RESEARCH PAPER

Hybrid Solar - Wind Power Prediction Using Advance Stacked Ensemble Learning: System For Indian Telecom Networks

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Abstract: - The use of renewable energy in Indian Telecom sites is increased in recent times for enhancing the energy efficiency of networks. This study proposes a machine learning–based framework for accurately predicting the power output of a simulated hybrid wind and solar photovoltaic (PV) energy system. The methodology integrates advanced regression techniques, including feature selection, boosting methods, Gaussian process regression, and stacked ensemble learning, to enhance prediction performance. A comparative analysis is conducted between the hybrid wind–PV system and a standalone PV configuration to evaluate the benefits of hybridization. Synthetic datasets are generated to model the power output of the hybrid system by incorporating wind-related parameters, such as wind speed and torque measurements, alongside PV-related variables, including solar irradiance, solar load, and ambient temperature. Data preprocessing involves normalization and feature selection using the ReliefF algorithm to identify the most influential input variables. Multiple machine learning models are trained and evaluated. The best-performing model for the hybrid system is identified as a stacked ensemble with 0.97017 R^2 Values. This model stacked predictions from boosted trees and Gaussian process regression. The hybrid system's performance is compared to a PV-only model, revealing superior prediction accuracy for the hybrid configuration.

Key Words: Hybrid Solar-Wind System, Telecom Networks, Machine Learning, Power Prediction, Wind Torque, Solar load, Boosted Trees, Gaussian Process Regression, Stacked Ensemble.

How to cite this article: Khare N, Rai ASD. Hybrid Solar - Wind Power Prediction Using Advance Stacked Ensemble Learning: System For Indian Telecom Networks. Int J Drug Deliv Technol. 2026;16(8s): 880-895; DOI: 10.25258/ijddt.16.8s.97

1. Introduction

Combining the solar and wind power helps reduce problems tied to relying on just one type of renewable source. Still, making these combined setups work well demands careful planning plus precise management. Predicting how much electricity they generate gets tough because sunlight and wind change unpredictably. These changes depend heavily on weather patterns along with how equipment operates at any moment. Older methods built on fixed rules struggle to handle such shifting conditions. That pushes researchers toward tools like machine learning to better model what happens next. Learning from data lets models adapt where traditional formulas fall short. One recent smarter ways to manage power output have popped up for solar-wind setups that use DFIG designs - showing how prediction tools driven by real-world data can tackle unpredictable shifts [1]. In similar cases, machine learning (ML) approaches for finding peak power perform better than older techniques when weather keeps changing [2]. When wind strength swings wildly and mixes with sunlight patterns, it has become clearer that flexible models are needed to design, ones that spot hidden links between inputs to boost overall results [3]. Beyond these a hybrid models with Bayesian layers has lifted forecasts for green power spots [4]. Still, picking the right signals, adapting across shifting conditions, and threading time patterns stay tricky. That keeps drawing attention toward smarter, clearer, and wider-reaching setups that is driven by data when sizing up solar-wind systems.

The proposed methodology focuses on predicting the output power of a hybrid wind and solar system using advanced machine learning (ML) regression techniques. Separate models are developed for hybrid wind-solar systems and PV-only systems to assess the benefit of incorporating wind-related features. Actual vs. predicted power plots and residual histograms are generated for best-performing models. The major research problems for designing hybrid power systems are illustrated in Figure 1. The methodology integrates wind and solar features effectively, capturing complex nonlinear interactions for more accurate power output prediction.

Figure.1 Cluster Diagram Representing Problem and Challenges of RES

Method proposed using features selection using the ReliefF algorithm to identify the most relevant predictors, reducing dimensionality and improving model efficiency. Employing Bayesian hyperparameter tuning and cross-validation ensures optimized model parameters and reliable performance assessment. work additionally incorporate LSTM networks for modelling temporal dependencies, enhancing prediction for sequential data.

Unlike many models focusing solely on solar or wind, this approach simultaneously incorporates multiple torque sensor readings, wind speed, solar irradiance, solar load, and ambient temperature, capturing a holistic environmental and mechanical state. Synthetic datasets are created simulating multiple torque sensors (torque1, torque2, torque3), wind speed, solar irradiance, solar load, and ambient temperature data randomly generated as in Bhoopendra et al. [21]. The target variable is the output power, modelled with nonlinear interactions and noise to reflect real-world conditions. Data preprocessing includes removing missing values and standardizing features via z-score normalization.

A. Proposed Contributions of Work

This research aimed to design and investigate the comprehensive and systematic research framework for accurate power prediction by integrating data-driven modelling. The synthetic data for three senser based random wind system torque and solar irradiance are generated as referred by Bhoopendra et al [21]. The research uses the advanced feature engineering, and ensemble learning strategies for designing the hybrid solar -wind energy system to be used for Indian Telecom base stations. First, a realistic synthetic dataset is generated to emulate real-world operating conditions for solar and wind systems, by incorporating multiple torque sensor measurements, wind speed, solar irradiance, solar load, and ambient temperature. The output power to be predicted is modelled through nonlinear interactions with added noise to reflect practical uncertainties, followed by rigorous data preprocessing that includes handling missing values and applying z-score normalization to ensure numerical stability and model convergence. To enhance model efficiency and reduce redundancy, in this research a ReliefF feature selection algorithm is proposed to identify the most informative predictor. Thus, in this process proposed method thereby improving generalization performance.

Subsequently, paper contributed to investigate the diverse set of predictive regression-based ML models. These models are ranging from classical linear regression (LR) to advanced techniques such as Bagged Tree, Gaussian Process regressions (GPR) and ensemble learners. As novel contribution research extends the work to stacked ensemble approach regression meta-model, leading to improved predictive accuracy and robustness. Model robustness is assessed across multiple train–test splitting ratios using standard performance metrics especially aiming to improve coefficient of determination (R^2). The predictive performance of individual solar PV system is compared with that of proposed hybrid Solar-Wind system design. Unlike many models focusing solely on solar or wind, this approach simultaneously incorporates multiple torque sensor readings, wind speed, solar irradiance, solar load, and ambient temperature, capturing a holistic environmental and mechanical state. As novel solution a stacked ensemble learning for hybrid systems is proposed which combining predictions from diverse models into a meta-learner tailored for hybrid power systems is a novel approach that improves prediction robustness.

2. Literature Review

Salman et al [1] The goal of the current study is to create efficient simulation and management methods for a grid-connected HSWES. The objective is to maximize power tracking effectiveness in a wind-generated double Fed Induction Generators (DFIG) coupled with an electrically connected solar energy system. The investigation uses vector manipulation to regulate the rotor & grid conversions. The present research applies the Maximum PowerPoint Tracking (MPPT) methodology to solar and wind technologies in order to maximize energy extraction effectiveness and hybrids systems integration with electricity grids.

Solanke et al [2] In this research, we compare the traditional Perturb & Observe (P&O) method with a machine learning (ML) oriented strategy for improved MPPT (maximum power point tracking) of the hybrid energy system (HES). This guarantees that we get the most power out of the infrastructure at any given time. To lessen the ambiguity surrounding the accessibility of any particular renewable resource (such as solar or windy) at any given moment, the PVS & WECS can be integrated. Bhoopendra Patel et al [3] This strategy may result in renewable energy solutions that are more economical and effective. The investigation uses MATLAB Simulations to construct a hybrid solar-wind power system. It balances energy contributions, finds the best PV panels and the wind's scaling factor using a grid search optimizing (GSO) loop, and assesses efficiency using a score formula.

K. P. Natarajan et al [4] In order to forecast the production of solar power, this research suggests summing and stacked combined models. The least absolute shrinkage and selection operators (LASSO) estimation, random forest (RF), multilayer perceptron model (MLP), support vector machines recovery (SVR), & extreme gradient boosting (XGB) are some of the machine learning (ML) models. Two ensemble techniques are proposed to enhance model effectiveness: stacked model ensembles and averaging ensembles using linear weighting average. Zakria Qadir et al [5] The current study compares multiple models using machine learning to calculate the power & energies of hybrids photovoltaic (PV)-wind solar power plants utilizing seven weather elements that significantly affect the PV-wind renewable energy system's power output. The machine learning algorithm that may be effective and helpful in predicting power and energy was categorized in this investigation. Patel et al [6] Predicting energy and power output according to shifting weather conditions is crucial to the clean energy sector's economic success in the contemporary technological era. In contrast to conventional fossil petroleum-based resources, sources of renewable energy have a chance to be crucial for maintaining a nation's economy and raising living standards. This investigation could be useful in achieving accurate predictions in smart energy systems using various weather conditions, as our world is currently facing significant challenges owing to changing climates and global warming.

D. I. Alvarez et al [7] The transformation of energy equations that describe the actions of a combination of technologies for electricity power production that combines photovoltaics and wind turbines are modeled, simulated, and analyzed. Based on the previously given equations, a mathematical model was created, coded, and the outcomes were compared with experimental data. For such complex systems, the model is meant to be a tool for design & optimization. When contrasted with the data collected under different circumstances, the model's predictions were reasonably accurate. Y. Boujamaoui et al [8] The present paper provides a comprehensive review of methods for predicting production from photovoltaic-wind hybrids power plants, emphasizing the need of accurate clean energy predictions for power grid development, administration, and operation. The main problems caused by the sporadic and chaotic nature of green energy data have been addressed through the use of mathematical models, statistical methods, AI methods, and their combinations. J. L. San Juan et al [9] With the help regarding this innovative framework, managers can use machine learning concepts to collect and evaluate pertinent parameters in order to forecast the anticipated return of the HRES elements. They can also take into account all of the traditional RE technologies found in the model's parts, including solar, wind, hydroelectricity, geothermal, nuclear, biomass, and fossil fuel. The design was evaluated on a fictitious dataset once it was created. A sensitivity study was used to confirm the validity of the structure and resulting model. Roy, Subhajit, et al [10] The next section emphasizes the crucial problem of forecasting solar power plants' electrical production at various locations, which is closely related to local climate conditions. Forecasting solar power plants' generated electricity is difficult because to the variety of elements that affect their efficiency, such as weather patterns, seasonal fluctuations, and the kinds of solar panels used. For solar energy to full-fill demand and develop into a reliable source of electricity, precise forecasting of solar photovoltaic (PV) power production is essential.

Sengar, S et al [11] This research presents a hybrid algorithm-based ensemble technique for short-term load forecasting (STLF) in renewable energy systems. The deep neural network (DNN) method & Chicken Swarm Optimizing (CSO) are combined in the hybrid approach. In order to train the DNN networks and analyse the load forecasts, 24-hour wind energy network load data is first gathered from the Northeast ISO. K. P. Natarajan et al [12] In order to forecast the generation of solar energy, this research suggests averaging and layering combination models. The least absolute shrinkage and selection operator (LASSO) estimation, random forest (RF), multi-layer perceptron

(MLP), support vector machines regression (SVR), & extreme gradient boost (XGB) are some of the machine learning (ML) methods. Two ensemble techniques are proposed to enhance model effectiveness: stacked combined models and average ensembles with linear weighting averages. Khan, P.W. et al [13] This study uses several forms of pollutants on all of the solar panels and records the amount of power they produce. Gradient booster, extra tree, and randomly generated forest classifications are all part of the suggested model; the additional tree classifier functions as a meta-learner. In order to improve its accuracy and resilience in recognizing sources of pollution on the PV panel, the model considers a variety of weather parameters throughout the training procedure, such as temperatures and irradiance.

M. A. Khan et al [14] The machine learning-based forecasting of energy for an integrated solar and wind energy extractor utilizing MPPT is compared in this work. Machine learning techniques are used for optimal multi-mode operation under different environmental conditions, and solar-wind hybrid devices connected with MPPT can concurrently capture all wind as well as solar energy. Support Vector Machines (SVM), Random Forests Regressions (RF), K-Nearest Neighbors (KNN), Linear Regression (LR), Decision Tree (DT), & Linear Discriminant Analysis (LDA) are some of the models that were employed to evaluate the mixed energy harvester's efficiency. Rai, A et al [15] This investigation offers an empirical assessment of various generation machine learning algorithms for solar energy estimation, which can aid in understanding further studies on the best approach based on the advantages and disadvantages of each model. As a result, an efficient forecasting technique is identified based on factors including computing complexity, resolution time, and performance errors. I. Hassan et al [16] Grid-connected solar power systems (PV) have revolutionized the world's energy landscape by providing efficient and sustainable substitutes for traditional energy sources. Reliable electricity forecasting and oversight are made more difficult for grid operators by the inherent unpredictability and irregularity of solar energy. In order to improve the dependability and process of decision-making, it is crucial to create a model of prediction that additionally produces precise forecasts but also integrates uncertainties assessment. Azad et al [17] In this regard, artificial intelligence (AI) has become a vital tool for handling the intricacy and unpredictability of HRES design and operation. With an emphasis on neural networks, deep learning, or meta-Heuristic optimizing methods, this systematic review summarizes the most recent state of knowledge on AI-driven frameworks for making decisions applied to HRES. While reinforcement programming allows for flexible management under unknowns, uses for neural network structures, such as CNN, GRU, and LSTM show higher performance in simulating nonlinear temporal changes.

Aparna Unni et al [18] This chapter proposes a novel approach to boost solar energy output using computer vision using machine learning. Measurements of solar energy, historical meteorological data, and information on the performance of the solar panels are combined. Cloud cover alongside other atmospheric variables are approximated by computer vision techniques using satellite or land-based imagery. N. Jannah et al [19] The critical function of forecasting techniques in solar power plants is examined in this paper. Our goal is to offer a thorough grasp of contemporary developments, datasets, and methods for improving forecasting accuracy for solar energy production. Although AI has dominated earlier research, more recent studies show that it can be difficult to achieve optimal precision and efficacy. Sengar et al [20] This research presents a hybrid algorithm-based ensemble technique for forecasting short-term load (STLF) in wind energy systems. The deep neural network (DNN) & Chicken Swarm Optimization (CSO) are combined in the hybrid approach. The suggested approach will be put into practice in Matlab/Simulink, and its results will be contrasted with those of current approaches like DNN and ANN, correspondingly.

Bhoopendra Patel et al [21] The present investigation compares various ML models to estimate the power & energy of hybrids photovoltaic (PV)-wind solar power system utilizing seven weather elements that significantly affect the PV-wind renewable energy system's electrical output. A machine learning approach that may be effective and helpful in predicting power and energy consumption was categorized in this study. Both data modification and non-data modification are applied to the historical hourly data. Zakria Qadir et al [22] The present investigation compares various machine learning models to estimate the generating capacity and power of hybrid photoelectric (PV)-wind solar power systems utilizing seven weather elements that significantly affect the PV-wind regenerative energy system's output. A machine learning approach that may be effective and helpful in predicting power and energy was categorized in this investigation. Rajaperumal et al [23] The incapacity of conventional mathematical models to capture intricate, nonlinear seasonal variations, inadequate use of real-time, geographically specific data, an absence of statistical comparisons across various models and data sets, and the lack of methodical choosing models methods for subsequent projections are some of the major research gaps in renewable energy projections that this study attempts to fill. Rushdi, M.A et al [24] The data were analysed and used to create a regression model with the goal of predicting the system's capacity for output while understanding a set of features. The procedure of choosing features was guided by a sensitivity analysis. This study used a number of machine learning algorithms, and the best model was selected using temporal and predictive quality standards. Our initial model, a straightforward regression technique, was unreliable.

3. Machine Learning Models for Hybrid Power Prediction

Multiple advanced regression models are employed to learn the nonlinear mapping between the selected features and the hybrid output power. The random torque signals for wind system for three sensers are considered for initial data. the Figure 2 is shows the first 50 samples of 1000 samples for three torques.

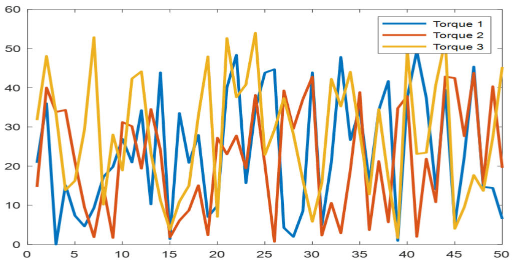

Figure.2 Random Torque Samples as Input

First, bagged decision trees (Bagged Trees) model is employed and since it fairly handles tricky patterns between variables. These models build many small predictors one after another. Each new predictor aims to fix errors from the last. They tweak things step by step using gradients squared errors which guide the adjustments. This allows to increase accuracy over single tree.

Second, Gaussian Process Regression (GPR) is applied to capture probabilistic relationships and quantify uncertainty in power prediction. An automatic relevance determination (ARD) squared exponential kernel is used, allowing the model to adaptively learn feature-specific length scales and improve prediction robustness. To further enhance accuracy, a stacked ensemble model is constructed by combining the predictions of the boosted trees and GPR models. A linear meta-learner is trained on the base model outputs, effectively leveraging complementary strengths of tree-based and kernel-based learners. This ensemble strategy significantly improves prediction reliability and reduces overfitting.

4. Proposed Methodology

This study proposes an advanced data-driven methodology for accurate output power prediction of a hybrid wind–photovoltaic (PV) energy system by integrating physical insights, statistical learning, and modern machine-learning (ML) techniques. The overall framework systematically models the nonlinear relationship between wind turbine mechanical variables, solar irradiance conditions, environmental parameters, and the resulting electrical power output of both PV-only and hybrid energy systems.

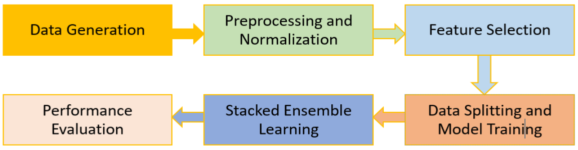

Figure.3 Proposed Methodology of Hybrid Solar Wind System

Investigation with Synthetic Data

4.1. Problem Definition

The hybrid energy system consists of wind and PV subsystems operating in parallel. The wind subsystem is characterized by multiple torque sensor measurements and wind speed, while the PV subsystem is described by solar irradiance, solar load factor, and ambient temperature. For each time instance i, the input feature vector is defined as:

$$\mathbf{x}^{(i)} = \left[T_1^{(i)}, T_2^{(i)}, \ldots, T_{n_T}^{(i)}, V_w^{(i)}, G^{(i)}, L_s^{(i)}, T_a^{(i)}\right] \quad (1)$$

where $T_j$denotes turbine torque measurements, $V_w$represents wind speed, $G$is solar irradiance, $L_s$is the solar load factor, and $T_a$is ambient temperature. The proposed data generation model is referred from Bhoopendra et al. [3]. The true hybrid output power is modelled as a nonlinear combination of wind and PV contributions, incorporating physical interactions and stochastic noise to emulate real-world measurement uncertainty. The PV power component is modelled as a function of irradiance, load, and temperature, while the wind power component captures the nonlinear dependency on turbine torque and wind speed. This hybrid formulation provides a realistic ground-truth representation for training and evaluating learning models. We want to predict the output power P_{out} of a hybrid wind + photovoltaic (PV) system based on sensor and environmental measurements:

$$P_{\text{out}} = f(\mathbf{x}) + \epsilon \tag{2}$$

where:

- $\mathrm{x} = [T_1, T_2, \dots, T_{n_T}, V_w, G, L_s, T_a]^T$ is the feature vector
    - T_i= torque from wind turbine sensors ($i = 1 \dots n_T$)
    - V_w= wind speed (m/s)
    - G= solar irradiance (W/m²)
    - L_s= solar load (normalized or kW)
    - T_a= ambient temperature (°C)
- $f(\cdot)$= unknown nonlinear mapping function
- $\epsilon \sim \mathcal{N}(0, \sigma^2)$= noise/error

We also consider PV-only prediction:

$$P_{\text{PV}} = g(G, L_s, T_a) + \epsilon_{\text{PV}} \tag{3}$$

4.2 Synthetic Data Generation (Ground Truth)

A boost shows up when using solo Neural Networks, hitting an R² score of 0.952 according to study [21]. When switching to the suggested Gaussian Process Regression approach, the number climbs - reaching 0.96917 - a sign of better adaptability and sharper handling of uncertainty. Performance creeps even higher with the layered ensemble strategy, landing at 0.97071, topping every other tested option. It turns out this combined system beats current top models, proving it can map tangled patterns in solar-wind energy forecasts more precisely. PV-related features consist of solar irradiance varying between 200 and 1000 W/m², a unitless solar load factor ranging from 0.2 to 1.0, and ambient temperature between 15 °C and 30 °C, collectively representing realistic solar and environmental variability. The ground-truth PV power output is computed using a physically motivated formulation that models the combined influence of irradiance and solar load while accounting for thermal degradation effects due to ambient temperature, with additive Gaussian noise introduced to emulate measurement uncertainty. Subsequently, the hybrid power output is derived by integrating wind and PV contributions, where wind power is modelled as a nonlinear function of wind speed squared and aggregated torque sensor readings, combined with the PV power component and additional noise to reflect real-world fluctuations. This structured yet flexible synthetic data framework enables robust training and benchmarking of machine learning models by capturing nonlinear interactions, cross-domain dependencies, and stochastic behavior inherent in hybrid renewable energy systems. The hybrid and PV powers are simulated as follows:

4.2.1 PV Power

$$P_{\text{PV}}^{(i)} = 0.02\, G^{(i)}\, L_s^{(i)} - 0.01\, T_a^{(i)} + \eta_{\text{PV}}^{(i)} \tag{4}$$

where $\eta_{\text{PV}}^{(i)} \sim \mathcal{N}(0, \sigma_{\text{PV}}^2)$represents random noise.

4.2.2 Wind Power Contribution

Using torque and wind speed:

$$P_{\text{wind}}^{(i)} = 0.1 \sum_{j=1}^{n_T} T_j^{(i)} + 0.5 (V_w^{(i)})^2 \frac{\sum_{j=1}^{n_T} T_j^{(i)}}{100} \tag{5}$$

4.2.3 Hybrid Power

$$P_{\text{Hybrid}}^{(i)} = P_{\text{wind}}^{(i)} + P_{\text{PV}}^{(i)} + \eta_{\text{Hybrid}}^{(i)}, \eta_{\text{Hybrid}}^{(i)} \sim \mathcal{N}(0, \sigma_H^2) \tag{6}$$

4.3 Proposed Data Preprocessing and Feature Normalization

To ensure numerical stability and fair model comparison, all input features are standardized using z-score normalization. For each feature X_j, normalization is performed as:

$$\tilde{X}_j = \frac{X_j - \mu_j}{\sigma_j} \qquad (7)$$

where μ_j and σ_j represent the mean and standard deviation of the feature, respectively. This step prevents feature dominance due to scale differences and improves convergence during model training. Features are standardized to zero mean and unit variance:

$$\tilde{X}_j = \frac{X_j-\mu_j}{\sigma_j}, \mu_j = \frac{1}{N}\sum_{i=1}^{N} X_j^{(i)}, \sigma_j = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(X_j^{(i)} - \mu_j)^2} \qquad (8)$$

This ensures all features are on a comparable scale for machine learning models.

4.4 Feature Selection (ReliefF)

Because wind and solar data act unpredictably and change in complicated ways, picking the right inputs matters a lot for better forecasts and stable models. This study checks how useful each input is by using the ReliefF method - an approach built for messy relationships in number-based predictions. Instead of testing every combination, it pulls random examples from the data, then looks at which nearby points are closest in behaviour. Every time one example is picked, the system studies its neighbours - those with alike power outputs and those with different ones. Features get stronger scores when they keep showing clear differences between high and low energy outcomes across close matches. What sets this apart is how it weighs small but consistent patterns others might overlook during comparison rounds. The top-ranked features are retained to reduce dimensionality, eliminate redundancy, and enhance generalization performance. This step ensures that only the most informative wind and solar parameters contribute to the prediction models. We rank features based on their relevance to the output P_{Hybrid} using the ReliefF algorithm. Let the best k features be:

$$\mathrm{x}_{\text{top}}^{(i)} = [x_{f_1}^{(i)}, x_{f_2}^{(i)}, \ldots, x_{f_k}^{(i)}] \qquad (9)$$

where $f_1, \ldots, f_k$ are indices of selected features.

The key advantages of ReliefF are how it picks up on close-range patterns and twisted connections, no fixed equations needed. For combined solar and wind setups, that matters - because things like torque, wind strength, sunlight levels, and air warmth don't behave the same way all the time. Instead of relying on rigid models, it weighs each factor by how well it tells situations apart. That sorting cuts down extra data, trims messy signals, and speeds up processing behind the scenes.

The complete prosed methodology is summarized in the sequential Flow chart given in the Figure 4. the respective metaethical modelling is also mapped with each step where applicable. It is clear that the data is randomly and synthetically generated and then different data splitting ratios are selected. The proposed work is using the stacked ensemble based prediction model and compare the performance with other basic models as given in Figure 4.

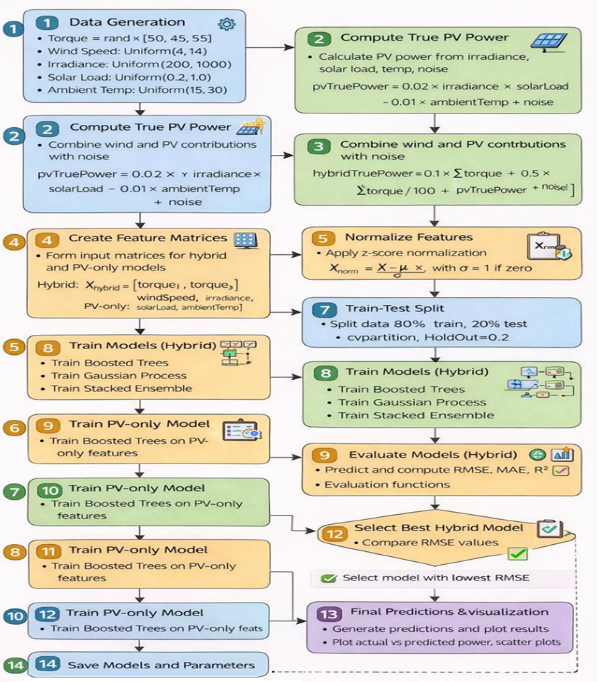

Figure.4 Prosed Flow Chart of The Hybrid Solar-Wind Power System Design

5. Model Training

In this research the multiple ML models are used to learn predict the output power of hybrid system as $P_{\text{Hybrid}} = f(\mathrm{x}_{\text{top}})$ and $P_{\text{PV}} = g(\mathrm{x}_{\text{PV}})$: The used models are described sequentially as;

5.1 Boosted Trees

The bagged tree model is an ensemble learning technique designed to improve prediction accuracy and robustness by reducing variance through aggregation of multiple decision tree learners. In this framework, several decision trees, referred to as weak learners $h_m(\cdot)$, are trained independently on different bootstrap samples drawn from the original training dataset. Each tree learns distinct data patterns due to variations in the sampled subsets. The final hybrid power prediction $\hat{P}_{\text{Hybrid}}$ is obtained by combining the outputs of all trained trees using weighted averaging, as expressed by;

$$\hat{P}_{\text{Hybrid}}^{\text{Boost}} = \sum_{m=1}^{M} \gamma_m \, h_m(\mathbf{x}_{\text{top}}) \qquad (10)$$

- h_m= decision tree (weak learner)
- γ_m= learning rate weighting
- M= number of boosting iterations

Model is trained using gradient descent on squared error between the actual hybrid power and the aggregated model output defined as:

$$\min_{\gamma_m, h_m} \sum_i \left(P_{\text{Hybrid}}^{(i)} - \hat{P}_{\text{Hybrid}}^{(i)}\right)^2 \qquad (11)$$

Although bagging typically assigns equal weights to all learners, the formulation allows for adjustable weights to further refine the ensemble output. By averaging multiple independently trained trees, the bagged tree model effectively suppresses overfitting and improves generalization, making it particularly suitable for modelling complex nonlinear relationships and noisy data commonly encountered in hybrid renewable energy power prediction tasks.

5.2 Gaussian Process Regression (GPR):

It is a probabilistic, nonparametric learning approach that models the hybrid power output as a distribution over functions rather than a single deterministic estimate. In this framework, the predicted hybrid power $\hat{P}_{\text{Hybrid}}^{\text{GPR}}$ is assumed to follow a Gaussian process characterized by a mean function and a covariance (kernel) function, expressed as;

$$\hat{P}_{\text{Hybrid}}^{\text{GPR}} \sim \mathcal{GP}\left(m(\mathrm{x}_{\text{top}}), k(\mathrm{x}_{\text{top}}, \mathrm{x}'_{\text{top}})\right) \qquad (12)$$

- Mean function $m(\mathrm{x}) = 0$
- Kernel: ARD Squared Exponential

$$k(\mathrm{x}, \mathrm{x}') = \sigma_f^2 \exp\left(-\frac{1}{2}\sum_j \frac{(x_j - x_j')^2}{\ell_j^2}\right) \qquad (13)$$

where l_j represents feature-specific length-scale hyperparameters that control the relevance and influence of each input dimension, and σ_f^2 denotes the signal variance governing the overall output magnitude. These hyperparameters are learned by maximizing the marginal likelihood of the training data, enabling the model to automatically identify the most informative features while suppressing irrelevant ones. Owing to its probabilistic nature, GPR not only delivers accurate hybrid power predictions but also provides uncertainty estimates, making it particularly effective for modeling complex, nonlinear, and noisy behaviors in hybrid solar–wind energy systems.

5.3 Stacked Ensemble

The stacked ensemble model is designed to enhance hybrid power prediction accuracy by combining the complementary strengths of Boosted Trees and Gaussian Process Regression (GPR). In this approach, the individual predictions generated by the base learners are treated as meta-features and are integrated through a linear regression meta-model. Mathematically, the stacked prediction is expressed as:

$$\hat{P}_{\text{Hybrid}}^{\text{Stack}} = \beta_0 + \beta_1 \hat{P}_{\text{Hybrid}}^{\text{Boost}} + \beta_2 \hat{P}_{\text{Hybrid}}^{\text{GPR}} \qquad (14)$$

where $\hat{P}_{\text{Hybrid}}^{\text{Boost}}$ and $\hat{P}_{\text{Hybrid}}^{\text{GPR}}$ denote the predictions from the boosted tree and GPR models, respectively. The coefficients $\beta_0, \beta_1,$ and β_2 are learned using linear regression on a validation dataset, ensuring that the ensemble optimally balances the contributions of each base model. By leveraging the nonlinear learning capability of boosted trees and the probabilistic, smooth-function modeling of GPR, the stacked ensemble effectively reduces individual model bias and variance, leading to improved robustness and superior predictive performance for hybrid solar–wind power estimation.

5.4. Model Evaluation Metrics

The performance of the proposed ML models for output power prediction are evaluated based on RMSE. MAE, and R^2 metrics. The model with minimum RMSE is selected as the best predictor:

$$\text{Best Model} = \arg\min_{\text{model}} \text{RMSE}_{\text{model}} \qquad (15)$$

Final predictions for hybrid system:

$$\hat{P}^{\text{best}}_{\text{Hybrid}} = \begin{cases} \hat{P}_{\text{Boost}} & \text{if Boosted Trees is best} \\ \hat{P}_{\text{GPR}} & \text{if GPR is best} \\ \hat{P}_{\text{Stack}} & \text{if Stacked Ensemble is best} \end{cases} \quad (16)$$

The various range of the input and simulation parameters used for the hybrid solar-wind system design are illustrated in the Table 1.

Table.1 Simulation Parameters Ranges and Description

Parameter	**Typical Value / Range**	**Description**	**Units**
$N_{Samples}$	1000	Number of data samples generated	Count
$N_{Torque_{Sensors}}$	3	Number of torque sensors measuring wind torque	Count
Torque	Random values scaled by [50, 45, or 55]	Torque measurements from each sensor	Newton-meters (Nm) *(assumed)*
$Wind_{Speed}$	4 – 14	Wind speed affecting the hybrid system	m/s
Irradiance	200 – 1000	Solar irradiance impacting the PV system	W/m² *(assumed)*
$Solar_{Load}$	0.2 – 1.0	Solar load factor representing PV system load	Unitless (fraction)
$Ambient_{Temp}$	15 – 30	Ambient temperature around the PV system	°C
$Pv_{True_{Power}}$	Computed (with noise)	True photovoltaic power output (ground truth)	kW *(assumed)*
$Hybrid_{True_{Pow}}$	Computed (with noise)	True hybrid power output (wind + PV) (ground truth)	kW *(assumed)*

5.5 PV-Only Power Prediction Model

In addition to the hybrid system, a dedicated PV-only model is developed using boosted regression trees. This model predicts PV output power solely from irradiance, solar load, and temperature, enabling direct performance comparison between PV-only and hybrid systems. Such comparison highlights the advantages of hybrid energy integration under varying environmental conditions. In this section the performance of the only solar PV system output power is estimated using the Bagged Tree ML model. The output solar PV system power is modelled as;

$$\hat{P}^{\text{Boost}}_{\text{PV}} = \sum_{m=1}^{M} \gamma_m \, h_m(\mathrm{x}_{\text{PV}}) \quad (17)$$

The ground-truth PV power output is computed using a physically inspired linear relationship in which power generation increases proportionally with the product of solar irradiance and load factor, while higher ambient temperatures slightly degrade performance due to thermal losses. Gaussian noise is incorporated into the model to emulate real-world measurement uncertainty and system fluctuations. The resulting PV feature matrix, comprising irradiance, solar load, and temperature, is normalized and used to train a boosted trees regression model, enabling the learning of nonlinear dependencies among the inputs.

5.5.1 Model Training and Validation

The dataset is divided into training and testing subsets using an 80:20 hold-out strategy to prevent data leakage. Hyperparameters for ensemble models are optimized using cross-validation and Bayesian optimization where applicable. Model performance is evaluated using root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2), ensuring comprehensive assessment of both accuracy and robustness.

All model objects, scaling parameters (μ, σ), and selected feature indices are saved. This allows future prediction on new unseen samples via:

$$bbb\ \hat{y}_{\text{new}} = f_{\text{best}}\left(\frac{x_{\text{new}} - \mu}{\sigma}\right) \quad (18)$$

5.5.2 Model Deployment and Reusability

Finally, the optimal trained models, along with feature normalization parameters and selected feature sets, are stored for future deployment. This enables real-time prediction of hybrid and PV-only power outputs for unseen operational conditions, supporting intelligent energy management, forecasting, and decision-making in smart grid environments.

6. Results and Discussion

The results demonstrate the effectiveness of the proposed machine learning approach in accurately predicting the power output of a hybrid wind and PV system, highlighting its potential for optimizing the design and operation of such systems. The developed models and their associated parameters are saved for future use in real-world applications.

6.1 Performance Evaluation and Model Selection

The best-performing model is selected based on minimum RMSE on the test dataset. Prediction performance is further analysed through actual-versus-predicted scatter plots and residual error distributions, providing visual validation of model reliability and bias characteristics. For predictions $\hat{y}$vs ground truth y:

Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (19)$$

Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i | \quad (20)$$

Coefficient of Determination (R²)

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2}, \bar{y} = \frac{1}{N}\sum_i y_i \quad (21)$$

The performance of the hybrid solar wind system is investigate based on the above-mentioned parameters.

6.2 Results of Prosed Stacked Ensemble Methods

This section has presented the results and outcomes drawn from the simulation of the stacked ensemble base prediction and regression models for solar -Wind PV systems. Figure 5 illustrates the convergence behaviour of the machine learning (ML) optimization process by plotting the objective function value against the number of function evaluations. At the initial stage, a sharp reduction in the objective function is observed, indicating rapid learning and effective exploration of the solution space during the early evaluations. Both the minimum observed objective and the estimated minimum objective decrease significantly within the first few iterations, demonstrating the efficiency of the optimization algorithm in quickly identifying promising regions. As the number of evaluations increases, the objective function values gradually stabilize, showing only marginal improvements beyond approximately 5–7 evaluations.

This convergence trend indicates that the ML solution reaches an optimal or near-optimal state with minimal computational effort. The close overlap between the observed minimum and estimated minimum curves further confirms the robustness and reliability of the optimization process, suggesting that the model consistently converges toward a stable and well-defined optimal solution.

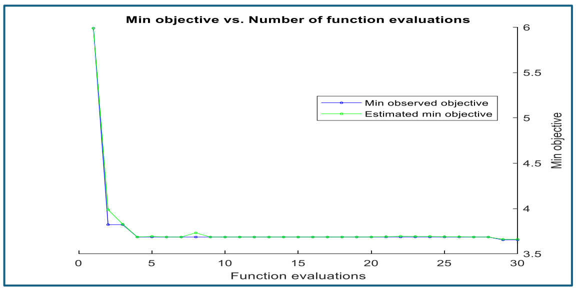

Figure.5 The Objective Function Vs Number of Evaluations for ML Solution

Figure.6 presents a comparative analysis of the actual and predicted power outputs for both the Solar PV system and the hybrid solar–wind system, highlighting the robustness and accuracy of the proposed machine learning model. In the upper plot, the predicted PV power closely follows the actual PV power across all sample indices, effectively capturing rapid fluctuations and peak variations caused by changes in solar irradiance and environmental conditions. The minimal deviation between the two curves demonstrates the model's strong generalization capability and its robustness against noise and short-term variability. In the lower plot, a similar trend is observed for the hybrid system, where the predicted hybrid power output aligns closely with the actual measurements over a wider operating range and higher power levels. Despite the increased complexity and variability associated with the combined wind and solar sources, the prediction model maintains stable performance and accurately tracks both low and high-power regimes. The consistent overlap between actual and predicted signals in both cases confirms the robustness of the model, indicating its ability to reliably predict power outputs under diverse operating conditions and dynamic system behaviour.

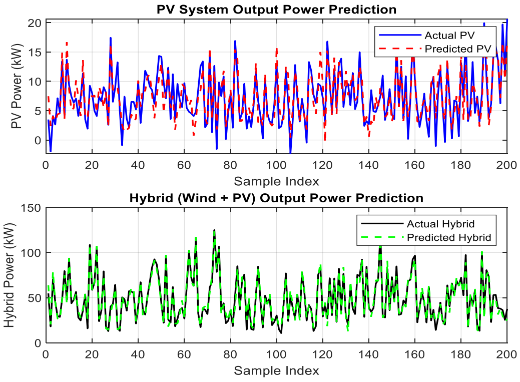

Figure.6 The Actual Power Vs Predicted Power of Solar PV System Using ML Solution

Figure 7 illustrates the regression model fitting results of the stacked ensemble regression model for the solar PV–based hybrid power system by comparing the predicted hybrid power against the actual measured values. The scatter points are tightly clustered around the ideal 45° reference line, indicating a strong linear agreement between the predicted and actual power outputs across the full operating range. This close alignment demonstrates that the stacked ensemble model effectively captures the underlying nonlinear relationships between input variables and system power output. The high coefficient of determination (R^2 = 0.96963) further confirms the excellent predictive capability of the model, showing that more than 96% of the variance in the actual hybrid power is accurately explained by the regression model.

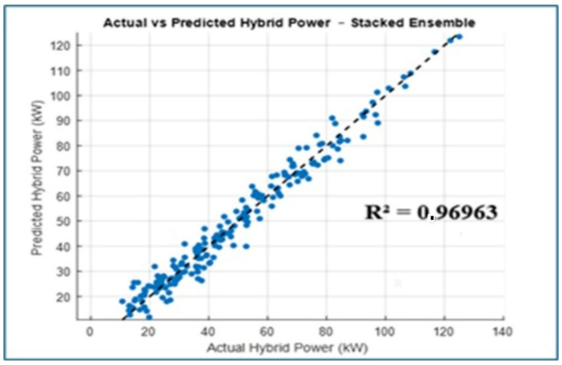

Figure.7 Results of The Regression Model Fitting for Data Splitting Ratio of 80/20 For
Stacked Ensemble Regression Model for Solar PV System

The limited dispersion of points around the regression line, even at higher power levels, highlights the robustness and stability of the model under varying operating conditions. Overall, these results validate the effectiveness of the stacked ensemble regression approach for accurate and reliable power prediction in solar PV–based hybrid energy systems.

6.2 Validation Performance of Solar PV System Alone

This section has presented the simulation and validation of the stand-alone Slokar PV system performance. Figure 8 illustrates the parametric performance of the validated Solar PV–only system using the stacked ensemble learning method, evaluated in terms of RMSE, MAE, and R^2.

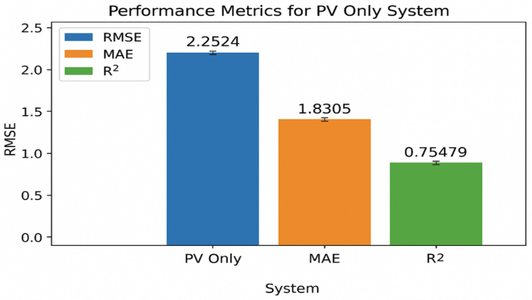

Figure.8 Parametric Performance of The Validated Solar PV System Only Using Stacked Ensemble Method

The results demonstrate that the stacked ensemble model achieves a low RMSE of 2.2524 and MAE of 1.8305, indicating high prediction accuracy with minimal deviation between the predicted and actual PV power outputs. These low error values confirm the model's effectiveness in learning the underlying relationship between solar irradiance, temperature, and PV power generation. Furthermore, the R^2 value of 0.75479 reflects a reasonably strong correlation between the predicted and measured outputs, showing that the model explains a substantial portion of the variability in the PV system performance.

Although the R^2 is lower compared to the hybrid system results, this behaviour is expected due to the relatively simpler and less variable nature of standalone PV generation. Overall, the validation results in Figure 8 confirm that the stacked ensemble method provides reliable and robust performance for Solar PV power prediction, making it suitable for accurate modelling and forecasting of PV-only energy systems.

6.3 Hybrid Solar-Wind System Performance Comparisons

Table 2 compares the prediction performance of the Solar PV–only system with that of the Hybrid solar-wind system using RMSE, MAE, and R^2 metrics. The PV-only system achieves lower RMSE (2.2524) and MAE (1.8305), indicating smaller absolute prediction errors, which can be attributed to the relatively simpler and more stable behavior of standalone PV power generation. However, its R^2 value of 0.75479 suggests a limited ability to capture the overall variability in power output. In contrast, the Hybrid system exhibits higher RMSE (4.3743) and MAE (3.4962), reflecting increased prediction complexity due to the integration of wind and solar sources, but it attains a substantially higher R^2 value of 0.96963. This indicates that the hybrid model explains the variance in power output much more effectively, demonstrating superior capability in capturing the combined dynamics of solar irradiance, wind speed, and torque effects despite the increased prediction error magnitude.

Table.2 Results Comparison for The Solar PV Vs Hybrid System Performance

System	RMSE	MAE	R^2
PV Only	2.2524	1.8305	0.75479
Hybrid System	4.3743	3.4962	0.96963

In this section the Table 3 presents a comparative analysis of the performance of different machine learning models for predicting hybrid solar–wind power output. The Boosted Trees model exhibits the weakest performance, with the highest RMSE (6.0961) and MAE (4.7633), indicating larger prediction errors despite achieving a relatively high R^2 value of 0.94102. In contrast, the Gaussian Process model significantly improves prediction accuracy, reducing RMSE and MAE to 4.4073 and 3.5143, respectively, while achieving a higher R^2 of 0.96917, which reflects its strong capability to model the nonlinear behavior of the hybrid system. Finally, the Proposed Stacked Ensemble model delivers the best overall results, achieving the lowest RMSE (4.3743) and MAE (3.4962) along with the highest R^2 value of 0.96963, demonstrating that integrating multiple learning algorithms enhances prediction robustness and accuracy.

Table.3 Comparative Performance Of 90/20 Splitting for Different ML Models for The Hybrid Solar-Wind Power Systems Prediction

Model	RMSE	MAE	R^2
Boosted Trees	6.0961	4.7633	0.94102
Gaussian Process	4.4073	3.5143	0.96917
Stacked Ensemble	4.3743	3.4962	0.96963

Overall, these results indicate that ensemble-based approaches are more effective than single models for capturing the complex interactions inherent in hybrid solar-wind power systems. As an another experiment the performance of different production methods are compared for the different data splitting ratios. Looking at Table 4, various ML models were tested using two different train-test splits - 80% or 70%. Performance was measured through RMSE, MAE, and R^2. Notably, Boosted Trees showed weaker predictions than others, carrying larger errors in both setups. Still, shifting from 80/20 to 70/30 brought minor gains, seen in R^2 creeping up slightly. On another note, Gaussian Process Regression cut down errors sharply, posting much better numbers across all indicators. Its strength likely comes from handling complex patterns more effectively.

Meanwhile, the top performer overall was the Stacked Ensemble method - it led every category, maintaining tight error control and peak R^2 values regardless of split. What stands out is how steady its performance stays, no matter how the data gets divided - R^2 never drops below 0.969 in either setup. This shows stacking strong models doesn't just lift prediction quality; it makes outcomes more reliable, less swayed by where you draw the line between training and testing.

Table.4 Comparative Performance for The Different Splitting Ratios

Model	Splitting ration of 80/20			Splitting ration of 70/30			T test for R^2
	RMSE	MAE	R^2	RMSE	MAE	R^2	
Boosted Trees	6.0961	4.7633	0.94102	5.9698	4.6888	0.94542	0.94322
Gaussian Process	4.4073	3.5143	0.96917	4.3851	3.4892	0.97055	0.96986
Stacked Ensemble	4.3743	3.4962	0.96963	4.3732	3.4744	0.97071	0.97017

The Figure 9 presented the results of the regression-based fitting for proposed data splitting ratio of 70/30 for proposed stacked Ensemble regression model for solar PV system. it can be observed that for the 70% train -test split data ration has outperformed in this case with the 0,9707 R^2 measure. data are closely distributed across the hyper plane.

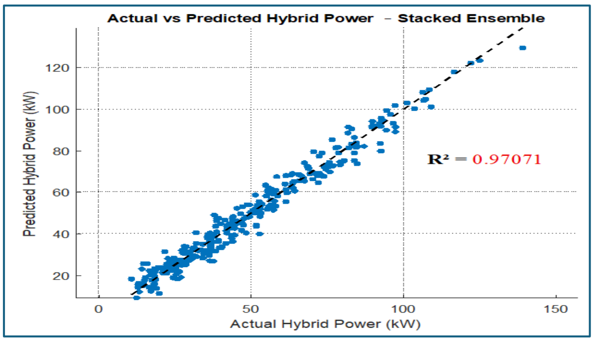

Figure.9 Results of The Regression Model Fitting for Proposed Data Splitting Ratio Of 70/30 for Stacked Ensemble Regression Model For Solar PV System

Looking at the results as in Table 5, one thing stands out: hybrid solar and wind system beats solar alone when predicting energy output. Solar by itself shows low error scores either way - small mistakes on average - but it only explains about three quarters of the changes in power. Switch that around, try a different data split, and sure, errors dip just a bit more. Yet the fit weakens slightly, showing how much depends on which data gets picked. Now take the combo system.

Table.5 Results Comparison for Different Split Rules for Solar PV Only Vs Hybrid System

System Splitting	RMSE	MAE	R^2
PV Only with 80/20	2.2524	1.8305	0.75479
PV Only with 70/30	2.2242	1.7968	0.74559
Hybrid System With 80/20	4.3743	3.4962	0.96963
Hybrid System With 70/30	4.3732	3.4744	0.97071

Nearly every time, it nails the pattern, grabbing almost all variation, hitting R^2 near 0.97 no matter the setup. That kind of consistency suggests it actually learns how sun and wind interact - not just guesses. Even so, the hybrid setup handles shifting conditions without much change in results. Because there is more going on inside it, errors like RMSE and MAE go up a bit. Still, every time we test it, the numbers stay close together. That steadiness shows it adapts well no matter how data gets split. On their own, solar-only models make fewer mistakes when things are straightforward. Yet they do not explain variations as clearly under complex demands. When real-world energy mixes come into play, this combined method holds up better overall.

Table.6 State of Art Methods Performance Compression

Reference	Method	R^2
Bhoopendra Patel [21] (2025)	Linear Regression (LR)	0.877
Abdullah et al. [25] (2024)	Multilayer Perceptron (MLP)	0.938
Bhoopendra Patel [21] (2025)	Neural Network	0.952
Proposed Method	Gaussian Process (GPR)	0.96917
Proposed Method	Stacked Ensemble	0.97071

Looking at Table 6, it is observed that, new method stacks up next to top techniques from recent studies - measured by R^2. Not far off, but not great either, traditional Linear Regression hits 0.877 according to Bhoopendra Patel [21]. That number suggests it struggles with complex patterns in hybrid energy setups. A step ahead, the MLP model from Abdullah et al. [25] reaches 0.938. Clearly, bending the math helps when things aren't straight lines. A boost shows up when using solo Neural Networks, hitting an R^2 score of 0.952 according to study [21]. When switching to the suggested Gaussian Process Regression approach, the number climbs - reaching 0.96917, represented the better adaptability and sharper handling of uncertainty. Performance creeps even higher with the layered ensemble strategy, landing at 0.97071, topping every other tested option. It turns out this combined system beats current top models, proving it can map tangled patterns in solar-wind energy forecasts more precisely.

7. Conclusions and Future Scopes

The research has designed a ML solution for predicting the output power of the solar-wind hybrid power sputum to be used for Telecomm base stations. Results demonstrated that how well this ML method predicts power output in combined wind and solar setups. Instead of relying on a single model, the technique uses a mix of Boosted Trees with Gaussian Process Regression, each bringing something unique to the table. Results show it handles data more precisely, scoring nearly 0.97 on the R^2 scale while keeping errors low - under 4.4 for RMSE, just above 3.4 for MAE. That level of accuracy beats what either model achieves alone: pure GPR lands slightly below 0.97, and Boosted Trees fall near 0.94. What stands out is how combining methods captures complex patterns across different kinds of weather inputs. Not every fusion strategy works this smoothly, yet here the blend makes a clear difference.

For the PV-only system, the stacked ensemble model achieves an RMSE of 2.2524, MAE of 1.8305, and $R^2 = 0.75479$, demonstrating its capability to accurately model the comparatively simpler dynamics of standalone photovoltaic generation. Comparative analysis further reveals that hybrid system models explain over 96% of the variance in power output, emphasizing their ability to capture complex cross-domain interactions between wind and solar inputs. Although hybrid systems exhibit higher absolute prediction errors due to increased system complexity, the ensemble framework maintains stable and consistent performance across different train–test splitting ratios, reinforcing its robustness and suitability for practical deployment.

The future research adding pieces like batteries, electric car charging needs, or flexible user demands into the method, building a fuller picture of how mixed energy setups can work. Instead of fixed rules, trying out systems that learn on the fly might help handle shifting weather patterns and changing usage over time. Starting with smarter ways to pull meaningful details from data, paired with complex network designs, could lead to better forecasts and clearer reasoning behind decisions. Testing these ideas with actual grid performance records, then running them inside live smart networks, would move things closer to practical use at scale.

References

[1]. Salman, M., Kashif, S.A.R., Fakhar, M.S. *et al.* Optimizing power generation in a hybrid solar wind energy system using a DFIG-based control approach. *Sci Rep* **15**, 10550 (2025). https://doi.org/10.1038/s41598-025-95248-8

[2]. Solanke, Aman & Kumar Verma, Suman & Kumar, Satyam & Oyinna, Benneth & Okedu, Kenneth. (2024). MPPT For Hybrid Energy System Using Machine Learning Techniques. Journal of Modern Technology. 1(1). August 2024. https://doi.org/10.71426/jmt.v1.i1.pp19-37 .

[3]. Bhoopendra Patel, H. N. Suresh, Designing Machine Learning Solution to Optimize Hybrid Solar-Wind Energy System Performance: Impact of Wind Speed, Journal of Electrical Systems, Vol. 21 No. 01 (2025), https://doi.org/10.52783/jes.9107

[4]. K. P. Natarajan and J. G. Singh, "Solar Power Forecasting using Stacking Ensemble Models with Bayesian Meta-Learning," *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Delhi, India, 2023, pp. 1-6, doi: 10.1109/ICCCNT56998.2023.10308202.

[5]. Zakria Qadir, Sara Imran Khan, Erfan Khalaji, Hafiz Suliman Munawar, Fadi Al-Turjman, M.A. Parvez Mahmud, Abbas Z. Kouzani, Khoa Le, Predicting the energy output of hybrid PV–wind renewable energy system using feature selection technique for smart grids, Energy Reports, Volume 7, 2021, Pages

8465-8475, https://doi.org/10.1016/j.egyr.2021.01.018 .

[6]. Bhoopendra Patel, Dr. H. N. Suresh, Predicting Output Power of Hybrid Solar-Wind Energy system using ML based Neural Network Regression Model, High Technology Letters, Volume 31, Issue 9, 2025, http://www.gjstx-e.cn

[7]. D. I. Alvarez, C. J. Calle Castro, F. C. Gonzalez, A. L. Uguña and J. F. T. Toledo, "Modeling and simulation of a hybrid system solar panel and wind turbine in the locality of Molleturo in Ecuador," *2017 IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA)*, San Diego, CA, USA, 2017, pp. 620-625, doi: 10.1109/ICRERA.2017.8191134.

[8]. Y. Boujamaoui and T. Jarou, "Analysis, production prediction, modeling, and supervision of photovoltaic-wind hybrid power plants – A systematic literature review," *2025 11th International Conference on Optimization and Applications (ICOA)*, Kenitra, Morocco, 2025, pp. 1-6, doi: 10.1109/ICOA66896.2025.11236852

[9]. J. L. San Juan and C. Sy, "A Machine Learning Augmented Game Theory-Based Approach to Hybrid Renewable Energy System Optimization," *2024 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Bangkok, Thailand, 2024, pp. 97-101, doi: 10.1109/IEEM62345.2024.10857214.

[10]. Roy, Subhajit, et al. "Machine Learning–Enabled Solar Photovoltaic Energy Forecasting for Modern-Day Grid Integration: A Virtual Power Plant Perspective." *Forecasting Methods for Renewable Power Generation* (2025): 243-277.

[11]. Sengar, S., Liu, X. Ensemble approach for short term load forecasting in wind energy system using hybrid algorithm. *J Ambient Intell Human Comput* **11**, 5297–5314 (2020). https://doi.org/10.1007/s12652-020-01866-7

[12]. K. P. Natarajan and J. G. Singh, "Solar Power Forecasting using Stacking Ensemble Models with Bayesian Meta-Learning," *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Delhi, India, 2023, pp. 1-6, doi: 10.1109/ICCCNT56998.2023.10308202

[13]. Khan, P.W., Byun, Y.C. & Jeong, OR. A stacking ensemble classifier-based machine learning model for classifying pollution sources on photovoltaic panels. *Sci Rep* **13**, 10256 (2023). https://doi.org/10.1038/s41598-023-35476-y

[14]. M. A. Khan, M. Taha, R. Shahid, M. S. Asad, H. Elahi and M. A. Tayyab, "Machine Learning Based Energy Prediction of Hybrid Solar-Wind Energy Harvesters Using MPPT," *2024 International Conference on Robotics and Automation in Industry (ICRAI)*, Rawalpindi, Pakistan, 2024, pp. 1-6, doi: 10.1109/ICRAI62391.2024.10894090.

[15]. Rai, A., Shrivastava, A., & Jana, K. C. (2023). An Empirical Analysis of Machine Learning Algorithms for Solar Power Forecasting in a High Dimensional. Uncertain Environment. *IETE Technical Review*, *40*(4), 558–573. https://doi.org/10.1080/02564602.2022.2136270

[16]. I. Hassan *et al.*, "A Predictive Stacking Framework for Energy Output in Photovoltaic System with Uncertainty Estimates," in *IEEE Access*, vol. 13, pp. 154046-154068, 2025, doi: 10.1109/ACCESS.2025.3604038.

[17]. Azad, Abdus Samad and Islam, Nahina and Nabi, Md. Nurun and De Silva, Shameenda and Sokkalingam, Rajalingam, Artificial Intelligence Applications in Hybrid Renewable Energy Systems: A Comprehensive Review of Techniques, Applications, and Challenges. Available at http://dx.doi.org/10.2139/ssrn.5292704

[18]. Aparna Unni, Harpreet Kaur Channi, Ramandeep Sandhu, Aayush Anand,Chapter 16 - Solar power prediction using computer vision and machine intelligence: Predicting and optimizing solar energy generation, Editor(s): Seifedine Kadry, Shubham Mahajan, In Advances in Reliability Science, Reliability Analysis and Modeling for Complex Systems, Elsevier, 2026, Pages 339-364, https://doi.org/10.1016/B978-0-443-33655-3.00005-5.

[19]. N. Jannah, T. S. Gunawan, S. H. Yusoff, M. S. A. Hanifah and S. N. M. Sapihie, "Recent Advances and Future Challenges of Solar Power Generation Forecasting," in *IEEE Access*, vol. 12, pp. 168904-168924, 2024, doi: 10.1109/ACCESS.2024.3496120.

[20]. Sengar, S., Liu, X. Ensemble approach for short term load forecasting in wind energy system using hybrid algorithm. *J Ambient Intell Human Comput* **11**, 5297–5314 (2020). https://doi.org/10.1007/s12652-020-01866-7

[21]. Bhoopendra Patel, Dr. H.N. Suresh, “Predicting Output Power of Hybrid Solar-Wind Energy system using ML based Neural Network Regression Model”, High Technology Letters, Volume 31, Issue 9, 2025.

[22]. Zakria Qadir, Sara Imran Khan, Erfan Khalaji, Hafiz Suliman Munawar, Fadi Al-Turjman, M.A. Parvez Mahmud, Abbas Z. Kouzani, Khoa Le, Predicting the energy output of hybrid PV–wind renewable energy system using feature selection technique for smart grids, Energy Reports, Volume 7, 2021, Pages 8465-8475, https://doi.org/10.1016/j.egyr.2021.01.018.

[23]. Rajaperumal, T.A., Christopher Columbus, C. Enhanced wind power forecasting using machine learning, deep learning models and ensemble integration. *Sci Rep* **15**, 20572 (2025). https://doi.org/10.1038/s41598-025-05250-3

[24]. Rushdi, M.A.; Yoshida, S.; Watanabe, K.; Ohya, Y.; Ismaiel, A. Deep Learning Approaches for Power Prediction in Wind–Solar Tower Systems. *Energies* **2024**, *17*, 3630. https://doi.org/10.3390/en17153630

[25]. Abdullah, B.U.D.; Khanday, S.A.; Islam, N.U.; Lata, S.; Fatima, H.; Nengroo, S.H. Comparative Analysis Using Multiple Regression Models for Forecasting Photovoltaic Power Generation. Energies 2024, 17, 1564. https://doi.org/10.3390/en17071564

[26].