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Designing Machine Learning Solution to Optimize Hybrid Solar-Wind Energy System Performance: Impact of Wind Speed

Journal of Electrical Systems

Abstract: - It is an open field of research to design an efficient hybrid system for Solar PV and Wind energy systems. The study demonstrates the use of machine learning (ML) techniques to optimize the design of a hybrid solar-wind energy system. This approach can lead to more efficient and cost-effective renewable energy solutions.The study designs a hybrid solar-wind energy system using MATLAB Simulation. It uses a grid search optimization (GSO) loop to find optimal PV panels and wind speed scaling factor, balancing energy contributions and evaluating performance using a scoring function. By optimizing the number of solar panels and wind speed characteristics, the study shows how to minimize energy deficits and maximize battery state of charge, resulting in a more reliable and efficient energy system. The optimization process takes into account local solar irradiance and wind speed profiles, allowing the system design to be tailored to specific geographical locations and environmental conditions.The system uses machine learning to optimize PV panels and wind speed, achieving a predicted energy deficit of 0.00 Wh and a surplus of 11,831.86 Wh, indicating strong generation capacity..

Keywords: Solar PV system, Wind Energy, Wind Speed, Optimization and Machine learning, Grid Search Optimization, SOC, Battery Management.

I. NTRODUCTION

It’s a significant field of research to optimize hybrid renewable energy systems using machine learning (ML) techniques. This study has integrated solar photovoltaic (PV) system and wind energy system for preferences improvement. This research has aimed to design and simulate a standalone hybrid solar-wind energy system(HSWES), including solar panel power generation, wind turbine power generation, battery storage, and load management systems.The proposed system combines solar and wind energy, leveraging the complementary nature of these sources. This integration can potentially provide more consistent power generation across varying weather conditions. The study illustrates how to effectively manage energy balance between generation, storage, and consumption in a standalone hybrid system, which is crucial for off-grid applications. Several studies ([1]–[4], [6]–[10]) utilize MATLAB/Simulink to model and simulate hybrid PV-wind systems, demonstrating the technical feasibility and performance under varying environmental conditions.

These works highlight the importance of accurate system modelling for optimizing energy output and ensuring grid stability. Recent advancements incorporate AI/ML for forecasting, adaptive energy management, and system optimization ([12]–[13], [15]–[18], [21]–[22], [25]). These techniques enable predictive maintenance, intelligent load balancing, and enhanced energy storage coordination, marking a shift toward autonomous and resilient energy systems.

This paper provides a framework for sizing key components such as inverters, PV arrays, and battery storage, which are essential for real-world implementation of such systems.The graphical representations of energy generation, consumption, and storage patterns offer a clear understanding of the system's behaviour over time, aiding in system analysis and decision-making. The use of a machine learning-inspired optimization loop allows for dynamic adjustment of system parameters. This approach can lead to improved system performance by finding the optimal number of PV panels and wind speed characteristics. Table 1 presented the abbreviations used.

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Table 1 Abbreviations Used

Figure 1. Abbreviation	Figure 2. Details	Figure 3. Abbreviation	Figure 4. Details
Figure 5. PV	Figure 6. Photovoltaic	Figure 7. GSO	Figure 8. Grid Search Optimization
Figure 9. ML	Figure 10. Machine Learning	Figure 11. AI	Figure 12. Artificial Intelligence
Figure 13. O&M	Figure 14. Operation And Maintenance	Figure 15. DC	Figure 16. Direct Current
Figure 17. HSWES	Figure 18. Hybrid Solar-Wind Energy System	Figure 19. MPPT	Figure 20. Maximum Power Point Tracking
Figure 21. EV	Figure 22. Electric Vehicle	Figure 23. DL	Figure 24. Deep Learning

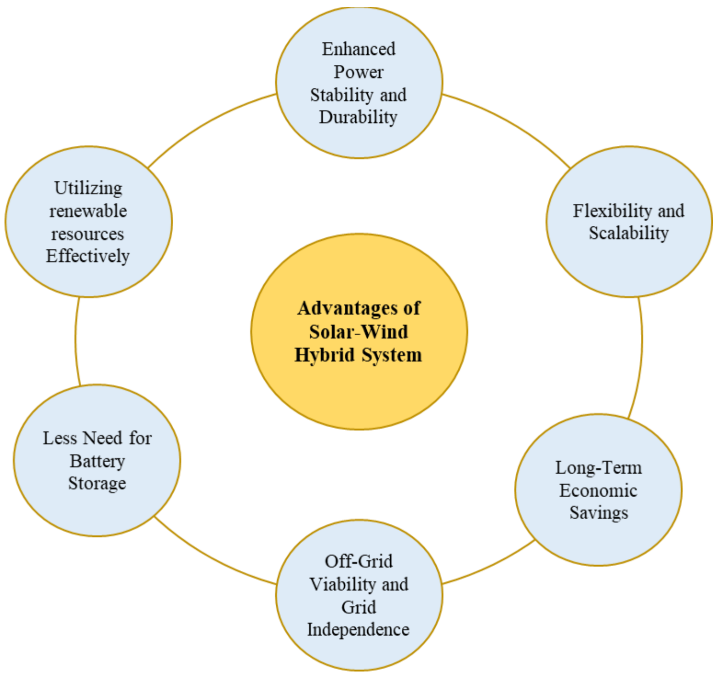

Figure 1 Advantages of Solar-Wind Hybrid System

Figure 1 highlights the principal advantages of a solar-wind hybrid power system, emphasizing its potential to enhance energy reliability and sustainability**.** One of the foremost benefits is the improved power stability and resilience achieved through the complementary characteristics of solar and wind energy, which collectively mitigate the intermittency inherent in each individual source. The system also demonstrates significant flexibility and scalability, enabling adaptation to diverse energy requirements and varying geographical conditions. Economically, the hybrid configuration contributes to long-term cost savings by decreasing dependence on fossil fuels and reducing operational expenditures. Its capacity for off-grid functionality further enhances its suitability for remote or underserved regions where grid access is limited or inconsistent. Moreover, the system facilitates efficient utilization of renewable resources by concurrently harnessing solar and wind energy, thereby optimizing overall energy output. Importantly, the integration of dual energy sources reduces the reliance on extensive battery storage, which in turn lowers system complexity and capital investment.

Figure 2 Challenges of Solar-Wind hybrid System Designs

Figure 2 delineates the primary challenges and unresolved issues associated with the design and implementation of solar-wind hybrid power systems. A major obstacle is the high initial capital investment, encompassing the costs of photovoltaic panels, wind turbines, energy storage units, and auxiliary infrastructure. Additionally, the complexity of system design and integration presents significant technical hurdles, requiring careful selection and coordination of components to achieve efficient and reliable performance. The operation and maintenance (O&M) of such systems also demand sustained attention, including routine inspections, cleaning, and upkeep of both solar and wind apparatuses, as well as the energy storage mechanisms. Another critical concern is resource assessment and site selection, which necessitates thorough evaluation of solar irradiance, wind patterns, and environmental conditions to identify optimal deployment locations. Moreover, the intermittent nature of renewable energy sources complicates system control and monitoring, calling for sophisticated algorithms and real-time data analytics to maintain operational stability. Finally, the management of energy storage systems remains a pivotal challenge, as effective storage solutions are essential to buffer fluctuations in energy supply and ensure consistent power delivery.

Optimizing renewable energy systems, as demonstrated by this study, plays a crucial role in broader initiatives to diminish reliance on non-renewable energy sources. This directly contributes to the global imperative of reducing dependence on fossil fuels and, consequently, alleviating the adverse impacts of climate change. The methodology and results presented in this study can serve as a basis for further research in renewable energy system optimization, integration of other energy sources, and application of more advanced machine learning techniques.

1.2. Contribution of Work

This study integrates a solar PV system with a wind energy system to achieve enhanced performance and reliability in renewable energy solutions. Specifically, this research focuses on the design and simulation of a standalone HSWES system, encompassing solar panel power generation, wind turbine power generation, battery storage, and comprehensive load management systems.

Proposed methodology primarily incorporates a ML-inspired optimization loop to predict optimal wind speed characteristics (via a scaling factor) and solar PV design (selection of number of panels) for improved system performance. By optimizing the number of PV panels and wind speed scaling factor, the system can potentially achieve better resource utilization, reducing energy deficits and excess energy production. Simulation implements a ML-inspired optimization loop to predict optimal wind speed characteristics and solar PV design. This approach aims to enhance the overall performance of the hybrid energy system. the proposed work uses the grid search-based optimization for the optimal power performance and prediction of Npv numbers for wind speeds. the system works energy efficient manner and offers the good battery management also. the MATLAB is used for the simulation of random 24-hour data.

2BASIC SOLAR-WIND HYBRID SYSTEM DIAGRAM

Figure 3 illustrates the architecture of a solar-wind hybrid energy system, integrating multiple renewable sources with intelligent control and optimization. The system comprises a Solar PV Array and a Wind Turbine System, each responsible for converting solar and wind energy respectively into direct current (DC) electricity. To ensure optimal energy harvesting, both sources are equipped with Maximum Power Point Tracking (MPPT) controllers. The generated DC power is then consolidated at a common DC Bus, which serves as the central node for energy distribution.

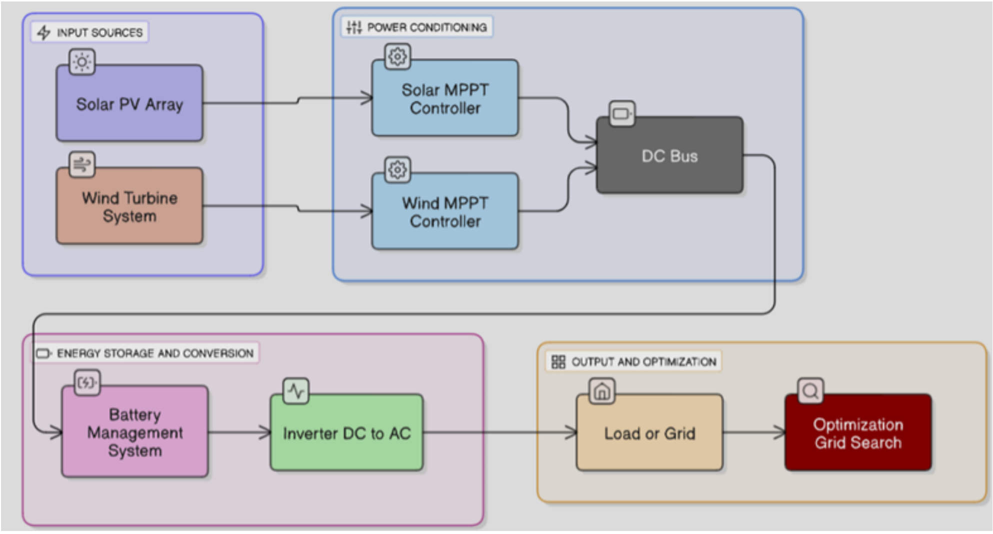

Figure 3 Basic proposed Block diagram of the Hybrid siar0wind system

A Battery Management System (BMS) is connected to the DC Bus to regulate battery charging and discharging processes as in Figure 3, thereby safeguarding battery health and performance. The stored or directly supplied DC power is subsequently converted into alternating current (AC) via an inverter, making it suitable for consumption by electrical loads or for grid integration. Finally, the system incorporates an optimization module based on Grid Search algorithms, which dynamically adjusts operational parameters—such as inverter settings and battery thresholds—to enhance overall efficiency and minimize operational costs.

3, LITERATURE REVEW AND CLASSIFCATION WORKS

Hybrid solar-wind energy systems are increasingly recognized as a viable and sustainable solution to address rising global energy demands. The existing literature illustrates a clear evolution from basic modelling techniques to sophisticated control and optimization frameworks. Prajapati and Sukhadiya [1] conducted a simulation-based review emphasizing the integration of solar-wind systems with smart grids, highlighting how hybridization enhances energy reliability and minimizes grid dependency. Their research underscored the significance of system architecture and control mechanisms in achieving efficient energy distribution. Lodin et al. [2] developed a dynamic simulation model using MATLAB/Simulink to evaluate the performance of wind-solar hybrid systems under varying environmental conditions. Their findings reinforced the necessity of robust simulation platforms for accurate system analysis. Kumar and Dewangan [3] extended this approach by modelling PV-wind hybrid systems and analysing their energy output and operational efficiency, particularly in the context of rural electrification and decentralized energy access.

Mewara and Sharma [4] focused on grid-connected hybrid systems, using Simulink to assess the effects of grid integration on system stability and load management. Their results supported the integration of hybrid systems within smart grid infrastructures. Saleh et al. [5] contributed to practical design considerations by simulating hybrid renewable systems for on-grid applications, incorporating realistic load profiles and operational parameters. Their work provided valuable insights into deployment challenges and scalability in real-world energy networks. Devi et al. [6] developed a comprehensive simulation framework for photovoltaic (PV) and wind hybrid energy systems, emphasizing detailed component-level modelling and performance assessment. Published in a Springer volume, their study offers a systematic methodology suitable for both academic research and industrial design applications. Abdelhamid et al. [7] examined hybrid energy systems within the broader context of energy transition, incorporating artificial intelligence-based control strategies to improve system responsiveness and adaptability. Their work effectively connects traditional renewable energy modelling with emerging intelligent technologies. Mugarura et al. [8] applied maximum power point tracking (MPPT) algorithms to hybrid solar-wind systems, demonstrating significant improvements in energy harvesting efficiency. Through experimental simulations, they validated the robustness of intelligent tracking techniques under variable weather conditions. Mishra et al. [9] contributed to the advancement of hybrid system analysis by introducing real-time simulation methods, which facilitate dynamic performance evaluation and control strategy validation. Their research serves as a critical link between theoretical modelling and practical implementation, enhancing the reliability and applicability of hybrid renewable energy systems.

Saha et al. [10] conducted a comparative study of PV-wind hybrid systems, analysing system behaviour under different load and irradiance conditions. Their findings reinforced the adaptability of hybrid systems in diverse operational scenarios. Acharya et al. [11] proposed ANFIS-based distributed controllers to enhance grid integration in hybrid systems. Their intelligent control approach improved load balancing and fault tolerance, paving the way for smarter energy networks. Koca [12] applied machine learning to manage energy flow in hybrid PV-wind systems, particularly for electric vehicle charging stations. His work demonstrated the potential of adaptive algorithms in optimizing energy usage and reducing operational costs. Mamodiya et al. [13] explored AI-based hybrid solar systems with smart materials and adaptive photovoltaics, offering a futuristic perspective on sustainable power generation. Their study emphasized the synergy between material science and intelligent control. Hassan et al. [14] provided a comprehensive review of hybrid renewable systems, discussing technical challenges, policy frameworks, and deployment strategies. Their work served as a roadmap for integrating solar-wind solutions into national energy plans.

Benitez and Singh [15] reviewed machine learning applications in forecasting PV and wind power output, highlighting the accuracy and efficiency of predictive models. Their analysis supported the integration of AI in energy planning and grid management. AlShammari, et al [16] have used the good optimization approach for improving the grid connect4ed PV systems design. Tomal et al. [17] and Sofian et al. [18] examined deep learning and machine learning strategies for renewable energy, focusing on innovations in energy storage and autonomous control. Their contributions advanced the discourse on intelligent energy systems. Raj [19] reviewed hybrid green energy technologies for smart cities, emphasizing the role of solar-wind systems in urban sustainability. His work advocated for policy-driven adoption and infrastructure development. Kouihi et al. [20] employed genetic algorithms to optimize standalone hybrid system design, achieving improved performance and cost-effectiveness.Their study demonstrated the value of evolutionary computation in energy system engineering.

The integration of artificial intelligence and machine learning into renewable energy systems is comprehensively explored across recent studies. Entezari et al. (2023) provide a bibliographic analysis that maps the evolution of AI/ML methodologies in energy applications, highlighting their growing influence in forecasting, optimization, and autonomous control. Afridi et al. (2023) build on this by examining specific machine learning techniques—both supervised and unsupervised—for enhancing solar and wind energy systems, with a focus on prediction accuracy and fault resilience. Complementing these theoretical insights, Sharmila et al. (2022) offer a practical implementation through the development of a hybrid solar-wind charger using ML-based control, demonstrating the tangible benefits of intelligent energy management in small-scale systems. Together, these works underscore the transformative potential of AI in driving innovation and efficiency in renewable energy technologies.Keyvandarian and Saif [24] introduced dynamic uncertainty sets for robust sizing of hybrid systems, addressing variability in resource availability. Their optimization framework enhanced system resilience and planning accuracy. Agrawal et al. [25] developed a next-generation hybrid energy converter using machine learning, integrating photovoltaic and grid power with intelligent control. Their innovation marked a significant step toward autonomous energy systems. Yazdanpanah [26] provided early insights into modelling and sizing optimization of PV/wind systems, establishing foundational principles for hybrid system design. His work remains relevant for system planners and researchers. Nascimento et al. [27] optimized hybrid power plant configurations by analysing resource complementarity and capacitor factors, enhancing energy production efficiency. Their study contributed to strategic planning in large-scale renewable deployments.Summary of litterateur is given in Table 2.

Table 2 Summary of the Literature review and limitations

Reference	Methodology Description	ML/AI Use	Limitations
Prajapati et al. [1]	Simulation of solar-wind hybrid with smart grid integration	No	Limited real-time validation; lacks intelligent control
Lodin et al. [2]	MATLAB/Simulink-based	No	Focused on static modelling; no

	modelling and simulation		adaptive control
Kumar et al. [3]	MATLAB/Simulink modelling of PV-wind hybrid system	No	No optimization or intelligent control strategies
Mewara et al. [4]	Grid-integrated hybrid system simulation using Simulink	No	No dynamic performance analysis; lacks scalability
Saleh et al. [5]	Design and simulation for on-grid hybrid systems	No	Limited to design phase; lacks intelligent energy management
Devi et al. [6]	Component-level modelling and performance evaluation	No	No AI integration; theoretical focus
Abdelhamid et al. [7]	AI-based control in hybrid PV/wind systems	Yes	Limited experimental validation
Mugarura et al. [8]	MPPT algorithm implementation in hybrid systems	No	Focused on tracking; lacks broader system optimization
Mishra et al. [9]	Real-time simulation for dynamic analysis and control validation	Yes	Limited scalability; hardware implementation not addressed
Saha et al. [10]	Simulation and modelling of hybrid systems	No	No intelligent control or optimization
Acharya et al. [11]	ANFIS-based distributed controllers for grid integration	Yes	Complexity in controller design; limited generalizability
Koca et al. [12]	ML-based adaptive energy management for EV charging stations	Yes	Focused on EV context; limited to specific use-case
Mamodiya et al. [13]	AI-based hybrid solar systems with smart materials	Yes	Experimental scope; integration challenges
Hassan et al. [14]	Review of solar-wind hybrid systems and policy implications	No	Lacks technical depth; review-based
Benitez et al. [15]	Review of ML applications in forecasting PV/wind output	Yes	Focused on forecasting; not system-level modelling
AlShammari et al. [16]	Optimization of grid-connected hybrid systems	No	No intelligent control; optimization limited to sizing
Tomal et al. [17]	Review of ML/DL strategies for renewable energy	Yes	Broad scope; lacks implementation details
Sofian et al. [18]	ML in solar/wind energy and storage innovations	Yes	Conceptual focus; limited empirical validation
Raj et al. [19]	Review of hybrid technologies for smart cities	No	General overview; lacks technical modelling
Kouihi et al. [20]	Genetic algorithm-based optimization for standalone systems	Yes	Focused on design; lacks real-time adaptability
Entezari et al. [21]	Bibliographic review of AI/ML in energy systems	Yes	No modelling or simulation; literature-focused
Afridi et al. [22]	ML applications in renewable energy autonomy	Yes	Conceptual; lacks system-level implementation
Sharmila et al. [23]	Hybrid solar-wind charger with ML integration	Yes	Limited scalability; hardware constraints
Keyvandarian	Robust sizing using dynamic	No	No intelligent control; focused on

et al. [24]	uncertainty sets		sizing
Agrawal et al. [25]	ML-powered hybrid energy converter for grid integration	Yes	Novelty in concept; limited experimental validation
Yazdanpanah et al. [26]	modelling and sizing optimization of hybrid systems	No	No intelligent control; dated methodology
Nascimento et al. [27]	Optimization using complementarity and capacitor factor	No	Focused on plant configuration; lacks intelligent control

Despite diverse methodologies and increasing interest in hybrid renewable energy systems, there are certain common limitations of literature consistently highlights. Most studies lack real-time validation, intelligent control mechanisms, and adaptive optimization strategies. While some incorporate machine learning or AI, their applications are often narrow—focused on forecasting, sizing, or specific use-cases—without broader system-level integration. Additionally, many works remain confined to simulation or conceptual frameworks, with limited scalability, hardware implementation, or empirical validation. limited use of ML is used for investigating the power and energy management. It is required to access optimum solar cells required for energy demands. These gaps underscore the need for more robust, intelligent, and experimentally grounded hybrid system designs.

4. Hybrid Solar Wind Energy System Design

This paper aimed to design and investigate the ML based solution for the hybrid solar-Wind system. the various input simulation parameters are given in the Table 3.

Table 3 Design Parameters for Solar PV and Wind system

System	Parameter	Value	Description
Solar PV System	Rated Power (Ppv,rated)	Rated Power (Ppv,rated)	Rated Power (Ppv,rated)
	300 W	300 W	300 W
	The maximum power output of a single PV panel.	The maximum power output of a single PV panel.	The maximum power output of a single PV panel.
Parameters for Wind System Design	Rated Power (Pwind,rated)	2000 W	The maximum power output of a single wind turbine.
	Number of Turbines (Nwind)	2	The fixed number of wind turbines in the system.
	Cut-in Speed (Vcut−in)	3 m/s	The minimum wind speed required for the turbine to start generating power.
	Rated Speed (Vrated)	12 m/s	The wind speed at which the turbine reaches its maximum rated power output.
	Cut-out Speed (Vcut−out)	25 m/s	The wind speed at which the turbine shuts down to prevent damage.
	Air Density (ρair)	1.225 kg/m3	The density of the air, a key factor in calculating wind power.
	Rotor Radius (Rrotor)	2 m	The radius of the turbine's rotor, used to calculate the swept area.
	Power Coefficient (Cp)	0.4	A measure of the turbine's efficiency in converting wind energy to mechanical energy.

Table 3 presents the key design parameters for both the solar PV system and the wind energy system used in the hybrid configuration. For the solar PV system, the rated power of each panel is specified as 300 W, representing the maximum electrical output under standard test conditions. This value is repeated to emphasize uniformity across all installed panels.The wind system design parameters include a rated turbine power of 2000 W, with two turbines integrated into the system. Critical operational thresholds are defined by the cut-in speed (3 m/s), rated speed (12 m/s), and cut-out speed (25 m/s), which determine the turbine's power generation behaviour under varying wind conditions. Additional parameters such as air density (1.225 kg/m³) and rotor radius (2 m) are essential for calculating the available wind power. The power coefficient (Cp = 0.4) reflects the efficiency of the turbine in converting kinetic wind energy into mechanical energy.

4.1 Mathematical Modelling

The mathematical modelling of PV and Wind systems are presented in this section.

A. Solar Photovoltaic (PV) Power

The hourly power output from the solar PV array, denoted as $P_{pv}(t)$, is modeled as a linear function of the solar irradiance, G(t), at a given time t. The model assumes that the PV panels operate at standard test conditions (STC) for their rated power and that their output scales directly with the available irradiance.

The equation for the total power generated by the PV array is:

$$P_{pv}(t) = N_{pv} \cdot P_{pv-\text{ rated}} \cdot \frac{G(t)}{G_{std}} \quad (1)$$

where:

- $P_{pv}(t)$is the total hourly PV power output (W).
- $N_{pv}$is the number of PV panels, which is a key optimization variable.
- $P_{pv-rated}$,rated is the rated power of a single PV panel (W).
- G(t) is the hourly solar irradiance at time t (W/m2).
- G_{std} is the standard irradiance under which $P_{pv-rated}$is measured (1000W/m2).

B. Wind Power Generation:

The wind system is defined as per the V cut in and cut out limits. Wind system power is calculated as follows;

For $V\_cut_{in} <= V_{wind} < V_{rated}$:

$$P_{wind} = N_{wind} * 0.5 * rho_{air} * A_{swept} * Cp * V_{wind}^3 \quad (2)$$

For $V_{rated} <= V_{wind} <= V_{cut_{out}}$:

$$P_{wind} = N_{wind} * P_{wind_{rated}} \quad (3)$$

Where:

- P_{wind}: Power output from wind turbines
- N_{wind}: Number of wind turbines
- rho_{air}: Air density
- A_{swept}: Swept area of wind turbine rotor
- Cp: Power coefficient
- V_{wind}: Wind speed
- $P_{wind_{rated}}$: Rated power of a single wind turbine

C. Battery State of Charge (SOC):

The third major contribution of the work is to estimate the battery charging and discharging characteristics for management. the charging state parameters are defined as;

For charging:

$$\mathrm{SOC}_{\mathrm{new}} = \mathrm{SOC}_{\mathrm{current}} + \frac{\left(\mathrm{E}_{\mathrm{charge}} * \mathrm{eff}_{\mathrm{battery}_{\mathrm{charge}}}\right)}{\left(\mathrm{C}_{\mathrm{battery}} * \mathrm{V}_{\mathrm{bus}}\right)} \tag{4}$$

For discharging:

$$\mathrm{SOC}_{\mathrm{new}} = \mathrm{SOC}_{\mathrm{current}} - \frac{\left(\frac{\mathrm{E}_{\mathrm{discharge}}}{\mathrm{eff}_{\mathrm{battery}_{\mathrm{discharge}}}}\right)}{\left(\mathrm{C}_{\mathrm{battery}} * \mathrm{V}_{\mathrm{bus}}\right)} \tag{5}$$

This research has independently measured and investigated the optimal performance parameters to achieve the fast charging of battery system.

5 PROPOSED HSWES SYSTEM DESIGN

This proposed methodology includes a sophisticated battery management system that considers state of charge (SOC), depth of discharge (DOD), and charging/discharging efficiencies. This helps in maintaining battery health and ensuring reliable energy storage.

5.1 Proposed Optimization Loop:

A methodical and well-structured optimization loop methodology ins give in Figure 4 present tailored for the design of a hybrid solar-wind energy system (HSWES). The framework is organized into three distinct phases—Setup, Optimization Loop, and Post Processing—each playing a critical role in refining and identifying the most effective system configuration. The Setup phase initiates the process by defining the design space and establishing performance evaluation metrics. This includes specifying key parameters such as component dimensions, energy thresholds, and operational constraints, alongside formulating quantitative criteria to assess system efficiency. The Optimization Loop constitutes the central mechanism of the methodology, wherein simulations are systematically conducted across a wide range of parameter combinations. During each iteration, the system's performance is evaluated against the predefined metrics, and both the performance scores and corresponding parameter sets are meticulously recorded. This iterative procedure facilitates a thorough exploration of the design space, ensuring that all viable configurations are considered. In the Post Processing phase, the optimal design is selected based on the accumulated performance data. This configuration is then compared with a baseline model to assess improvements in terms of efficiency, reliability, and cost-effectiveness. The comparative results are documented to substantiate the efficacy of the proposed optimization strategy. Collectively, this methodology provides a robust and transparent framework for the systematic design of hybrid renewable energy systems, empowering engineers and researchers to make informed, data-driven decisions that advance energy sustainability and operational excellence.

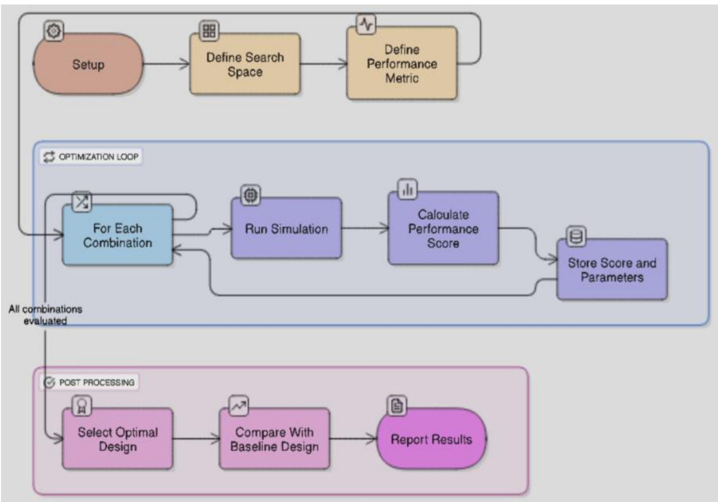

Figure 4the proposed Design Methodology of hybrid HSWES system

The proposed ML based optimization process as illustrated in Figure 4 systematically identifies the ideal configuration for the proposed HSWES system using a grid search optimization algorithm. The procedure begins by defining a comprehensive search space for two critical design parameters: the number of photovoltaic (PV) panels (Npv) and a wind speed scaling factor. The optimization is governed by a multi-objective performance metric designed to maximize the final battery state of charge (SOC) and minimize any energy deficit while simultaneously penalizing the production of excessive energy. The algorithm exhaustively iterates through every possible combination of these parameters within the defined search space. For each unique combination, a full system simulation is executed to calculate the resulting energy deficit, excess energy, and final battery SOC. A performance score is then computed based on these simulation outputs. The configuration that achieves the highest performance score is selected as the optimal system design. Finally, the efficacy of this optimized design is validated through a direct comparison with a non-optimized baseline system, demonstrating the tangible improvements achieved by the machine learning approach.

The mathematical modelling of the optimization process for a hybrid solar-wind energy system with battery storage can be described as follows:

1. The goal is to maximize a performance score, which can be expressed as:

$$\max(S) = (SOC_{final} - SOC_{min}) * E_{battery} - E_{deficit} - 0.1 * E_{excess} \qquad (6)$$

Where: S: Performance score SOC_{final}:

Final state of charge of the battery SOC_{min}:

Minimum allowable state of charge $E_{battery}$:

Battery capacity in kWh $E_{deficit}$:

Total energy deficit in Wh $E_{deficit}$, and Total excess energy in WhE_{excess}

2. The optimization problem is formulated as

$$\max S(x1, x2) \text{ subject to: } 5 \leq x1 \leq 50, x1 \in \mathbb{Z}\, 0.5 \leq x2 \leq 2.0 \; (7)$$

where,decision variables are defined as $x1 = N_{pv}$is the Number of PV panels and x2 = windspeedscale-factor

3. The optimization is performed using a grid search over the discrete space of x1 and x2. The optimization process iteratively evaluates these equations for different combinations of x1 and x2 to find the combination that maximizes the performance score S. and is implemented using the folioing Algorithm 1.

Algorithm 1: GSO Algorithm

for x1 in {5, 10, 15, ..., 50}:
for x2 in {0.5, 0.6, 0.7, ..., 2.0}:
$S_{current} = evaluate_{system(x1,x2)}$ (8)
if $S_{current} > S_{best}$:
$S_{best} = S_{current}$ (9)
$x1_{best}$ = x1
$x2_{best}$ = x2 (10)
End
end
end

End Algorithm

6. Results and Discussions

Paper allows for a comparison between the optimized system and a baseline system without ML optimization. This comparison can demonstrate the potential benefits of using machine learning in renewable energy system design.Paper generates various plots and summaries that allow for detailed analysis of system performance, including hourly power generation, load demand, and battery SOC. This can aid in system understanding and further improvements.

6.1 Input data:

The input data used in each simulation run for the hybrid solar-wind energy system includes wind speed, solar irradiance, and load demand and the source and nature of this data are sequentially described;

1. Solar Irradiance Data:

The solar irradiance data utilized in this analysis is represented as a diurnal profile, spanning a 24-hour period to model a typical daily pattern. The values within this profile range from 0 to a peak of 1000 W/m. The pattern adheres to a predictable cycle: irradiance is zero during the night, gradually increases from the morning, reaches its maximum at midday, and then decreases as the evening approaches. It is important to note that this dataset is a simplified, synthetic representation of a typical day, rather than empirically measured or historical data. The use of such a predefined pattern allows the optimization process to function with a consistent and repeatable baseline for energy generation.

2. Wind Speed Data:

The wind speed data for the simulation is derived from a synthetic diurnal profile, which represents a 24-hour pattern of wind speeds ranging from 4 to 12 m/s. This baseline profile is not a set of historical or real-time measurements but a standardized pattern designed for consistent analysis. To account for variations in wind resource availability, the profile is dynamically modified by a multiplicative scaling factor. This factor is a key parameter within the machine learning optimization framework, allowing the algorithm to explore different wind conditions and determine the optimal system design that best leverages this variable resource.

3. Load Demand Data:

In the context of renewable energy system design, the load demand profile is a critical parameter, this paper has represented a 24-hour pattern of power consumption. data is randomly generated as nearest best possible profile of 24-hour environmental conditions. As described, this synthetic profile exhibits typical daily variations, with lower demand during the night and a peak in the afternoon or evening, ranging from 400W to 2200W. It is essential to recognize that this, along with the solar and wind profiles, constitutes a simplified, idealized representation of a real-world scenario. While these synthetic datasets are valuable for initial optimization, their limitations necessitate a cautious interpretation of the results, as actual system performance would be influenced by a much greater degree of variability and unpredictability.

The optimization process employs a linear scoring function to balance competing objectives, namely maximizing battery State of Charge (SOC), minimizing energy deficit, and penalizing excess energy. The function is structured to heavily penalize energy deficit (with a weight of 1.0), indicating that the primary objective of the system is to ensure all energy demands are met. Excess energy is penalized at a significantly lower rate (0.1), suggesting that surplus generation is considered a less critical issue than unmet demand. The weight of the final SOC is directly proportional to the battery's capacity, providing a reward for efficient energy storage. This methodology effectively finds a configuration that prioritizes reliability over efficiency, but it's important to note that this is a simplified model. More complex real-world applications would likely require a multi-objective optimization approach to better address a wider range of technical and economic constraints.

6.2 Experiment 1: Results of ML Optimization

The first experiment is performed to demonstrate the grid search-based ML optimization results and validation. The results presented in Table 4 demonstrate the effectiveness of machine learning-based optimization in configuring a hybrid solar-wind energy system. The model identified an optimal configuration with 10 photovoltaic panels and a wind speed scale factor of 0.9, achieving a predicted total energy deficit of 0.00 Wh—indicating complete fulfilment of energy demand. Additionally, the system produced a surplus of 11,831.86 Wh, suggesting strong generation capacity beyond consumption needs. The final battery state of charge (SOC) reached 100%, confirming efficient energy storage and utilization. The overall performance score of 18.02 reflects a well-balanced and highly optimized system, validating the potential of machine learning techniques in enhancing hybrid renewable energy system design and operation.

Table 4ML Optimization Results

Parameter	Value
Optimal Number of PV Panels (Npv)	10
Optimal Wind Speed Scale Factor	0.9
Predicted Total Energy Deficit	0.00 Wh
Predicted Total Excess Energy	11831.86 Wh
Predicted Final Battery SOC	100.00%
Optimal Performance Score	18.02

The grid search have simulated the wind scaling factor vs the desired optimal number of solar PV (Npv) system. the results as shown in Figure 5.

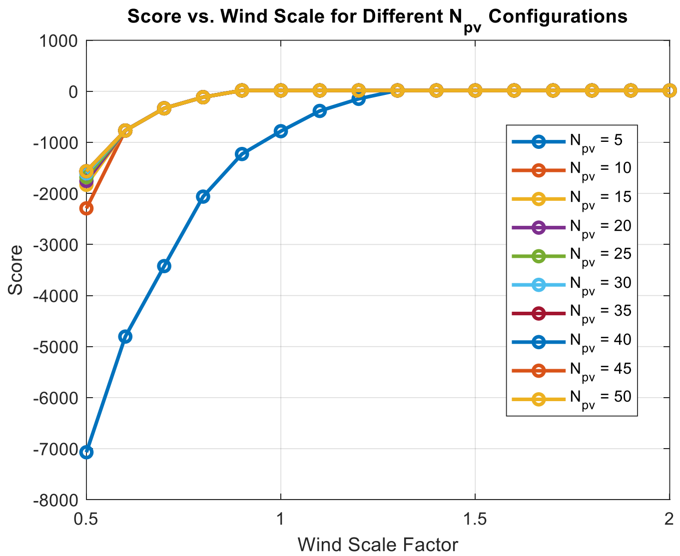

Figure 5ML based optimal production results for Wind scale for different Npv Configurations

The analysis presented in Figure 5 highlights the effectiveness of ML in optimizing the performance of a HSWES system. By evaluating performance scores across varying wind scale factors and different photovoltaic panel configurations (Npv), the results demonstrate that higher Npv values, particularly Npv = 50, consistently yield superior performance with minimal energy deficits. In contrast, lower Npv configurations exhibit reduced efficiency, especially under low wind conditions. Mid-range configurations show moderate improvement but lack the stability of higher panel counts. Overall, the study confirms that increasing PV capacity enhances system resilience and energy reliability, validating the role of machine learning in guiding optimal design choices.

6.3 Experiment 2: Energy Optimization Results

this section has presented the result of energy optimization across the one fill day stretch. The results presented in Table 5 provide a comprehensive overview of the optimal daily energy performance of the solar-wind hybrid system. The system generated a total of 72.06 kWh of renewable energy, with 22.29 kWh from photovoltaic sources and 49.77 kWh from wind energy. This production significantly exceeded the total AC load demand of 24.45 kWh, resulting in zero energy deficit and confirming the system's ability to fully meet consumption needs. Additionally, 11.83 kWh of excess energy was produced, indicating surplus generation beyond storage capacity. The final battery state of charge reached 100%, demonstrating efficient energy storage and optimal system operation under the given configuration.

Table 5 Optimal Daily Energy Summary

Summary Item	Value
Total PV Energy Generated	22.29 kWh
Total Wind Energy Generated	49.77 kWh
Total Renewable Energy Generated	72.06 kWh
Total Load Demand (AC)	24.45 kWh
Total Energy Deficit (not met by system)	0.00 kWh
Total Excess Energy (curtailed or not stored)	11.83 kWh
Final Battery SOC	100.00%

6,4 Experiment 3: Battery Charging State Results

Figure 6 presents the simulation results of the optimal (HSWES) system, focusing on battery State of Charge (SOC) and energy curtailment. Over a 5-hour period, the SOC steadily increases from approximately 60% to 90%, indicating efficient charging and strong energy availability. The 24-hour energy curtailment plot reveals dynamic fluctuations, with excess energy peaking around 3000 Wh at hours 6 and 18, and dropping to zero by hour 24. These results underscore the system's capability to store renewable energy effectively while minimizing waste, demonstrating the significance of optimized storage in enhancing energy reliability and sustainability.

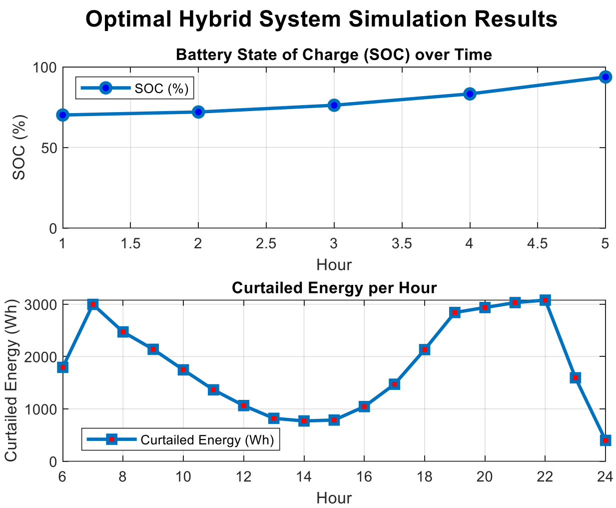

Figure 6 Results of Optimal HSWES simulation for SOC and energy plots

The MATLAB is used for the simulation of a HSWES system under varying design configurations. The results of Table 6 outline the key design sizing parameters for the optimal configuration of the proposed HSWES system. The peak AC load demand is estimated at 2200.00 W, guiding the recommendation for an inverter size of 2750.00 W—sized at 1.25 times the peak load to ensure reliable power conversion and system stability.

Table 6 Optimal Design Sizing Considerations

Parameter	Value
Peak AC Load Demand	2200.00 W
Recommended Inverter Size	2750.00 W (1.25x Peak Load)
Total PV Array Peak Power	3000.00 W
Total Wind Farm Peak Power	4000.00 W
Battery Days of Autonomy	0.79 days

As clear from Table 6 that the total PV array and wind farm are designed to deliver peak powers of 3000.00 W and 4000.00 W respectively, indicating a robust renewable generation capacity. Additionally, the battery system offers 0.79 days of autonomy, reflecting its ability to sustain energy supply during periods of low generation. These sizing considerations collectively support a resilient and well-balanced energy system tailored to meet demand efficiently.

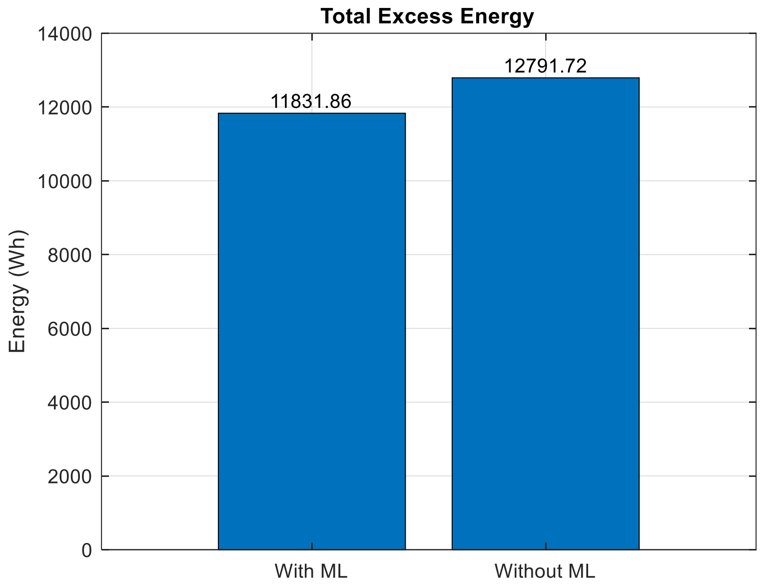

Figure 7Results of energy saving in terms of excess Energy comparison with and without using ML

Figure 7 presents a comparative analysis of excess energy generation in a hybrid solar-wind system with and without the application of machine learning (ML). The bar graph illustrates that the system using ML produced 11,831.86 kWh of excess energy, whereas the non-ML configuration resulted in 12,791.72 kWh. This reduction of approximately 960 kWh in excess energy highlights the efficiency gains achieved through ML-based optimization. By minimizing surplus energy that cannot be stored or utilized, the ML-enhanced system demonstrates improved resource utilization and operational effectiveness, underscoring the value of intelligent control strategies in renewable energy management.

When there's excess energy, it's used to charge the battery. When there's a deficit, energy is drawn from the battery. This helps balance the intermittent nature of both solar and wind generation. If the combined generation exceeds both the load demand and the battery's capacity to store, the excess energy is curtailed. If the combined generation plus available battery energy is insufficient to meet the load demand, the system records an energy deficit.

6.5 Experiment 4: ML Based Power Generation and Load Demand Result

This section presented the results for a detailed graphical representation of the operational dynamics of a proposed HSWES system optimized through ML techniques as illustrated in Figure 9. The four distinct subplots are compared in Figure 9, that collectively illustrate the system's behaviour over a 24-hour period. The first subplot depicts the hourly solar irradiance, which follows a typical diurnal cycle, is beginning at zero during early morning hours, peaking around midday, and gradually declining toward evening. This pattern reflects the natural availability of solar energy and serves as a fundamental input for PV power generation. The second subplot presents the ML-optimized wind speed, which exhibits a similar trend to solar irradiance, increasing during daylight hours and decreasing at night.

This optimization ensures that wind energy is effectively harnessed when it is most abundant, thereby complementing solar power generation. The third subplot, which forms the core of the analysis, compares PV power, wind power, total renewable power, and load demand. The ML-based optimization aligns the total renewable power output closely with the load demand curve, thereby minimizing energy mismatches and reducing dependence on non-renewable backup sources. Such alignment is critical for maintaining grid stability and maximizing the utilization of renewable resources. The final subplot illustrates the battery state of charge (SOC) throughout the day, beginning at approximately 50% and gradually rising to stabilize near 100% by the end of the cycle. The SOC remains within predefined operational limits, indicating effective energy storage management.

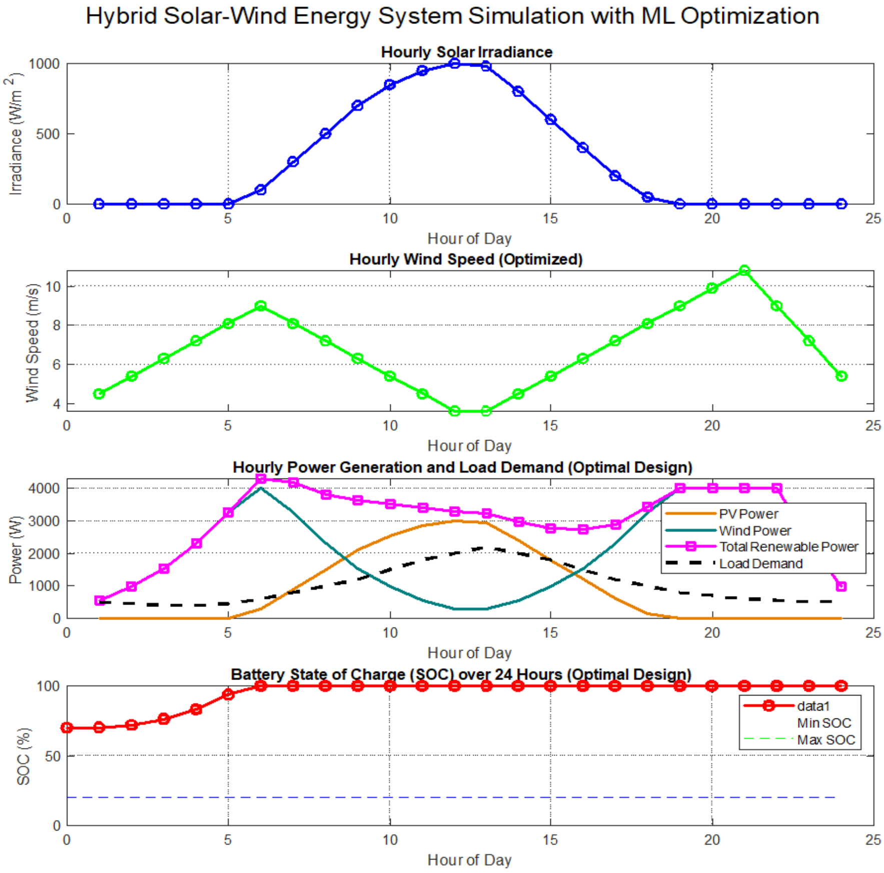

Figure 9Representations of results for ML based power generation and load demand

The hybrid solar-wind energy system handles the balance between energy generation from solar and wind sources. The system calculates the total renewable energy generated by summing the power from both solar panels and wind turbines for each hour. For each hour, the system calculates the net energy by subtracting the load demand from the total renewable energy generated. This determines whether there's an energy excess or deficit

Collectively, these results highlight the significant role of ML in enhancing the performance of renewable energy systems. By accurately forecasting resource availability and optimizing power dispatch, ML facilitates efficient energy generation, minimizes excess energy and curtailment, improves battery utilization, and strengthens overall system reliability. Ultimately, ML serves as the intelligent control mechanism of the hybrid system, enabling it to meet dynamic load demands while promoting energy sustainability and paving the way for smarter, more resilient energy infrastructures.

6. Conclusions and Future Scopes

This study has aimed to design the hybrid solar-Wind energy system(HSWES) using MATLAB Simulation.The system uses a ML based grid search optimization loop to find the optimal number of PV panels (N_pv) and a wind speed scaling factor. This helps in balancing the contribution from each source based on the given conditions. The system's performance is evaluated using a scoring function that considers energy deficit, excess, and battery state of charge. This indirectly encourages a balance between solar and wind generation that best meets the load demand while minimizing both deficits and excessive surpluses.

The wind speed data is a synthetic profile, ranging from 4 to 12 m/s, allowing the optimization process to function with a consistent baseline for energy generation. The load demand data is a 24-hour pattern of power consumption, exhibiting typical daily variations. The study demonstrates the effectiveness of machine learning-based optimization in configuring a hybrid solar-wind energy system. The model identified an optimal configuration with 10 photovoltaic panels and a wind speed scale factor of 0.9, achieving a predicted total energy deficit of 0.00 Wh. The system produced a surplus of 11,831.86 Wh, indicating strong generation capacity beyond consumption needs.he system generated 72.06 kWh of renewable energy, with 22.29 kWh from photovoltaic sources and 49.77 kWh from wind energy. The final battery state of charge reached 100%, confirming efficient energy storage and utilization. The study also presents the results of energy optimization across a one fill day stretch, demonstrating the optimal daily energy performance of the solar-wind hybrid system.

7. Conclusion and Future scopes

The approach can potentially be adapted to different locations and energy demands, making it a valuable tool for renewable energy system planning. In future the large-scale rich dataset of the system for long term can be used for the optimal solutions.

Acknowledgment

Authors acknowledge every one contributing to research directly or indirectly including all referred authors too.

Declaration

It is to declare the research is our own research and not copy from anywhere else. This is also to declare that there is no conflict of interest involved amongst the authors for the research. There is no funding involved with the research.

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