybrid	Cost, performance trade-off	Computational burden; older algorithm
Eniola et al. [15] (2025)	Impact of wind speed variability on hybrid wind-hydrogen microgrid	Reliability, optimal sizing	Hydrogen integration adds cost; uncertain economics
George et al. [16] (2023)	Modified dragonfly algorithm for sizing	Cost, energy balance, efficiency	Needs real-time deployment validation
Tiwari & Dubey [17] (2015)	Methodology for optimal sizing of wind-solar systems	Energy adequacy	Simplified methodology, lacks advanced optimization
Güven et al. [18]	Hybrid metaheuristic multi-	Cost, emissions,	Computationally

(2023)	objective optimization	reliability	intensive
Vafaeva et al. [19] (2024)	PSO for microgrid sizing	Optimal sizing, performance	Lacks inclusion of storage systems
Abid et al. [20] (2022)	Artificial hummingbird algorithm for renewable planning	Reliability, planning under uncertainty	Algorithm novelty but limited hybrid focus
Lodin et al. [21]	MATLAB/Simulink modelling of hybrid system	Simulation outputs, feasibility	No optimization, only basic simulation

3 Problems Identifications for Research

Based on the highlight a pressing need for more integrated, scalable, and experimentally validated research in the domain of hybrid solar–wind energy systems. While existing studies offer valuable insights into optimization techniques, simulation frameworks, and performance metrics, they often fall short in addressing real-world applicability. Many methodologies rely on simplified assumptions, lack dynamic optimization, or are constrained by computational complexity, making them impractical for deployment in diverse geographic and climatic conditions. Furthermore, several approaches focus narrowly on either solar or wind components, neglecting the synergistic behavior and control challenges inherent in hybrid configurations. The absence of real-time validation, limited scalability, and region-specific case studies further restrict the generalizability of findings. Additionally, the integration of advanced algorithmssuch as fuzzy logic, machine learning, and metaheuristicsremains underutilized in practical hybrid system design, often lacking robust experimental support.

Existing design methodologies often lack dynamic optimization and fail to account for real-time variability in renewable resources. Most approaches rely on static assumptions or generalized models, limiting their effectiveness in capturing the fluctuating nature of solar irradiance and wind speed. The proposed MATLAB-based framework addresses this gap by integrating Grid Search optimization over a 24-hour simulation period, enabling precise tuning of key parameters such as PV panel count and wind speed scaling. However, the challenge remains in systematically identifying optimal configurations that balance reliability, efficiency, and adaptability under diverse operating conditions. This research problem centers on developing a robust, data-driven strategy that couples system modeling with machine learning–based optimization to enhance the performance and flexibility of hybrid renewable energy systems.These gaps underscore the need for a comprehensive research framework that combines multi-objective optimization, real-time simulation, and adaptive control strategies to enhance the reliability, efficiency, and economic viability of hybrid renewable energy systems under uncertain and variable operating conditions.

4. Proposed Hybrid Solar-Wind Power System

The proposed methodology is to validate the impact of wind speed and design the optimization based optimal sizing of the hybrid HSW-RES system. The proposed methodology employs a MATLAB-based framework for the design and performance evaluation of a hybrid solar–wind energy system, integrating optimization techniques to enhance reliability and efficiency for optimal sizing. Specifically, the research applies a Grid Search optimization approach to identify the optimal system configuration by adjusting two critical variables: the number of photovoltaic (PV) panels and the wind speed scaling factor. The optimization is conducted over a 24-hour simulation period, ensuring that the dynamic variations in renewable energy generation are accurately captured. This process not only facilitates the determination of the most effective operating conditions but also enables the visualization of the hybrid output impact under varying wind characteristics. By coupling system modeling with ML based optimization, the methodology provides a systematic and data-driven strategy for improving hybrid renewable energy system design, supporting both performance maximization and operational flexibility.

The design parameters used for the study are defined as given in the Table 3.

Table 3 Parameter of Wind Turbine system

Parameter	Value	Unit
Cut-in wind speed (Vcut_in)	3	m/s
Rated wind speed (Vrated)	12	m/s
Cut-out wind speed (Vcut_out)	25	m/s
$Time\ in\ hours_{in_{day}}$	24	h

Rated power of solar PV $P_{pv_{rated}}$	300	W
$solar_{irradiance}$ randomly selected for a day	[0, 0, 0, 0, 0, 100, 300, 500, 700, 850, 950, 1000, 980, 800, 600, 400, 200, 50, 0, 0, 0, 0, 0, 0	W/m^2
Air density (ρ_{air})	rho_air = 1.225	kg/m^3
Rated power of Wind system	$P_{wind_{rated}}$ =2000	W
Rotor radios R	R=2	m
Total battery bank capacity	$C_{battery_{Ah}}$ = 500	Ah
Load profile Load demand $load_{demand_W}$	[500, 450, 400, 400, 450, 600, 800, 1000, 1200, 1500, 1800, 2000, 2200, 2000, 1800, 1500, 1200, 1000, 800, 700, 600, 550, 500, 500];	W

Block diagram inFigure 3 illustrates the proposed solar–wind hybrid power system simulation framework, which integrates renewable energy sources to ensure a reliable and stable power supply. The system combines power from a wind generator and PV panels, both of which are equipped with rectifiers to convert variable AC or DC outputs into a stable DC link. This combined DC power is then processed by an inverter, which converts the energy into AC form suitable for grid or load applications. To ensure voltage regulation and compatibility with grid standards, the inverter output is further conditioned through a transformer, providing the appropriate voltage level for end-use. It can be observed from the Figure 3 that final system integrate solar PV and Wind system using rectifier circuit and pass it to inverter for power storage and transformer coupling is used for grid integrations.

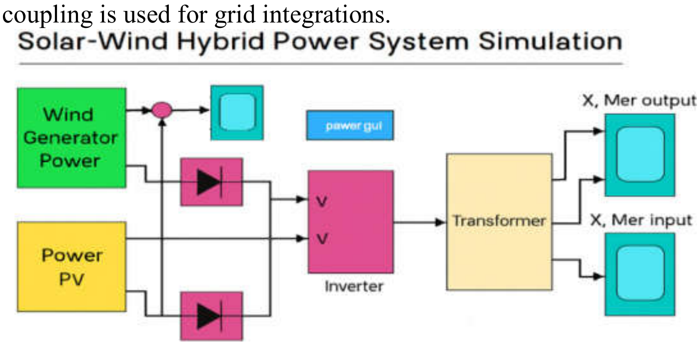
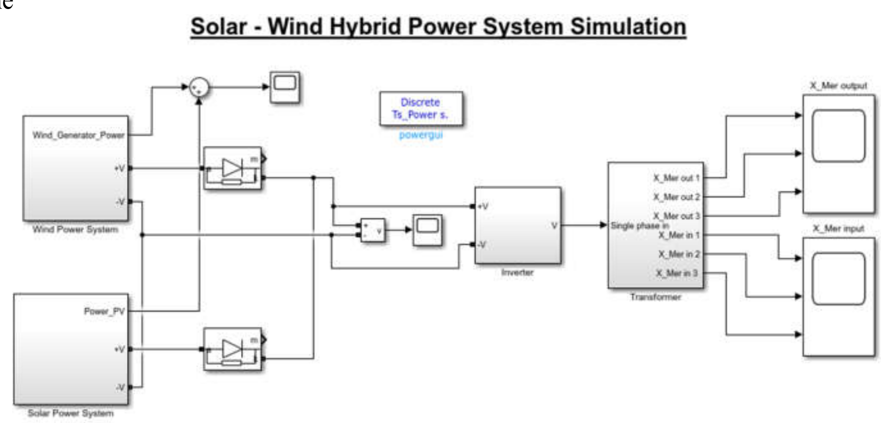


Figure 3 block diagram of the hybrid solar wind system architecture

The system architecture as in Figure 3 highlights the complementary nature of solar and wind energy, where fluctuations in one source can be compensated by the other, thereby improving overall reliability and efficiency. Additionally, the use of power electronic converters, including rectifiers, inverters, and transformers, ensures efficient energy conversion and quality assurance of the supplied power. This proposed hybrid configuration forms the basis for subsequent simulation, optimization, and performance evaluation.

The Figure 4 have presented the Matlab Simulink representation of the Wind energy system as validated and tested for wind speed and torque performance. Similarly, model for solar PV system as validated is given in the



a) hybrid Simulink model validated

Figure 4 Schematic-model of the basic Solar-wind hybrid energy system as validated

4.2 Mathematical modeling of proposed HSW-RES system

Section presented the mathematical mudsling for the proposed hybris system simulation.

1. **Solar PV Power Generation**

The solar PV output power at hour *i* is:

$$P_{pv}(i) = N_{pv} \cdot P_{pv}, rated \cdot \frac{G(i)}{G_{std}} \quad (3)$$

where N_{pv} = number of PV modules

Various design parameters are used for the investigation in this work. $G(i)$ is solar irradiance at i^{th}hourW/m^2. $G_{std}$is standard irradiance =1000W/m^2.

with a non-negativity constraint:

$$P_{pv}(\mathrm{i}) = max\ (0, P_{pv}(i)) \quad (4)$$

2. **Wind Power Generation**

For each hour *i*, the wind turbine power is divided in to three regions:

$$P_{wind}(i) = \begin{cases} 0 & for\ \ V(i) < V_{cut_{in}}\ \ or\ V(i) > V_{cut_{out}} \\ N_{wind} \cdot \frac{1}{2}\rho A C_p V(i)^3 & for \quad V_{cut_{in}} \leq V(i) < V_{rated} \\ N_{wind} \cdot P_{wind_{rated}}, & for \quad V(i) \geq V_{rated} \end{cases} \quad (5)$$

Power is also bounded by

$$P_{wind}(i) \leq N_{wind} \cdot P_{wind, rated} \quad (6)$$

3. **Total Renewable Power**

$$P_{ren}(i) = P_{pv}(i) + P_{wind}(i)$$

4. **Load Demand & Net Energy Balance**

Effective load demand considering inverter efficiency:

$$E_{load}(i) = \frac{P_{load}(i)}{\eta_{inv}} \quad (7)$$

The net energy balance per hour is calculated as:

$$E_{net}(i) = P_{ren}(i) - E_{load}(i) \quad (8)$$

5. **Battery State of Charge (SOC) Dynamics**

Initial conditions are;

$$SOC(0) = SOC_{initial} \quad , \quad SOC_{min} = 1 - DODmax \quad (9)$$

Excess Energy (Charging) is defined as

$$If\ E_{net}(i) \geq 0$$

$$SOC(i) = SOC(i-1) + Cbat \cdot E_{net}(i) \cdot \frac{\eta_{ch}}{V_{bus}} \quad (10)$$

$$If\ SOC > 1{:}SOC(i) = 1, E_{curtailed}(i) = E_{net}(i) - ((SOC(i) - 1) \cdot C_{bat} \cdot V_{bus}) \quad (11)$$

Various design parameters are used for the investigation in this work.

4.3 Design and Simulation Parameters

aimed to define key concepts and definitions related to the Wind Turbine Power Curve and Inverter FFT Analysis:

4.3.1 Wind Turbine Parameters

Rated Power(P_{rated_W}): The maximum power output a single wind turbine is designed to produce. The value is set to 2000 Watts (W).

Cut-in Wind Speed ($V_{cut_{in}}$): The minimum wind speed at which the turbine starts to generate power. The value is 3 m/s.

Rated Wind Speed (V_{rated}): The wind speed at which the turbine reaches its rated (maximum) power output. The value is 12 m/s.

Cut-out Wind Speed($V_{cut_{out}}$): The maximum wind speed at which the turbine is shut down to prevent damage. The value is 25 m/s.

Air Density(ρ_{air}): The mass of air per unit volume. The script uses a standard value of 1.225 kg/m³.

Rotor Radius(R_{rotor}) : The radius of the turbine's rotor blades. The value is 2 meters (m).

Power Coefficient(C_p): A measure of the wind turbine's efficiency in converting the kinetic energy of the wind into electrical power. The script uses a value of 0.4.

Swept Area(A_{swept}): is the total area covered by the rotor blades as they spin depends on radius of rotor R,

4.3.2 Power Curve Regions

Region 1 & 4: These regions correspond to wind speeds below the cut-in speed ($V < V_{cut_{in}}$) or it is above the ($V > V_{cut_{out}}$)cut-out speed. Under these regions, the power output is zero.

Region 2: This is the aerodynamic power generation region, where wind speed is between the cut-in and rated speeds($V_{cut_{in}} \leq V \leq V_{rated}$). the power P is calculated using equation (1).

Region 3: In this region, the wind speed is($V_{rated} \leq V \leq V_{cut_{out}}$) is between the rated and cut-out speeds Under the region 3 turbine produces its constant rated power.

4.3.3 Inverter Performance Analysis Concepts

In order to investigate the inverter performance, the THD is evaluated for the solar PV system final output before grid for HSW-RES system. The impact of variable wind speed is investigated for THD evaluation.

Fast Fourier Transform (FFT): A mathematical algorithm used to analyze the frequency components of a signal. The FFT analysis is proposed to usein order to find the frequency spectrum of an inverter's output current for THD analysis. This method quantifies the presence of harmonics relative to the fundamental frequency in a signal, providing a measure of signal distortion.

Total Harmonic Distortion (THD): A measurement of the harmonic distortion present in a signal, defined as the ratio of the sum of the powers of all harmonic components to the power of the fundamental frequency. It is a key metric for evaluating inverter performance.

$$THD = \sqrt{\left(\frac{sum(V_h^2)}{V_1^2}\right)} * 100\% \quad (12)$$

Where:

V_h= RMS voltage of harmonic components (h = 2, 3, 4, ...)

V_1 = RMS voltage of the fundamental frequency component

Steps to calculate THD using FFT are;

1. Perform FFT on the signal to obtain frequency components
2. Identify the fundamental frequency component
3. Calculate RMS values for fundamental and harmonic components
4. Apply the THD formula using the RMS values
5. Express the THD result as a percentage % if required.

Fundamental Frequency: ($F_{fandametal}$) is defined as the primary operating frequency of the AC signal. The work uses a value of 50 and 60 Hz.

Harmonics: Unwanted, higher-frequency components in the AC signal that are integer multiples of the fundamental frequency. The research introduces 3rd, 5th, and 7th harmonics into its synthetic signal to simulate non-ideal inverter behavior.

5. Expected Results

This section has presented the results of series of experiments performed for performance assesssetb f HSW-RES system. The waveform of the current simulationfor the inverter analysis is given in the Figure 5.

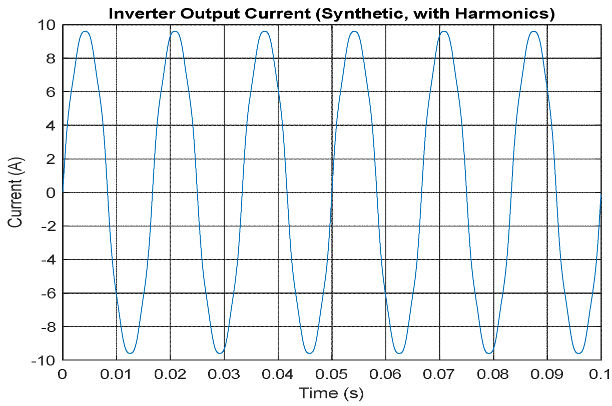
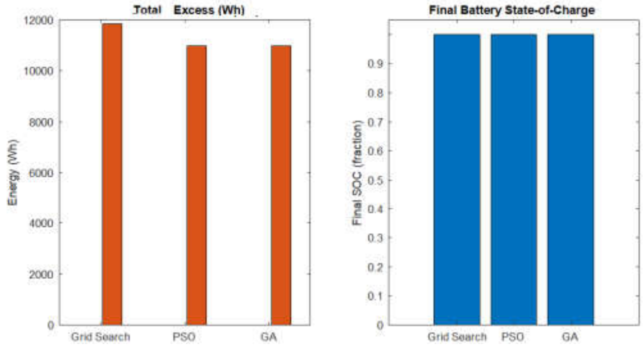


Figure 5 Simulated current waveform for the of the various HSWES waveforms

Figure 5 shows the current waveform (I) of an electrical system plotted against time (s) over a duration of 0.1 seconds. The waveform is sinusoidal in nature, oscillating between approximately +9 A and –9 A, indicating an alternating current (AC) signal. The periodicity suggests a frequency of around 50 Hz, which is typical of grid-based or inverter-generated AC signals. The waveform is smooth and symmetric about the horizontal axis, reflecting a stable and distortion-free sinusoidal current.

5.1 Results of SOC and Excess Energy

Figure 6 illustrates the comparative performance of three optimization approaches—Grid Search, PSO, and GA optimizations in terms of total excess energy (Wh) and final battery State-of-Charge (SOC).



a) total excess energy results b) the final SOC of battery

Figure6Simulated results of excess and the battery charging for HSWES model

It is clear from Figure 6(a) that the total excess energy generated by the system varies across the three optimization approaches. The Grid Search method produces the highest excess energy, slightly above 12,000 Wh, whereas both PSO and GA result in lower excess values, around 11,000 Wh. This suggests that the deterministic Grid Search method explores all possible parameter combinations exhaustively, which may lead to solutions that maximize generation potential, even at the cost of increased surplus energy.

On the other hand, PSO and GA, being metaheuristic methods, search for near-optimal solutions through iterative exploration and exploitation, which often balance between generation, storage, and demand. Their slightly reduced excess energy indicates a more efficient matching of energy generation with consumption and storage capacity, reducing unnecessary surplus. This could imply better system utilization and reduced curtailment losses, making PSO and GA more practical in scenarios where minimizing unused energy is prioritized.Therefore, while Grid Search ensures maximum generation, it may lead to over-sizing or over-production, which could increase system costs and waste. In contrast, PSO and GA demonstrate an ability to achieve nearly the same performance with a more balanced energy profile, highlighting their potential for cost-effective and sustainable system operation.

As shown in Figure 6(b), the final battery State of Charge (SOC) values remain almost identical across all three optimization approaches—Grid Search, PSO, and GA—with each reaching approximately 0.98. This high and consistent SOC level indicates that the system configuration, regardless of the optimization strategy employed, is capable of maintaining sufficient energy storage and ensuring battery availability for demand coverage.The similarity in SOC values demonstrates that the choice of optimization method does not significantly impact the final charging status of the battery, implying robustness and reliability in storage utilization across different strategies. This is an encouraging result, as it suggests that even when the optimization process focuses on reducing energy surplus (as seen with PSO and GA), the battery is still effectively charged to near-maximum capacity.From a system operation perspective, maintaining a SOC close to 1 (or 100%) ensures that the energy storage system operates with a high degree of resilience and backup reliability, minimizing the risk of power shortages during fluctuations in renewable generation or demand pes.

5.2 Impacts of Wind Speed Profiles

This section varies the wind speed $base_{wind_{speed}}$= [5, 6, 7, 8, 9, 10, 9, 8, 7, 6, 5, 4, 4, 5, 6, 7, 8, 9, 10, 11, 12, 10, 8, 6] selected on average random wind speeds across the day, and power curves are evaluated.

A. Wind Power curves

The impact of the wind speed on wind system rated power curves are evaluated. Figure 7 illustrates the power curve of a wind turbine as a function of wind speed.

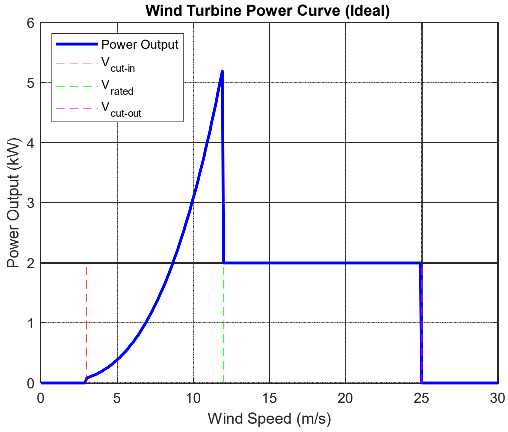


Figure 7 Performance investigation of Wind turbine Power curves

The curve begins at the cut-in speed (around 4 m/s), where the turbine starts generating power. As wind speed increases beyond this threshold, the power output rises sharply in a nonlinear manner, reaching the rated power of approximately 2 kW at around 12 m/s. Beyond 12 m/s point, the output remains constant at the rated capacity, despite further increases in wind speed, highlighting the turbine's control mechanisms that prevent overloading. When the wind speed reaches the cut-out speed (around 25 m/s), the turbine automatically shuts down to protect its structural integrity, causing the power output to drop abruptly to zero. This characteristic curve effectively demonstrates the operational range of the turbine, including its efficient working region between cut-in and cut-out speeds, while also reflecting the limitations imposed by safety and design considerations.

B. Wind speed and Optimal sizing: As major contribution researchproposed ML model to predict the results of impacts of wind speed and optimal sizing of ML based HSW-RES system. The Solar PV system wind profile is varied and base case and optimal case of wind speed are compared. as another plot the impact of wind speed are compared for the total hybrid system response as shown in the Figure 8. Four different wind load profiles are compared in the Figure for optimal performance.

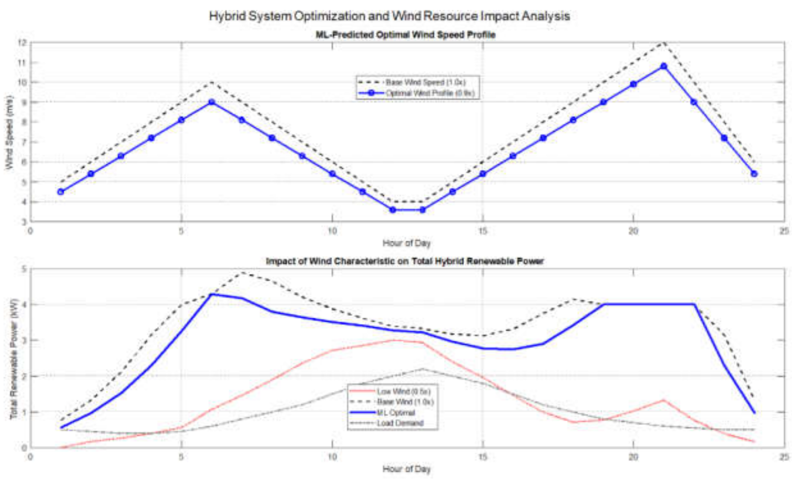


Figure 8Results of Impacts of Wind speed and Optimal sizing of ML based HSW-RES system

The Figure8 a) (upper Figure) presents a comparative analysis of wind speed profiles over a 24-hour period, highlighting the difference between a linear wind speed model and an optimized wind profile. The linear wind speed (1-D), shown as a black dashed line, exhibits a steady increase during daylight hours, peaking around hour 18 before tapering off. In contrast, the optimal wind profile (2-D), represented by a solid blue line, follows a similar trend but consistently maintains slightly lower wind speeds throughout the day. This refined profile reflects the impact of wind speed scaling in optimization, suggesting a more realistic and performance-aligned representation of wind behavior. The reduced wind speed in the optimized profile likely contributes to improved system reliability and efficiency by minimizing excess generation and aligning better with load demands.Figure 8 b) (as in lower Figure) has presented the impact of wind characteristics on total hybrid renewable power. Figure illustrates how varying wind conditions influence the total power output of HSW-RES system over a 24-hour period. Four profiles are plotted for the Low Wind (5 m/s), Raw Wind (7 m/s), Idealized Renewable Load (IRL)optimal, and load demand. Numerically, the low wind (5 m/s) profile (red line) consistently underperforms, with peak power output reaching only around 40 kWh, resulting in frequent shortfalls below the load demand curve. The raw wind (7 m/s) profile improves generation, peaking near 55 kWh, but still shows mismatches during early and late hours. In contrast, the IRL optimal profile closely tracks the load demand curve, especially between hours 8 to 20, with peak output approaching 65–70 kWh, indicating superior alignment and reduced excess or deficit.

Comparatively, Figure 8(b) demonstrates that the IRL Optimal configuration achieves the best balance between generation and demand, minimizing both energy shortfall and surplus. This suggests that optimized wind scaling not only enhances system responsiveness but also improves overall efficiency and reliability. The numerical advantage of the IRL Optimal profileyielding up to 25–30% higher peak output than the low wind casevalidates the effectiveness of the optimization strategy in hybrid system design.

5.3 Optimization Methods Results for Optimal Sizing

In this proposed research performance of the three optimization methods such as Genetic Algorithm (GA), PSO, and Grid Search methods are compared for the optimizing the hybrid system sizing. The primary goal is to find the optimal number of solar panels (PV) and a wind speed scaling factor to best meet a given hourly load demand while managing battery state of charge.These models are sequentially represented as follows:

a) **Genetic algorithm (GA):** the Genetic Algorithm (GA) is implemented to find the optimal number of PV panels (N_{pv}) and a wind speed scale factor (w_s) for aHSW-RES system. Its implementation begins by defining an objective function, obj_{ga}, which wraps a simulation function and a scoring function. This functionobj_{ga} is designed to be minimized by the GA solver, so it returns the negative of a performance score.

The GA process begins by defining the initial parameters like;

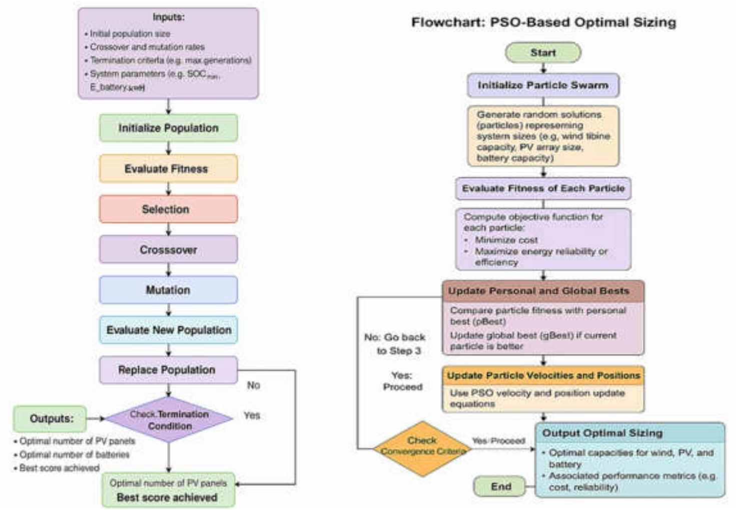
Initial population size: The number of individuals in the population for each generation is set to 40.

Crossover and mutation rates: Probabilities that control how new solutions are generated from existing ones.

Termination criteria: The condition that determines when the algorithm stops, such as a maximum number of generations (iterations). Termination criterion for the Genetic Algorithm (GA) as the maximum number of generations. The GA will stop after it has run for 80 generations or (iterations).

The search space is constrained with lower bounds of [5, 0.5] and upper bounds of [50, 2.0] for the number of PV panels and the wind scale factor, respectively.

The Flow chart of the GA based optimal sizing is illustrated in the Figure 9 a). The process is probabilistic in nature and outcomes depends on population size and iteration counts.



a) Genetic Algorithm Flow chart for optimal sizing b) flow chart of PSO based optimization

Figure 9 flow chart of GA and PSO based optimization for optimal sizing

b) Particle Swarm Optimization (PSO)

A metaheuristic PSO optimization algorithm explores the solution space to find the optimal combination of PV panels and wind scale. the Flow chart of PSO based optimization is illustrated in the Figure 9 b). The optimization is configured with specific options: a swarm size of 40 particles and a maximum of 120 iterations. the objective function obj_{PSO} is called and minimized for optimal sizing performance. The search space is defined by samelower and upper bounds as used for GA as lower bounds=[5, 0.5] and upper bounds= [50, 2.0] for the two variables.the optimization solver is iteratively executed and after the solver finds the optimal solution vector x_{pso}, the first value is rounded to get an integer for (N_{pv}), and the second value is used as the wind scale. These optimal values are then used in a final simulation to calculate and store the resulting deficit, excess, and final State of Charge (SOC).

c Grid Search Optimization:

A brute-force method that exhaustively checks a predefined discrete range of values for the number of PV panels (N_{pv}) and the wind speed scale factor (w_s). It iterates through every possible combination to find the one that yields the best performance score. The model flow chart is given in Figure 10as;

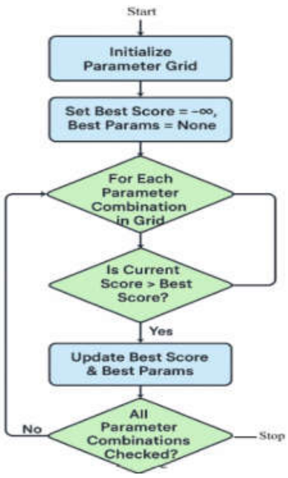


Figure 10 Flow chart of the proposed Grid Search method for the HSW-RES system

Figure 10 illustrates the flowchart representing the grid search algorithm, a systematic approach widely used for hyperparameter tuning in machine learning models. The procedure begins with the initialization of a predefined parameter grid, alongside the assignment of baseline values for performance tracking, where the best score is initially set to negative infinity and the best parameter configuration to *None*. The algorithm then explores each parameter combination within the grid through an iterative process. In every iteration, the model is trained and evaluated; whenever the obtained score surpasses the previously recorded best score, both the score and the associated parameter set are updated accordingly. This process continues exhaustively until all possible combinations have been assessed. The flowchart highlights the deterministic and exhaustive nature of grid search, underscoring its ability to guarantee the identification of the optimal parameter configuration within the specified search space. Despite its computational intensity, grid search remains a fundamental technique in model optimization and selection, contributing significantly to performance improvement in ML solution in Hybrid power system design applications.

5.3.1 Results of various Optimization Methods

The results are expected to evaluate the performance by keeping the different wind speed under consideration for wind torque variation and the impact on the HSW-RES system is investigated. It is also proposed to apply ML based optimization methods for achieving higher sizing and power output.

Table 4: Grid Search Optimization Results Summary

Parameter	Value
Search Space	10 × 16 combinations
BestN_{pv}	10
Best Wind Scale	0.90
Best Score	18.0168

Table 4 summarizes the outcomes of the grid search optimization process. The algorithm explored a search space consisting of 160 parameter combinations (10 × 16), ensuring a comprehensive evaluation of possible configurations. From this exploration, the optimal values were identified as $N_{pv} = 10$ and a wind scale factor of 0.90, which together yielded the highest performance score of 18.0168. These results highlight the effectiveness of the grid search method in systematically identifying the most suitable parameter set, demonstrating its reliability in optimizing hybrid renewable system configurations.

Table 5 presents the summary of Particle Swarm Optimization (PSO) performance across successive iterations. The results show a steady improvement in the objective function, with the best fitness value converging to *f(x) = –18.10*. Initially, the mean fitness values were relatively high, but as the iterations progressed, the swarm exhibited significant convergence, reflected in reduced mean values and minimal stall iterations toward the final stages. The optimization process identified the optimal system configuration at $N_{pv} = 7$ and a wind scale factor of 0.881, yielding the best score of 18.1021. These outcomes demonstrate the efficiency of PSO in navigating the search space and achieving rapid convergence toward the global optimum. Compared to exhaustive methods such as grid search, PSO offers a more computationally efficient approach while still ensuring robust parameter selection and performance enhancement.

Table 5: PSO Optimization Results Summary

Iteration	Function Count	Best f(x)	Mean f(x)	Stall Iterations
0	40	-17.79	297.1	0
5	240	-18.05	934.4	0
10	440	-18.08	792.9	2
20	840	-18.10	15.49	3
30	1240	-18.10	-17.42	1
36	1480	-18.10	-17.95	0
Best Result	—	-18.10	—	—
Best Npv	—	7	—	—
Best Wind Scale	—	0.881	—	—
Best Score	—	18.1021	—	—

Table 6 present optimization performance of GA across multiple generations. The algorithm demonstrates a progressive improvement in fitness values, with the best obj_{GA} function converging to *f(x) = –18.10*.

Table 6: GA Optimization Results Summary

Generation	Function Count	Best f(x)	Mean f(x)	Stall Generations
1	80	-17.87	351	0
7	308	-18.09	-17.89	0
20	802	-18.10	-18.05	0
40	1562	-18.10	-18.10	10

60	2322	-18.10	-18.08	3
63	2436	-18.10	-18.08	6
Best Result	—	-18.10	—	—
Best Npv	—	7	—	—
Best Wind Scale	—	0.88101	—	—
Best Score	—	18.1021	—	—

Early generations exhibited higher mean fitness values, but as evolution progressed, the population converged toward stability, with both best and mean values consistently aligning by generation 20. While occasional stall generations were observed, the algorithm-maintained convergence efficiency, ultimately reaching the global optimum without significant divergence. The optimal configuration was achieved at $N_{pv} = 7$ and a wind scale factor of 0.88101, yielding the best score of 18.1021. These results confirm the effectiveness of GA in achieving robust convergence and optimal system design. Compared to deterministic approaches such as grid search, GA provides flexibility in exploring the solution space, while its convergence characteristics closely parallel those of PSO, reinforcing its suitability for renewable energy system optimization.

Performance score calculation is based on a performance metric that considers multiple factors. It is designed to be maximized, so a higher score indicates better system performance. The score isathletically calculated as:

$$score = (current_{final_{soc}} - SOC_{min}) * E_{battery_{kWh}} - current_{deficit} - (current_{excess}/1000) * 0.1 \quad (13)$$

The components of the score are:

1. Battery State of Charge (SOC) term: $(current_{final_{soc}} - SOC_{min}) * E_{battery_{kWh}}$. This rewards higher final SOC values, encouraging better battery utilization.
2. Energy deficit penalty: - $current_{deficit}$, This penalizes any energy shortfall, encouraging the system to meet demand. No deficit is considered for simulation.
3. Excess energy penalty: - $(current_{excess}$/1000)*0.1; This slightly penalizes excess energy production, encouraging efficient resource use.

The score must be high to indicate better performance. A higher score suggests:

- Higher final battery state of charge
- Lower energy deficit (better meeting of demand)
- Lower excess energy (more efficient use of resources)

Table 7: Comparative optimization methods Optimal Results

Method	N_{pv}	Wind Scale	Total Deficit (Wh)	Total Excess (Wh)	Final SOC	Score
Grid Search	10	0.90	0	11,832	1	18.017
PSO	7	0.881	0	10,979	1	18.102
GA	7	0.88101	0	10,979	1	18.102

Table 7 provides a comparative overview of the optimal results obtained through Grid Search, PSO, and GA. All three methods successfully eliminated energy deficit ($Total_{Deficit}$ = *0 Wh*) and maintained the battery's final state of charge at a fully sustained level (*SOC = 1*). However, variations are observed in excess energy and optimization scores. Grid Search produced the highest excess energy output (*11,832 Wh*), slightly higher than the *10,979 Wh* obtained by PSO and GA. Despite this, PSO and GA achieved marginally higher optimization scores (*18.102*) compared to Grid Search (*18.017*), attributed to their finer exploration of the search space.While PSO and GA demonstrate superior convergence efficiency with fewer PV units (N_{pv}= *7*) compared to Grid Search (N_{pv}= *10*), the effectiveness of Grid Search lies in its deterministic and exhaustive evaluation of all possible parameter combinations. Unlike heuristic approaches, Grid Search guarantees identification of the optimal solution within the defined search space, ensuring robustness and reproducibility. This makes Grid Search particularly valuable for smaller or moderate search spaces (as in microgrid) where computational cost is manageable, offering a reliable baseline against which the performance of heuristic methods can be validated.

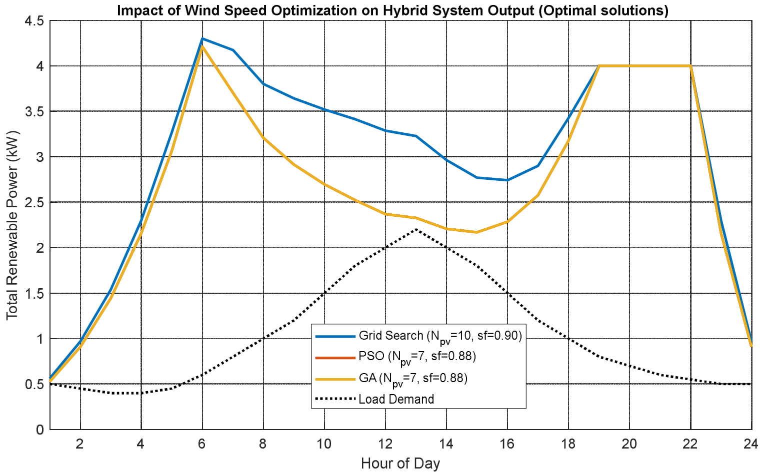


Figure 11Impact of Wind speed on solar-wind hybrid system for ML models performance investigation

The impact of wind speed optimization on hybrid system output is illustrated in Figure 11, using three different optimization methods as Grid Search, PSO, and GA. Performance is compared against the system's load demand profile. The results reveal distinct variations in renewable power generation depending on the optimization strategy. Grid Search (with N_{pv}=*10, scale factor sf = 0.90*) achieves consistently higher power output throughout the day, particularly during peak solar and wind resource hours (around 6–8 hours and 18–20 hours), where its generation exceeds 4 kW. In contrast, both PSO and GA (withN_{pv}=*7, sf=0.88*)show lower production levels, with noticeable underperformance during midday hours (10–15 hours) when output falls closer to the load demand curve. Despite these differences, all three methods successfully maintain renewable generation above demand during peak periods, ensuring supply reliability. Overall, the figure demonstrates that while heuristic methods (PSO and GA) converge to similar solutions with reduced PV capacity, Grid Search provides superior overall energy output, highlighting its effectiveness in maximizing renewable power availability across the daily cycle.

Table 8 Performance comparison of the all three Optimization Methods

Method	N_{pv}	Wind Scale	$Total_{Deficit}$(Wh)	$Total_{Excess}$(Wh)	Final SOC	Score
Grid Search	10	0.9	0	46,319	1	14.568
PSO	5	0.5	7,075.3	1,863.6	0.44233	-7,069.6
GA	5	0.5	7,075.3	1,863.6	0.44233	-7,069.6

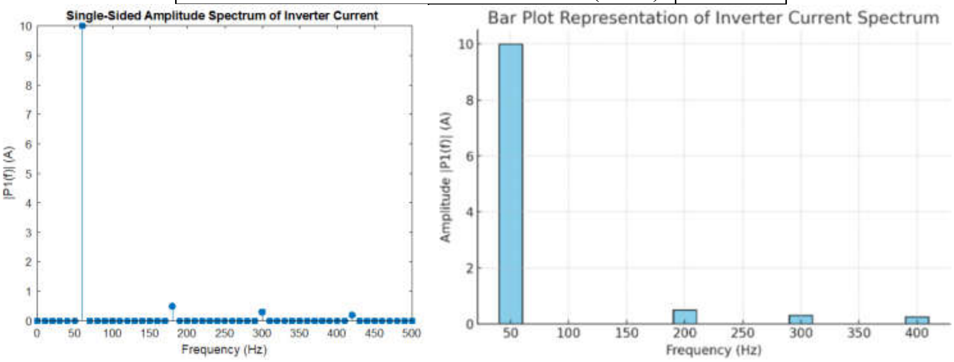
Table 8 presents a comparative analysis of the three optimization methods, Grid Search, PSO, and GAapplied to the hybrid energy system. The results indicate that Grid Search outperforms both heuristic methods in all evaluated metrics. Specifically, it achieves a total deficit of 0 Wh, ensuring that the energy demand is fully met, and delivers the highest total excess energy of 46,319 Wh, reflecting superior energy generation and utilization. Additionally, the final state of charge of the battery reaches its maximum value (SOC = 1), highlighting effective energy storage management. The overall optimization score of 14.568 further confirms its superior performance. In contrast, both PSO and GA exhibit significant energy deficits (7,075.3 Wh), much lower excess energy (1,863.6 Wh), and incomplete battery charging (SOC = 0.44233), leading to substantially negative scores (-7,069.6). These findings demonstrate that while heuristic algorithms like PSO and GA can offer computational efficiency, the deterministic and exhaustive evaluation of Grid Search ensures optimal system performance, particularly when the search space is manageable.

5.4 THD of Inverter Evaluation

The output current is evaluated under synthetically generated distortion for THD analysis. The resulting FFT plot is configured to focus on the low-order frequency range (0-500 Hz), which is most relevant for power quality analysis. This targeted visualization helps in easily identifying the magnitudes of the fundamental frequency and the unwanted harmonic components.Table 9 presents the evaluated performance of the inverter current in terms of harmonic distortion analysis. The fundamental operating frequency is observed at 60 Hz, with a corresponding fundamental RMS current of 7.07 A, indicating stable current delivery at the base frequency. The calculated % THD is 0.3%, which is well within the acceptable limits for power quality standards (typically below 5%). This ensuring efficient operation, reduced losses, and reliable performance of the hybrid energy system. The respective bar plots are presented in Figure 12.

Table 9 the performance of evaluated THD

Parameter	**Value**
Fundamental Frequency	60.0 Hz
Fundamental RMS Current (Conceptual)	7.07 A
Calculated Total Harmonic Distortion (THD)	0.3 %



a) THD stem plot b) Bar plot of THD evaluation

Figure 12 Performance evaluation of the THD of the Inverted current

5.5 ML based methods prediction Results for Solar Power

This section the additional experiment is performed to compare the performance of various ML regression-based prediction models for solar PV power output profile. The daily variation in solar power generation is presented in Figure 13 comparing actual measured values with predictions from five regression models: Linear, Support Vector Regression (SVR), Decision Tree, Ensemble, and Neural Network (NN). The measured curve (blue line) shows a clear diurnal pattern, with output beginning to rise around 8:00 AM, reaching its maximum between 12:00 PM and 2:00 PM, and gradually declining to nearly zero in the evening. Among the predictive approaches, the NN model provides the closest agreement with the measured data, particularly during peak hours, successfully replicating both the magnitude and curvature of the solar output.

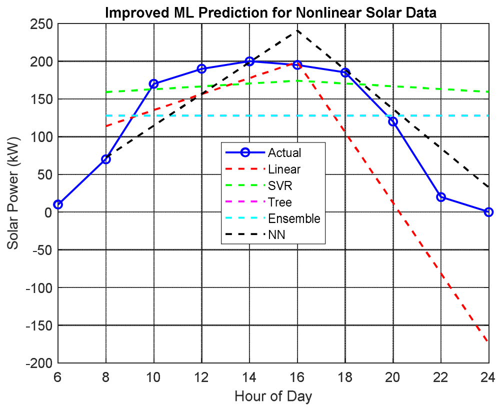
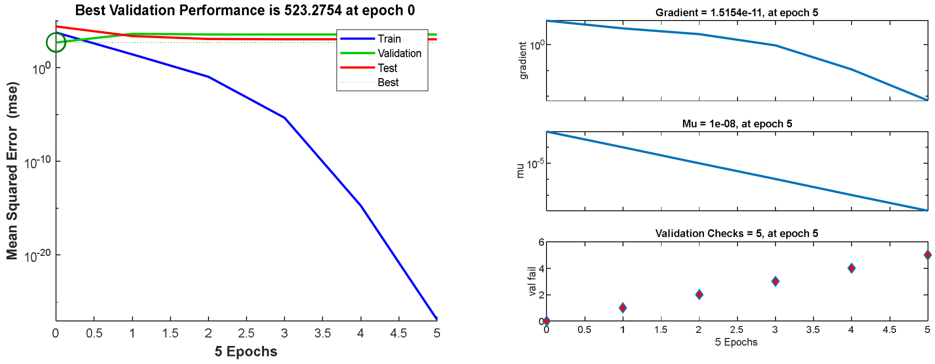


Figure 13 Performance of ML prediction methods for nonlinear solar data

The Linear regression substantially underestimates the peak and fails to capture the inherent non-linear dynamics, leading to notable discrepancies during midday. The SVR model achieves moderate improvement over the Linear model but continues to lag in accurately reproducing the peak region. The Decision Tree model approximates the overall shape but introduces abrupt fluctuations, likely attributable to overfitting or limited smoothness in its predictions. In contrast, the Ensemble model provides a more balanced representation, with improved smoothness and peak estimation, yet still does not match the fidelity of the NN based model.It can be observed the NN offered the maximum of 247 W power output.



a) training MSE error performance b) Parametric performance during Validation

Figure 14 results for the NN modeltraining

6. Conclusion and Future Work

The study demonstrates that hybrid solar–wind systems effectively enhance energy reliability and stability, with Grid Search optimization using ten PV panels identified as the optimal sizing solution, ensuring efficient performance while maintaining inverter power quality and accommodating wind speed variability. sequence of experiments including impact of wind seeped on wind power corves, optimal sizing based on ML optimization methods and also the inverted current THD analysis are carried out. Following main conclusions are drawn from the studies.

- This study systematically evaluated the performance of three optimization techniquesGrid Search, PSO, and GAfor the design and operation of proposed HSW-RES system design.
- The Grid Search method yielded the highest level of excess energy generation, whereas PSO and GA produced lower excess energy but demonstrated superior resource utilization efficiency.
- It is concluded that optimization method has no impact on battery charging and despite methodological differences, the final battery State of Charge (SOC) remained nearly identical across all approaches, stabilizing around 0.98, which reflects reliable storage management.
- The influence of wind speed on turbine power curves and its role in the optimal sizing of HSW-RES was analysed, highlighting its critical impact on system performance.
- Machine learning (ML) techniques were employed to predict the effects of wind speed variations and to assist in the optimal sizing process of the hybrid system.
- The inverter's current quality was assessed, showing a very low total harmonic distortion (THD) of 0.3%, thereby confirming compliance with power quality standards and efficient system operation.
- Comparative analysis of ML regression models for solar PV power prediction revealed that the Neural Network (NN) achieved the closest correspondence with 247 W measured values, outperforming other models in accuracy.

6.1 Future Work

In future incorporating other renewable energy sources, such as biomass or small-scale hydro, could further enhance system reliability and energy efficiency. Developing real-time or adaptive optimization algorithms that respond dynamically to changing weather and load conditions could improve system performance beyond static optimization methods is scope of future too.Another scope is to investigating the interaction of HSW-RES with the main grid, including smart control, demand response, and energy storage management, can optimize energy delivery and stability.

References

[1]. Mingqi Bai, Shuqi Liu, Meng Qi, Shangzhi Liu, Chi-Min Shu, Wei Feng, Yi Liu, Optimization of wind-solar hybrid system based on energy stability of multiple time scales and uncertainty of renewable resources, Energy, Volume 313, 2024, 133790, https://doi.org/10.1016/j.energy.2024.133790.

[2]. Alam, Farzana & Parvez, Sofi & Haque, Md Fozlul & Hasan, Md & Haque, Syed & Uddin, Mohin & Khatun, Joly. (2025). Design and Analysis of a Solar-Wind Hybrid Energy Generation System. American Journal of Energy and Natural Resources. 4. 9-13. 10.54536/ajenr.v4i1.3684.

[3]. M. Thirunavukkarasu, Yashwant Sawle, Himadri Lala, A comprehensive review on optimization of hybrid renewable energy systems using various optimization techniques, Renewable and Sustainable Energy Reviews, Volume 176, 2023, 113192, https://doi.org/10.1016/j.rser.2023.113192. .

[4]. Papazoglou, G.; Biskas, P. Review and Comparison of Genetic Algorithm and Particle Swarm Optimization in the Optimal Power Flow Problem. *Energies* 2023, *16*, 1152. https://doi.org/10.3390/en16031152

[5]. K. Narwat and M. Gupta, "A Study on Combined Batteries WithA Solar / Wind Hybrid Renewable Energy System," *2022 International Interdisciplinary Humanitarian Conference for Sustainability (IIHC)*, Bengaluru, India, 2022, pp. 1308-1312, doi: 10.1109/IIHC55949.2022.10060774.

[6]. Chouaib Ammari, Djamel Belatrache, Batoul Touhami, Salim Makhloufi,Sizing, optimization, control and energy management of hybrid renewable energy system—A review, Energy and Built Environment, Volume 3, Issue 4, 2022, Pages 399-411, https://doi.org/10.1016/j.enbenv.2021.04.002 .

[7]. Peng, H., Li, Z., Zhang, R., Xin, J., & Chen, R. (2025). Simulation study on the impact of photovoltaic arrays on wind turbine performance in a wind-solar hybrid system. *International Journal of Green Energy*, *22*(13), 2967–2980. https://doi.org/10.1080/15435075.2025.2481190

[8]. Khadija Sabri, Ouadia El Maguiri, Abdelmajid Farchi, Optimizing power output in hybrid photovoltaic/wind systems: a nonlinear back-stepping approach for enhanced efficiency and stability, *Clean Energy*, Volume 8, Issue 6, December 2024, Pages 205–224, https://doi.org/10.1093/ce/zkae083

[9]. Sina Ibne Ahmed, Kaiser Ahmed Bhuiyan, Irin Rahman, Hossein Salehfar, Daisy Flora Selvaraj, Reliability of regression based hybrid machine learning models for the prediction of solar photovoltaics power generation, Energy Reports, Volume 12, 2024, Pages 5009-5023, ISS https://doi.org/10.1016/j.egyr.2024.10.060.

[10]. D. Monika *et al.*, "Integrating Wind and Solar Energy: A Study on Measurement Accuracy and System Stability," *2024 7th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, Yogyakarta, Indonesia, 2024, pp. 605-609, doi: 10.1109/ISRITI64779.2024.10963525.

[11]. A. Ben Jemaa, N. Essounbouli and A. Hamzaoui, "Optimum sizing of hybrid PV/Wind/battery installation using a fuzzy PSO," *3rd International Symposium on Environmental Friendly Energies and Applications (EFEA)*, Paris, France, 2014, pp. 1-6, doi: 10.1109/EFEA.2014.7059940.

[12]. S. K. H. Shah, A. Hellany, M. Nagrial and J. Rizk, " Multiobjective Optimization of a Hybrid Wind/Solar BatteryEnergy System in the Arctic, Journal of Renewable Energy, Vol. 2021 , Issue 1, 8829561 https://doi.org/10.1155/2021/8829561

[13]. P. T. Staden, T. Adefarati, R. C. Bansal and R. Naidoo, "Design and Analysis of an Off-Grid Connected PV-Wind-Battery Hybrid Energy System," *2022 IEEE IAS Global Conference on Emerging Technologies (GlobConET)*, Arad, Romania, 2022, pp. 477-481, https://doi.org/10.1109/GlobConET53749.2022.9872417

[14]. A. Chauhan and V. K. Dwivedi, "Optimal sizing of a stand-alone PV/wind/MHP/biomass based hybrid energy system using PSO algorithm," *2017 6th International Conference on Computer Applications In Electrical Engineering-Recent Advances (CERA)*, Roorkee, India, 2017, pp. 7-12, doi: 10.1109/CERA.2017.8343292.

[15]. Victor Eniola, Jack Cimorelli, Christopher Niezrecki, David Willis, Xinfang Jin, Investigating the impact of wind speed variability on optimal sizing of hybrid wind-hydrogen microgrids for reliable power supply, International Journal of Hydrogen Energy, Volume 106, 2025, Pages 834-849, https://doi.org/10.1016/j.ijhydene.2025.01.444.

[16]. D.X. Tittu George, R. Edwin Raj, Ananth Rajkumar, M. Carolin Mabel, Optimal sizing of solar-wind based hybrid energy system using modified dragonfly algorithm for an institution, Energy Conversion and Management, Volume 283, 2023, 116938, https://doi.org/10.1016/j.enconman.2023.116938.

[17]. Avinash Nath Tiwari and Navnit Dubey, A Methodology of Optimal Sizing for Wind Solar Hybrid System, Asian Review of Mechanical Engineering Vol. 4 No. 1, pp. 11-16 2015,

[18]. A. F. Güven, N. Yörükeren, E. Tag-Eldin and M. M. Samy, "Multi-Objective Optimization of an Islanded Green Energy System Utilizing Sophisticated Hybrid Metaheuristic Approach," in *IEEE Access*, vol. 11, pp. 103044-103068, 2023, https://doi.org/10.1109/ACCESS.2023.3296589

[19]. Vafaeva, Khristina Maksudovna& Raju, V. & Ballabh, Jayanti & Sharma, Divya &Rathour, Abhinav &Rajoria, Yogendra. (2024). Particle Swarm Optimization for Sizing of Solar-Wind Hybrid Microgrids. E3S Web of Conferences. 511. 01032. https://doi.org/10.1051/e3sconf/202451101032 .

[20]. M. Shadman Abid, H. J. Apon, K. A. Morshed and A. Ahmed, "Optimal Planning of Multiple Renewable Energy-Integrated Distribution System with Uncertainties Using Artificial Hummingbird Algorithm," in *IEEE Access*, vol. 10, pp. 40716-40730, 2022, https://doi.org/10.1109/ACCESS.2022.3167395.

[21]. Obaidullah Lodin, Nitin khajuria, Satyanand Vishwakarma, Gazia Manzoor, Modeling and Simulation of Wind Solar Hybrid System using Matlab/Simulink, International Journal of Innovative Technology and Exploring Engineering (IJITEE) Volume-8, Issue-9S, July 2019

[22]. Kouihi, M., Moutchou, M., Ait ElMahjoub, A. (2024). Genetic Algorithm-Driven Optimization for Standalone PV/Wind Hybrid Energy Systems Design. In: Hamlich, M., Dornaika, F., Ordonez, C., Bellatreche, L., Moutachaouik, H. (eds) Smart Applications and Data Analysis. SADASC 2024. Communications in Computer and Information Science, vol 2168. Springer, Cham. https://doi.org/10.1007/978-3-031-77043-2_8

[23]. Paliwal, P. (2022). Reliability-Based Optimal Sizing for an Isolated Wind–Battery Hybrid Power System Using Butterfly PSO. In: Bansal, R.C., Agarwal, A., Jadoun, V.K. (eds) Advances in Energy Technology. Lecture Notes in Electrical Engineering, vol 766. Springer, Singapore. https://doi.org/10.1007/978-981-16-1476-7_16

[24]. Lodin, Obaidullah & Khajuria, Nitin & Vishwakarma, Satyanand & Manzoor, Gazia. (2019). Modeling and Simulation of Wind Solar Hybrid System using Matlab/Simulink. International Journal of Innovative Technology and Exploring Engineering. 8. 218-224. 10.35940/ijitee.I1034.0789S19.

[25]. Minakshi, Kumar, A. (2025). Optimal Sizing and Location of Hybrid Solar-Wind Based DG and Minimization of Cost for Sustainable Energy. In: Lather, J.S., Singh, A.K., Sushnigdha, G. (eds) Proceedings of the International Conference on Systems, Control and Automation. ICSCA 2023. Lecture Notes in Electrical Engineering, vol 1260. Springer, Singapore. https://doi.org/10.1007/978-981-97-7384-8_61

[26]. Lazaar, N., Fakhri, E., Barakat, M., Sabor, J., Gualous, H. (2021). A Genetic Algorithm Based Optimal Sizing Strategy for PV/Battery/Hydrogen Hybrid System. In: Masrour, T., El Hassani, I., Cherrafi, A. (eds) Artificial Intelligence and Industrial Applications. A2IA 2020. Lecture Notes in Networks and Systems, vol 144. Springer, Cham. https://doi.org/10.1007/978-3-030-53970-2_23

[27]. Seyed Mohammad Seyed Alavi, Akbar Maleki, Afsaneh Noroozian, Ali Khaleghi, Simultaneous optimal site selection and sizing of a grid-independent hybrid wind/hydrogen system using a hybrid optimization method based on ELECTRE: A case study in Iran, International Journal of Hydrogen Energy, Volume 55, 2024, Pages 970-983, https://doi.org/10.1016/j.ijhydene.2023.11.110.