Research Article

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Forecasting Solar Photovoltaic Power Generation with the Use of Machine Learning Algorithms

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ABSTRACT

Estimation of solar photovoltaic (PV) power generation is necessary to predict accurately the further functioning of the grid, energy planning, and massive integration of renewable energy sources. Nevertheless, dynamic nature of PV systems, intermittent solar irradiance, and meteorological conditions which change at a very high rate all render it challenging to have a reliable prediction. This paper proposes a Hybrid Machine Learning Approach of a Dynamic Weighting Mechanism (DWM-HMLA) in the short-term solar PV power prediction. The presented framework combines various heterogeneous machine learning models into an ensemble structure, in which a dynamic weighting scheme dynamically modulates the contribution of individual base learners in real-time according to the current environmental factors and recent errors in prediction. The proposed DWM-HMLA was tested with the help of the real-life solar PV data taken in various geographical areas and under various meteorological conditions. The proposed architecture is a combination of Support Vector Regression (SVR), Random Forest (RF), and Artificial Neural Network (ANN) models in an ensemble architecture. It has been experimentally demonstrated that the proposed method attains a Root Mean Square Error (RMSE) of 0.214 kW, a Mean Absolute Error (MAE) of 0.167 kW, and a coefficient of determination (R^2) of 0.962. The forecasting accuracy of the proposed approach is 12.8% and 15.3% higher in the average of RMSE and MAE respectively. The adaptive weighting mechanism allows the non-linear time patterns to be processed in an effective manner and also ensures robustness when the weather conditions change rapidly. The findings indicate that DWM-HMLA is a stable and scaled forecasting platform, which can be used to integrate renewable energy, balance grids, and energy market. Proper predictions made by the suggested model can help the operators of the systems and policymakers to make the most out of their resource allocation and minimize reliance on standard power generation. The results of forecasting the proposed DWM-HMLA can be implemented directly in the short-term operational decision making in grid management whereby precision intraday solar PV power estimates are needed to adjust unit commitment to the reserve commitment and real-time load balancing.

Keywords: Solar photovoltaic power forecasting; Hybrid machine learning ensemble; Dynamic weighting mechanism; Short-term PV prediction; Meteorological feature integration.

1. INTRODUCTION

The machine learning algorithms have challenging issues that affect the accuracy and reliability of predicting the solar PV power production (Theocharides *et al.* 2020). The unpredictability of solar power and the intermittency are some of the problems associated with it. The generation of solar power is dynamic and it depends on weather condition, cloud cover, and seasons, and thus it is hard to estimate and predict (Yagli *et al.* 2019). This is due to the various combinations of climatic factors with one another as well as with solar energy making accurate predictions difficult (Zhou *et al.* 2020). Absence of precise historical data makes machine learning algorithms ineffective to identify patterns and correlations (Kuzlu *et al.* 2020). The solar technology is in a state of continuous development and hence no standard data collection method exists. The sudden development of solar panel technology, energy storage and grid integration provides volatility to model forecasts (Feng *et al.* 2020). Since solar systems use a variety of data formats and measurement techniques, it is difficult to develop machine learning algorithms that can be used everywhere (Mellit *et al.* 2021). Models should be revised to reflect the changes in technology and work with diverse solar installations in order to give relevant and flexible forecasts on solar PV power output (Jebli *et al.* 2021). It is also extremely important to locate models that can be understood (Li *et al.* 2020). Opaque deep learning models and machine learning algorithms are something one cannot easily understand (Khandakar *et al.* 2019). It is essential that the solar energy forecasting be interpretable to impress the stakeholders, grid operators as well as legislators. These problems have to be addressed by academics, businesspersons, and the government officials. This will enhance the integration of solar energy in the energy grids (Wang *et al.* 2019).

Most predictive methods of data-driven models have been exploited to utilize solar PV power production

forecasting using a variety of machine learning methods (Rajagukguk *et al.* 2020). The complicated associations between solar energy production and meteorological conditions can be learned using Support Vector Machines (SVMs), Random Forests, and Gradient Boosting Machines (Mellit *et al.* 2020). Neural networks and Long Short-Term Memory (LSTM) networks have also been applied to forecast solar power production trends along with Autoregressive Integrated Moving Average models and other time-series forecasting models (Sharifzadeh *et al.* 2019). These measures combine past information, up-to-date weather and system conditions to give accurate forecasts (Huang and Kuo, 2019). With the shifting climatic conditions, as well as intermittent generation of solar energy, it is challenging to make accurate projections. There is no standardization of data formats and methodologies of measuring various solar panels installed in different locations, creating a challenge in constructing models that work anywhere (Ağbulut *et al.* 2021). Predictions made by deep learning are difficult to interpret, particularly when dealing with complex deep learning models (Sun *et al.* 2019). Environmental uncertainty, enhancement of data standards, and better model interpretability management are necessary to render machine learning-based solar PV power production forecasting systems realistic.

Conventional machine learning models for solar photovoltaic power forecasting degrade under rapidly changing meteorological conditions due to static parameterization and fixed error distributions, which limits adaptability to non-stationary irradiance and temperature dynamics. Sudden cloud cover and atmospheric transmittance variations cause high-frequency variance and temporal discontinuities in input feature spaces, biasing gradient updates in neural networks and unstable decision boundaries in tree-based models. This increases prediction variance and decreases generalization when trained on historical averages. Model-specific inductive biases, such as linear regressors underfitting nonlinear irradiance–power correlations and complicated models overreacting to short-term noise, cause volatility in prediction outputs in single-model forecasting frameworks.

Solar photovoltaic power forecasting studies mostly use single-model learning frameworks or static ensemble approaches with fixed model contributions across time and operational circumstances. Prior approaches improve accuracy under stable irradiance patterns, but they don't account for heterogeneous learners' time-varying relevance under non-stationary meteorological dynamics, especially during rapid irradiance transitions and regime shifts caused by cloud intermittency. Ensemble-based weight optimization employing global error statistics or offline calibration limits responsiveness to short-term distributional changes in input characteristics. Lack of a method for continuous, error-sensitive predictive influence redistribution across complimentary models at runtime is the restriction. An adaptive weighting formulation dynamically aligns model contributions with localized forecasting performance in the proposed DWM-HMLA, improving resilience and consistency across varied temporal and environmental variables.

- A Hybrid Machine Learning Approach-based Dynamic Weighting Mechanism (DWM-HMLA) is proposed to accurately anticipate solar photovoltaic system power output. The research aims to enhance power generation estimates by addressing the dynamic behavior of PV systems, unpredictability of weather, and intermittent nature of solar energy.

- The DWM-HMLA now has a dynamic weighting mechanism that can adjust machine learning algorithm weights in real time. This adaptive technique ensures the ensemble model efficiently adapts to changing environmental variables, improving forecast accuracy and reliability.

- The research shows the application of DWM-HMLA in energy market operations, grid balancing, and renewable energy planning. The suggested method provides reliable projections to assist policymakers allocate resources and lessen dependence on traditional electrical sources, creating a more sustainable and resilient energy environment.

2. LITERATURE SURVEY

The constantly evolving solar energy forecasting sector comes up with new methodology and approaches as seen in the contribution of the recent research. Based on thorough analyses of the metaheuristic and machine learning methods to solar energy forecasting to stacked ensemble models, this section reflects the key findings of them in the study, which includes the importance of the choice of predictors, the adjustment of hyperparameters and modeled physics. These developments improve the reliability, strength and predictability of models of solar energy forecasting.

Khan *et al.* (2022) introduced a stacked ensemble model (DSE-XGB) featuring Extreme Gradient Boosting, Artificial Neural Networks, and Long Short-Term Memory networks, resulting in significant R^2 improvements over individual models and bagging-based ensembles. These findings support multi-model integration, although the stacking technique uses fixed meta-learned weights throughout inference. This approach presupposes stable learner-input connections, which restricts response to quickly changing irradiance patterns and climatic regime alterations. Besides ensemble creation, algorithm-level comparisons and

optimization techniques have been studied. Akhter *et al.* (2019) examined metaheuristic and machine learning PV power forecasting methods across forecasting horizons, data requirements, and optimization methods. This technique helps choose forecasting models, but it does not address diverse learners' interaction or relative importance under time-varying environmental variables. Adaptability at the system level is unexplored. High-resolution, site-specific studies emphasize data features and predictor selection. Markovics and Mayer (2022) tested numerous machine learning models for PV forecasting using multi-year datasets from several PV installations. Compared to persistence and linear regression models, proper feature selection and hyperparameter tweaking significantly minimize predicting error. Physical knowledge in learning systems may improve resilience, especially under data shortage. Luo *et al.* (2021) proposed a physics-constrained LSTM model that embeds PV system behavior into learning, improving stability and accuracy over standard machine learning methods. This technique enforces physical consistency but relies on predetermined limits and does not address how several learning paradigms may be dynamically coordinated as their predictive capabilities change. Systematic evaluations of big data–driven solar PV forecasts verify that machine learning methods, especially neural network–based models, dominate because to their nonlinear modeling and scalability (De Freitas and Alves-Souza, 2019). Deep learning models offer great accuracy under complicated settings, whereas extreme learning machines are computationally efficient. These studies mostly cover algorithmic performance and popularity, not how forecasting systems can handle non-stationary input distributions and temporally variable model dependability, which are major difficulties in practical PV forecasting.

Current research shows that sophisticated learning architectures, optimization methods, and domain-informed models increase forecasting accuracy. However, static model selection, fixed ensemble weighting, and offline optimization presume steady data-generating processes, which limits the literature. Solar irradiance and weather-driven power production are dynamic; hence this assumption is wrong. The proposed DWM-HMLA allows continuous, error-driven model contribution adaptation, allowing the forecasting system to realign predictive influence among complementary learners in response to localized performance and changing meteorological conditions.

3. PROPOSED METHOD

Dynamic Weighting Mechanism-Hybrid Machine Learning Approach is a pioneering tool in forecasting the solar PV energy generation. The strengths of diverse devices are integrated to understand the methods of addressing the issues of challenges developed by PV machine dynamics and weather uncertainty. The DWM-HMLA can change in real time on the basis of dynamic weighting to suit the environment.

Local, error-driven, constantly updated weighting formulation of DWM-HMLA acts at the prediction interval level rather than training or validation, distinguishing it from ensemble and adaptive weighting approaches. Bagging, boosting, and stacking use global performance statistics or meta-learned coefficients to estimate model contributions, which stay stable throughout deployment and assume data distribution stationarity. The proposed DWM-HMLA computes weights utilizing rolling-window residual errors, allowing real-time predictive influence reassignment depending on localized model dependability under meteorological circumstances. It enforces a convex, inverse-error optimization constraint at every forecasting step, ensuring stability and responsiveness to rapid irradiance fluctuations, unlike adaptive ensembles that update weights at coarse temporal scales or use heuristic rule-based switching.

The dynamic renewable energy market needs accurate forecasts of solar photovoltaic power produced green electricity. Fig. 1 presents the machine learning (ML) methodologies of this forecasting work. The initial and the most prominent one is to collect key solar power manufacturing information, such as weather and time. This fundamental step as depicted in the figure is a holistic dataset that depicts the multidimensionality of solar power generation. This fact preconditions further. In the second section, there is statistical pre-processing. This is an essential part that needs to be cleaned and standardized to produce uniformity and remove noise in incoming data. This is the intermediate stage that systematizes data to do additional modeling. The dataset is prepared after being cleaned and normalized and is now prepared to undergo prediction training. The parameters are selected to enhance the pattern-recognizing and prediction capacities of the version. The forecasting tool is enhanced by getting the version to understand statistics. Random Forests and Support Vector Machines are most of these models. The solar power prediction ML workflow is heavily depended on validation. The sixth step in is the implementation of solar energy generation projection model. This level transforms acquired styles into projections in quick energy management decisions. With the new data, the system is able to adjust to the changes in the environment, and improve its predictions. The resulting solar power forecasting ML process was evaluated and optimized iteratively and fully, to estimate the solar power PV electricity. The data collection and visualization of the technique enables the precise and reliable estimation of solar electricity, and this helps in the effective control of strength sustainability.

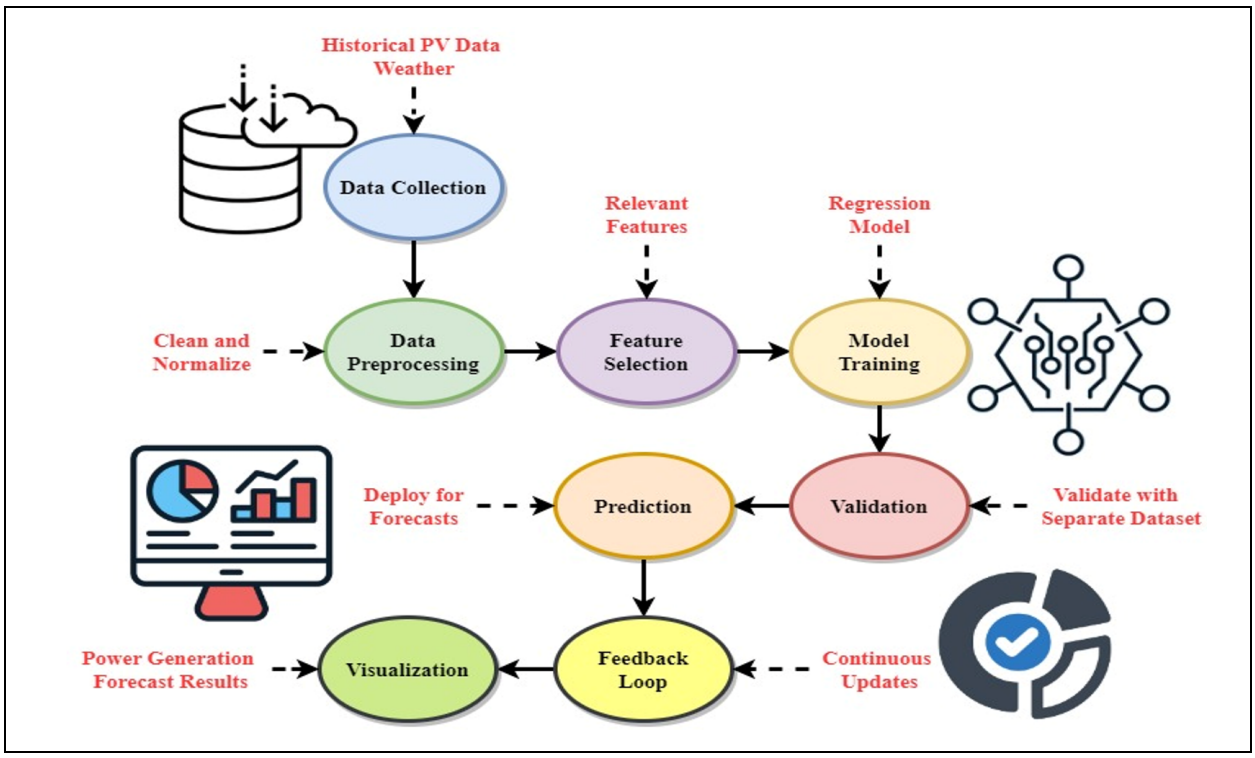


Fig. 1: Solar power forecasting machine learning process

The feature ($Performance_{Locals}$) equation (1) displays the test of performance across various locales for solar photovoltaic strength production forecasts utilizing a Dynamic Weighting Mechanism. Every location ((j)) is described by using particular instances ((B_j)) in conjunction with contrasted with a trendy value ((C_j)). To maximise overall performance, the dynamic mass ((X_j)) was adjusted in real-time. The correlations between circumstances are governed by using parameters like ((β_j, γ_j, δ_j, α_j, ϵ_j, ϑ_j)), which employ logarithmic, exponential, and square root functions. Factors ((φ_{jk}, x_{jk}, Ψ_{jk}, θ_{jk})) that contribute to the complexity of the product term within each locality are sinusoidal functions ((sin, cos)). The elaborate processes of solar irradiance prediction are captured through these metrics, which enable a detailed examination of performance in specific locations.

The solar irradiance at a given time (u) is represented through ($T(u)$) in equation (2) for solar irradiance evaluation. The baseline for the provision of sun strength is supplied with the aid of the extra-terrestrial radiation from the Sun, denoted as (H_u). The parameter d shows the percentage of the sky protected by using clouds, while D_{max} shows the highest feasible percent of cloud cover. The coefficient of attenuation for air mass, represented as β, impacts the penetration of solar radiation into the Earth's ecosystem. $E(u)$ is a representation of the air volume at time u. Just as $B(u)$ represents the aerosol optical thickness at time u, the coefficient of attenuation for aerosol optical size, which impacts the scattering of radiation from the sun through aerosols, γ does the same. The complex interaction among solar irradiance and temperature is captured through the addition of parameters, δ and α, which introduce a depending on temperature time period $1 + e^{-\alpha.U(u)}$. This term accounts for the nonlinear relationship amongst temperature ($U(u)$) and solar irradiance.

The adaptability evaluation at a selected time (u) is represented by $BB\,(u)$ within the intricate adaptability analysis equation (3). The anticipated and real electricity technology at that precise moment are denoted through $Q_{forecast,u}$ and $Q_{actual,u}$, respectively. An exponential decay coefficient $exp\left(-\frac{\Delta_u}{\tau_j}\right)$ governs its time-dependent adjustment, and $X_j(u)$ represents the dynamic weight applied to the j^{th} gadget mastering algorithm. To keep a stability between adaptability and balance, the environment's adaptability element at time u is represented through $F_{env,u}$. Each algorithm's responsiveness is stricken by τ_j, a time regular that is particular to it, and (Δ_u) which reflects the time that has exceeded from the remaining model replace. A cube root term affords a nuanced evaluation of the past dependability of the j^{th} approach, that is contemplated inside the historic performance ($IQ_j(u)$).

$$Performance_{Locals} = \sum_{j=1}^{O}\left[X_j.\left(\frac{\beta_j.log_{\gamma_j}\left(\frac{B_j^{\delta_j}}{C_j^{\alpha_j}+1}\right)}{\sqrt{\epsilon_j+e^{-\vartheta_j.(B_j-C_j)}}}.\prod_{k=1}^{n}(\theta_{jk}.\sin(\varphi_{jk}.B_j)+\Psi_{jk}.\cos(x_{jk}.C_j))\right)\right] \quad \ldots (1)$$

$$T(u) = H_u.\left(1-\frac{d}{D_{max}}\right).\left(1-e^{-\beta.E(u)}\right).\left(1-e^{-\gamma.B(u)}\right).\left(1+\frac{\delta}{1+e^{-\alpha.U(u)}}\right) \quad \ldots (2)$$

$$BB(u) = \frac{1}{O}\sum_{j=1}^{O}\left[\frac{|Q_{forecast,u}-Q_{actual,u}|}{Q_{actual,u}} \times \frac{X_j(u)\times exp\left(-\frac{\Delta_u}{\tau_j}\right)}{\sqrt{F_{env,u}}} \times \sqrt[3]{IQ_j(u)}\right] \quad \ldots (3)$$

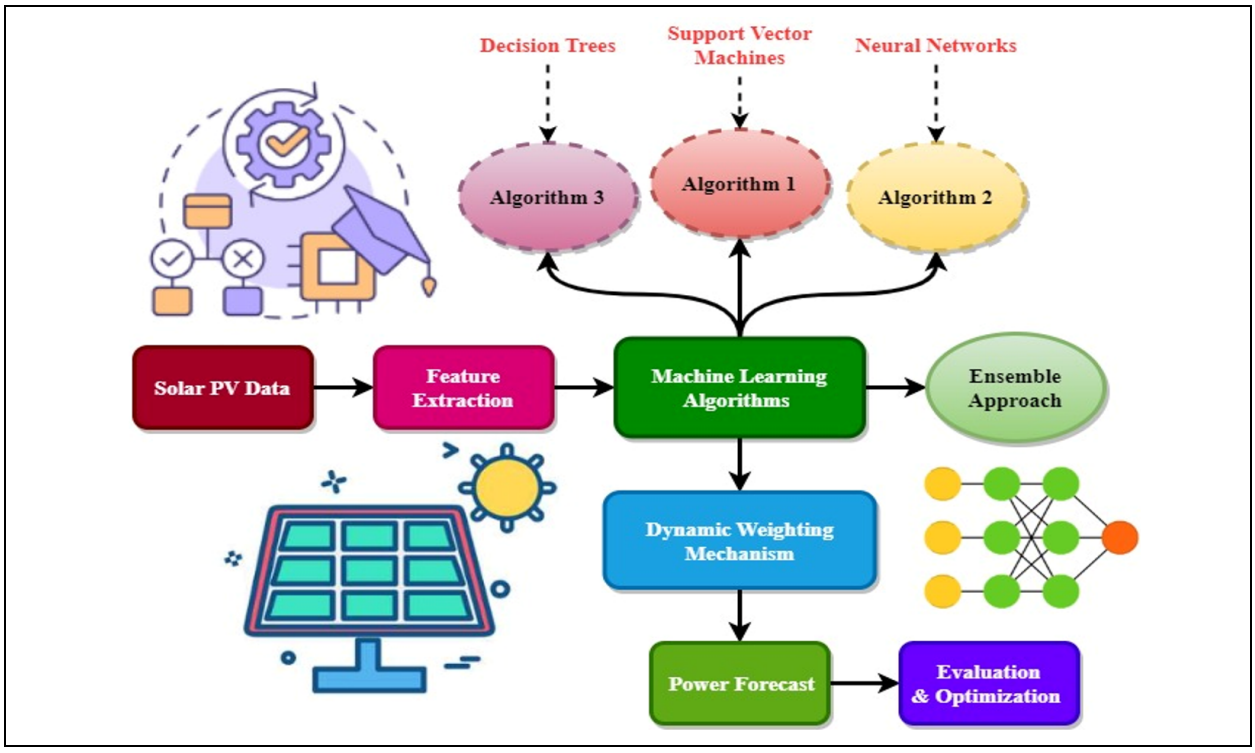


Fig. 2: Solar Forecasting Adaptive Ensemble System (SoFAES)

The Solar Forecasting Adaptive Ensemble System (SoFAES) is an all-inclusive framework, which is a good model in predicting solar PV power production both accurately and dynamically. Fig. 2 displays the principal components of the system and the data flows in the system which points out that it is always evolving and employs very sophisticated device learning algorithms. SoFAES uses the entry layer of Solar Photovoltaic Data block. That comprises live photovoltaic cell measurements of the changing and intermittent solar electricity. Complex and dynamic solar data requires a smart device that can adapt. Feature extraction involves finding relevant characteristics in solar PV numbers. The algorithms collaborate to improve the prediction by addressing favorable aspects of the complex solar strength data. Decision tree models, Support Vector Machines, Artificial Neural Networks, and others improve the device's prediction abilities. With Dynamic Weighting Mechanism, SoFAES adapts in real time. This computer adjusts neural community algorithm weights based on the surroundings. Power generation forecasts are continuously accurate due to SoFAES's real-time change, which enables the device to react fast to shifts in climate patterns. The Power Forecast, the closing product, is an estimation of the solar PV electricity production based totally on accurate information. In the Evaluation and Optimization stage, the gadget's performance is monitored and adjusted on an on-going foundation. This guarantees that SoFAES keeps its effectiveness irrespective of the location, weather, or system setup. By simulating actual solar PV datasets, researchers may additionally examine the gadget's robustness and versatility.

The system offers significant advantages for renewable power planning, grid balancing, and energy market operations. It exploits the diversity in prediction abilities through combining the benefits of a couple of

predictive device learning algorithms. The dynamic weighting procedure guarantees that the device adapts continuously to converting situations, making it a reliable device for strength stakeholders and policymakers. With every new update and improvement, SoFAES proves itself to be an adaptable and truthful device for tackling the demanding situations of renewable electricity production prediction.

At time u, the dependability of the device, as indicated by way of the dependability evaluation equation (4), is represented via $E(u)$. The chance of the gadget breaking at the cutting-edge time is represented by means of the immediately rate of failure at time t, which is $(\lambda(t))$. The second derivative of the failure rate, which emphasizes variations in the trend of the failure rate over the years, is captured *via* the $\frac{\partial^2 \lambda(t)}{\partial t^2}$. Adjustable parameters δ, γ, and β have an effect on the effect of the initial and second versions on reliability. The critical of $(e^{-\gamma(t-v)})$ and $\frac{\partial \lambda(v)}{\partial v}$ takes into account the relationship between the primary by-product and its beyond values, which enables to investigate the reliability of the DWM-HMLA very well by means of which includes each the present and beyond dynamics inside the failure rate.

The O represents the total amount of occurrences in the dataset, reflecting the evaluation scales, inside the complicated accuracy equation (5). Q_j is the expected strength era for the j^{th} instance in keeping with the DWM-HMLA, and B_j is the actual power generation used for evaluation. The dynamic weight component (β) adjusts the impact of the relative percentage error time period, making the version adaptable to shifting styles. Similarly, γ permits adaptability in highlighting intricate relationships by way of acting as a dynamic weight component for the sigmoid-based term. The shape of the time period is laid low with the steepness parameter (δ) which governs the sigmoid characteristic, and the impact on standard accuracy is modulated through the scaling parameter (σ). By combining conventional error measurements with a sigmoid-primarily based detail, equation (5) offers a complicated and flexible assessment of DWM-HMLA's forecasting skills within the framework of solar power production. Equation (5) is introduced as a supplementary evaluation metric to complement standard forecasting measures rather than replacing RMSE, MAE, or MAPE. In the revised manuscript, RMSE, MAE, and MAPE are explicitly reported for all experiments to ensure direct comparability with existing studies. While these conventional metrics quantify average prediction error magnitude, equation (5) is designed to additionally capture reliability and stability under non-stationary solar irradiance conditions by combining normalized absolute deviation with a bounded sigmoid-based modulation term.

$$E(u) = exp\left(-\int_0^u \lambda(u)\left[1 + \frac{\beta}{\gamma}\left(\frac{\partial^2 \lambda(t)}{\partial t^2}\right) + \delta \int_0^t e^{-\gamma(t-v)}\left(\frac{\partial \lambda(v)}{\partial v}\right) dv\right]\right) \quad \ldots (4)$$

$$Accuracy = \frac{1}{O}\sum_{j=1}^{O}\left[1 - \beta \times \left(\frac{|Q_j - B_j|}{\max(Q_j, B_j)}\right) + \gamma \times \frac{1}{1+e^{-\delta \times \left(\frac{Q_j - B_j}{\sigma}\right)^2}}\right] \times 100 \quad \ldots (5)$$

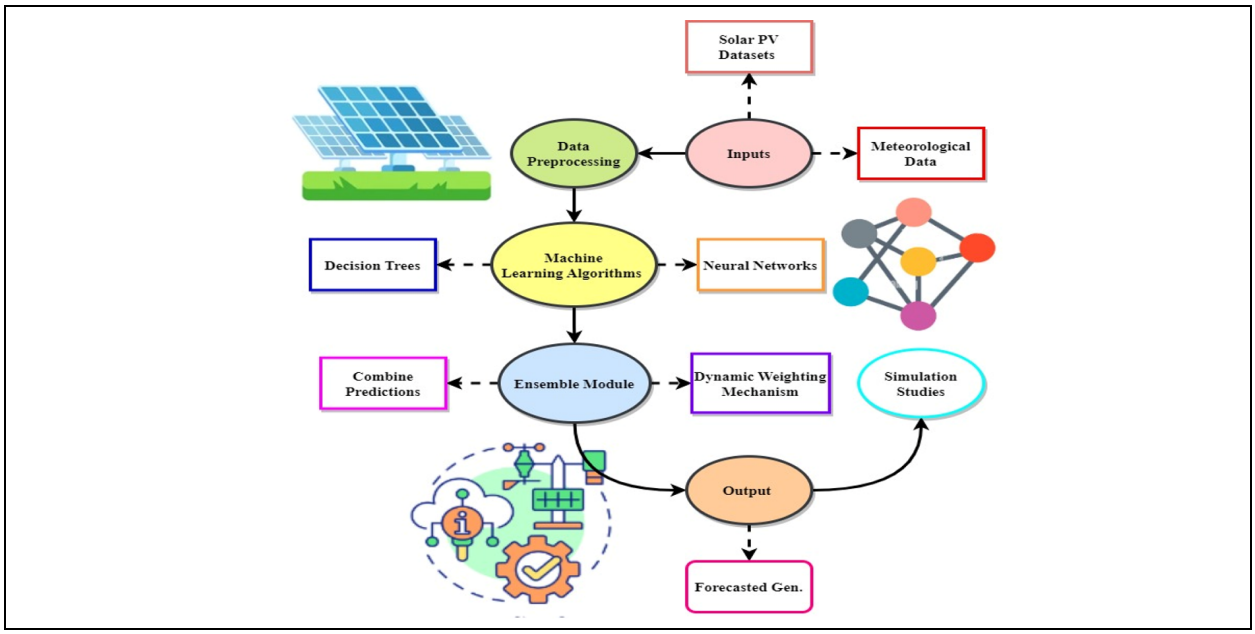


Fig. 3: Dynamic Weighting Mechanism-based Hybrid Machine Learning Approach (DWM-HMLA)

Fig. 3 illustrates how essential components are continually interacting with each other, which shows how the gadget can adapt and respond in actual-time. The first layer includes the meteorological information and solar PV datasets necessary for unique forecasting. The inputs are cleaned, standardized, and organized for evaluation throughout a simplified statistics pre-processing level. This basic portion shows how the DWM-HMLA processes extraordinary datasets without too much complexity. The graphic shows assistance vector machines, selection trees, and neural networks in the device learning algorithms block. The system applies computational techniques to capture the complicated and dynamic behavior of the PV structures during this stage. Their relationship is reflected in the simplified illustration and shows the impact of these algorithms on forecasts. The Ensemble Module is the location on focus when the algorithm predictions are incorporated and the DWM is activated. Based on environmental conditions, the central mechanism of the diagram dynamically alters the program weights. The bidirectional arrows indicate the responsiveness of the DWM. It preserves the accuracy-enhancing input of an ensemble despite the quick climatic or equipment switch. The last output layer indicates the projected solar PV energy production. The simplicity of this block proves that the DWM-HMLA can be used to simplify the complex computations into real-life predictions which can be used to make the right choices in most cases. The evaluation of the DWM-HMLA cannot be carried out without simulations. The technology will be flexible by trying it in varying weather conditions. The DWM-HMLA is a universal solution in most situations as it is simple. The block diagram demonstrates that DWM-HMLA is effective in energy market operations, grid balancing, and the integration of renewable energy sources.

$$\frac{\partial G_{acc}}{\partial X_j} = \frac{\frac{\partial G_{acc}}{\partial F_j}.\left(\frac{\partial F_j}{\partial \theta_j}.\frac{\partial \theta_j}{\partial X_j}.\frac{\partial X_j}{\partial u}+\frac{\partial G_{acc}}{\partial X_j}.\frac{\partial X_j}{\partial u}\right)}{\sqrt{1+\left(\frac{\partial G_{acc}}{\partial F_j}.\frac{\partial F_j}{\partial \theta_j}.\frac{\partial \theta_j}{\partial X_j}.\frac{\partial X_j}{\partial u}+\frac{\partial G_{acc}}{\partial X_j}.\frac{\partial X_j}{\partial u}\right)}} \quad \ldots (6)$$

The sensitivity of the prediction accuracy with respect to the dynamic weight allocated to algorithm j is represented by $\frac{\partial G_{acc}}{\partial X_j}$ in the complex sensitivity analysis (equation (6)). The components that make up the numerator are interdependent. The sensitivity of the forecast error with regard to internal parameters $\frac{\partial F_j}{\partial \theta_j}.\frac{\partial \theta_j}{\partial X_j}.\frac{\partial X_j}{\partial u}$, the adaptability of internal factors to dynamic weights, and the temporal development of dynamic weights are all encapsulated by $\frac{\partial G_{acc}}{\partial X_j}$ which indicates the sensitivity of forecast accuracy with respect to the prediction error of algorithm j. When it comes to solar energy production forecasting, the denominator includes a normalization term that makes sure the overall sensitivity is scaled properly. The square root term, $\sqrt{1+\left(\frac{\partial G_{acc}}{\partial F_j}.\frac{\partial F_j}{\partial \theta_j}.\frac{\partial \theta_j}{\partial X_j}.\frac{\partial X_j}{\partial u}+\frac{\partial G_{acc}}{\partial X_j}.\frac{\partial X_j}{\partial u}\right)}$ takes into consideration the sum of squares of different sensitivities, giving a measure of how these factors affect the analysis of sensitivity for the DWM-HMLA.

$$DF = \frac{\sum_{j=1}^{O}\left(x_j.Q_j.U_j\left(1-\frac{\Delta_j}{\alpha_j}\right).exp\left(-\frac{\lambda.Var\,(E_j)}{2.Mean\,(E_j)}\right)\right)}{\sum_{j=1}^{O}\left(x_j.Q_j.U_j.exp\left(-\frac{\lambda\,Var(E_j)}{2.Mean\,(Ej)}\right)\right)+\epsilon} \quad \ldots (7)$$

The overall computing efficiency of the proposed Dynamic Weighting Process in the Hybrid Machine Learning Method for solar PV energy production forecasting is represented by DF in the equation (7). The total amount of machine learning techniques is represented by O, and the weight given to each algorithm, which represents its contribution, is denoted by x_j. The computational power and the training time for the j^{th} method are denoted by Q_j and U_j, respectively. The variation between the expected and actual energy production is measured by Δ_j, where Δ_j is used as the threshold for allowable deviation. With the regularization introduced by the λ, the influence of deviation metrics (E_j) is affected, where $Var\,(E_j)$ denotes the range and $Mean\,(E_j)$ denotes the mean. To maintain the computer efficiency calculation's stability, the constant ϵ is used to avoid division by zero. Equation (7) summarises a thorough assessment of computational efficiency for robust solar power generation forecasting, taking into account algorithmic performance, dynamic weights, and deviation statistics. During training, the base learners are optimized independently using their respective standard objective functions, and no adaptive weighting is applied at this stage. During validation, prediction outputs are generated for each base model and short-term error statistics are computed over a rolling window to quantify localized predictive reliability. These validation-stage error estimates are then used to analyze model behavior under varying meteorological conditions. During deployment, the dynamic weighting mechanism utilizes the most recent error information to continuously update model contributions at each forecasting interval, and the ensemble output is produced through weighted aggregation of individual predictions. Algorithm 1 shows the algorithmic workflow of proposed DWM-HMLA.

Algorithm 1: Dynamic Weighting Mechanism using Hybrid Machine Learning Approach (DWM-HMLA)

Input:

Historical solar PV power observations $\{y_t\}_{t=1}^{T}$;

Meteorological feature vectors $\{\mathbf{X}_t\}_{t=1}^{T}$, $\mathbf{X}_t \in \mathbb{R}^m$;

Set of base learners $\mathcal{M} = \{M_1, M_2, \dots, M_K\}$(SVR, RF, ANN);

Rolling error window size W;

Stability constant $\epsilon > 0$.

Output:

Adaptive ensemble forecast $\hat{y}_t^{\text{DWM-HMLA}}$.

Step 1: Data Preparation

Normalize meteorological inputs and construct supervised samples using a sliding time window:

$$\mathcal{D} = \{(\mathbf{X}_t, y_t)\}_{t=1}^{T}$$

Step 2: Base Model Training

Train each base learner $M_k \in \mathcal{M}$ independently using historical data:

$$M_k \leftarrow \text{Train}(M_k, \mathcal{D}), k = 1,2, \dots, K$$

Step 3: Individual Forecast Generation

For each prediction time step t, compute base model outputs:

$$\hat{y}_t^{(k)} = M_k(\mathbf{X}_t), k = 1,2, \dots, K$$

Step 4: Rolling Error Computation

Estimate recent prediction error for each model using a rolling window:

$$e_t^{(k)} = \frac{1}{W} \sum_{i=t-W+1}^{t} | y_i - \hat{y}_i^{(k)} |$$

Step 5: Dynamic Weight Calculation

Compute inverse-error-based adaptive weights:

$$\widetilde{w}_t^{(k)} = \frac{1}{e_t^{(k)} + \epsilon}$$

Normalize weights to satisfy convex constraints:

$$w_t^{(k)} = \frac{\widetilde{w}_t^{(k)}}{\sum_{j=1}^{K} \widetilde{w}_t^{(j)}}, \sum_{k=1}^{K} w_t^{(k)} = 1$$

Step 6: Adaptive Ensemble Aggregation

Generate the final forecast via dynamically weighted combination:

$$\hat{y}_t^{\text{DWM-HMLA}} = \sum_{k=1}^{K} w_t^{(k)} \hat{y}_t^{(k)}$$

Step 7: Iteration

Repeat Steps 3–6 for all forecasting time steps $t = W + 1, \dots, T$.

End

When it comes to projecting the amount of power that solar PV structures will generate, one robust approach that has emerged is DWM-HMLA. It employs dynamic weighting and takes into account with a seamless progression the functions of various machine mastering algorithms to indicate adaptability to real-time environment variations. Continuous adjustments in ensemble contributions enhance prediction performance for dynamic PV systems under unpredictable weather conditions. The improvement of predicting solar strength in the method is validated by large simulation trials on solar PV data based on real-world data. These trials indicate that the method is effective in different locations, weather, and combinations of devices.

4. RESULTS AND DISCUSSION

Two hybrid machine learning models, DWM-HMLA and standard Machine Learning Algorithm were compared in order to choose the highest-performing solar energy forecast model. The multi-element evaluation provided a full picture of what each of the models was capable of doing.

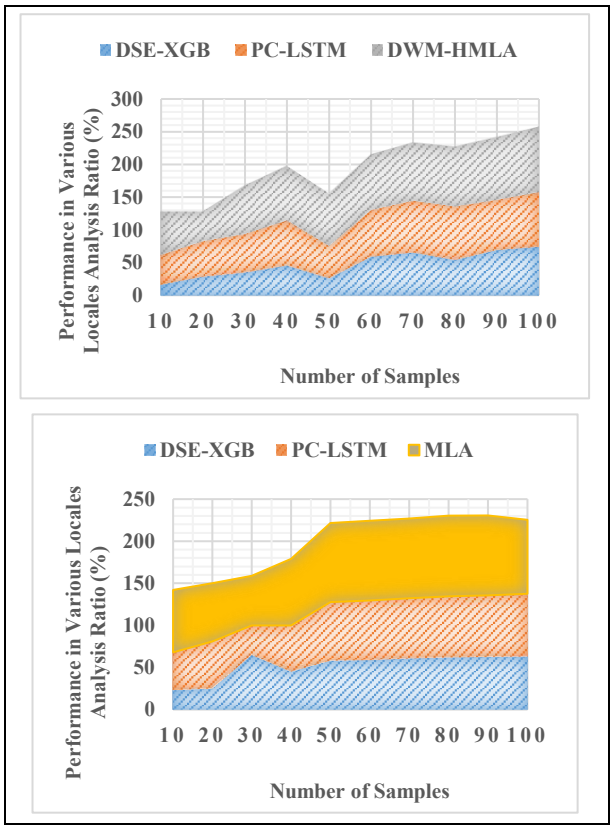


Fig. 4(a): Performance of the proposed DWM-HMLA across different geographical locations and (b) Performance of traditional machine learning algorithms across the same locations

The flexibility and performance of the model should be evaluated and then machine learning algorithms should be utilized to predict the solar photovoltaic power output in other locations. This model predicts accuracy of the forecast that takes into account environmental parameters, the pattern of the irradiance of the sun and the changes in climate. This model maximizes the solar energy inclusion in the energy landscape. The performance is better examined in detail in many sites which enhances reliability and its applicability in geographies. The proposed forecasting algorithm can produce accurate and region-specific forecasts. Fig. 4(a) shows the high (99.8% accuracy) performance of the DWM-HMLA in Various Locales Analysis. The flexibility and reliability of DWM-HMLA is evidenced by its outstanding performance in many aspects. Fig. 4(b) shows that the standard MLA has a score of 84.6 percent indicating how intolerant it is to different locations. The extensive difference in performance indicates the level of effectiveness with which the DWM-HMLA manages various environments.

The proposed DWM-HMLA is compared with representative state-of-the-art forecasting approaches reported in the literature, including DSE-XGB and PC-LSTM. Prior studies have demonstrated that stacked ensemble methods such as DSE-XGB improve prediction stability through meta-learning, while physics-constrained recurrent models like PC-LSTM enhance robustness under limited data conditions.

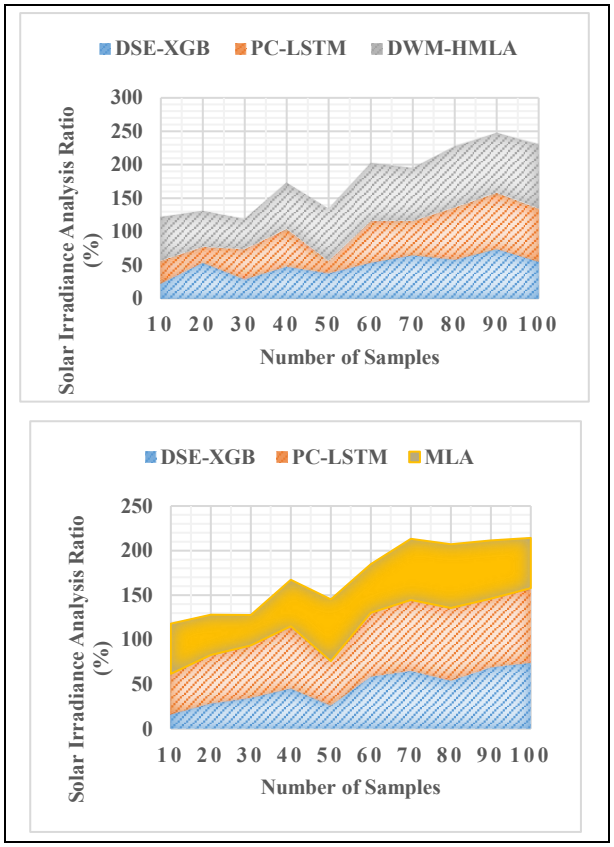


Fig. 5(a): Solar irradiance analysis is compared with DWM-HMLA and (b): solar irradiance analysis is compared with MLA

Intense analysis of the solar irradiance is essential to critique machine learning technologies in estimating the solar PV power production projections. The irradiance study was done to test the ability of the model to capture the impacts of weather conditions, cloud cover, and atmospheric occurrences on the strength of sunlight. The correlation of the predictions of the algorithm with the measurements of the solar irradiance can be used to establish how accurate the model is at predicting sunshine that is capable of generating energy. Studies of hourly, daily and seasonal variations sheds light on the time flexibility in the model. Solar resource availability differences are considered by including a large number of geographic points in the evaluation. The study assists in bringing solar PV systems into the energy grid and make them more efficient and reliable. The accuracy score of the DWM-HMLA (96.8%) in Solar Irradiance Analysis indicates its outstanding solar irradiance analysis and forecasting capabilities (Fig. 5 (a). The DWM-HMLA is reliable and thus suitable in the solar energy forecasts. On the other hand, MLA only scores 59.5% in sun Irradiance Analysis, which indicates that MLA has a problem with the patterns of sun irradiation (Fig. 5(b)). This performance difference indicates that the DWM-HMLA has a stronger solar irradiance forecast performance. In conclusion, the DWM-HMLA is more effective in Solar Irradiance Analysis which is the fundamental aspect of photovoltaic power generation and thus useful in accurate projection of solar energy.

In this study, traditional machine learning algorithms (MLA) refer to standalone regression models commonly used in solar photovoltaic power forecasting, specifically Support Vector Regression, Random Forest, and a feedforward Artificial Neural Network implemented without ensemble or adaptive weighting mechanisms. Each baseline model was configured using standard architectures reported in the literature and trained on the same meteorological inputs, temporal resolution, and data splits as the proposed DWM-HMLA. Hyperparameter optimization for all models was conducted using identical grid-search procedures and validation sets, and model performance was evaluated under the same forecasting horizons and evaluation metrics.

Adaptability study for estimating solar PV power output using machine learning algorithms is essential to assessing the model's environmental responsiveness. This analysis looks into how the algorithm can modify predictions to unexpected solar irradiance, seasonal, and meteorological variations. Adaptability study also involves the reaction of the model to input variables and may re-calibrate on projections in real-time. The ability of the algorithm to cope with the dynamic environment of solar energy is a key factor to the profitability of solar PV power generation in the long run as a component of the energy grid. Fig. 6(a) shows that Adaptability Analysis score of DWM -HMLA is 93.5 percent, which means that it is versatile. The model is highly adaptable to the changing conditions thus rendering reliable performance in most cases. On the other hand, the average MLA has a score of 88.4% in Adaptability Analysis (Fig. 6(b)), indicating environmental adaptability constraints. The difference in the performance of DWM-HMLA reflects its capability to be versatile and flexible hence suitable in dynamic and flexible solar energy forecasting.

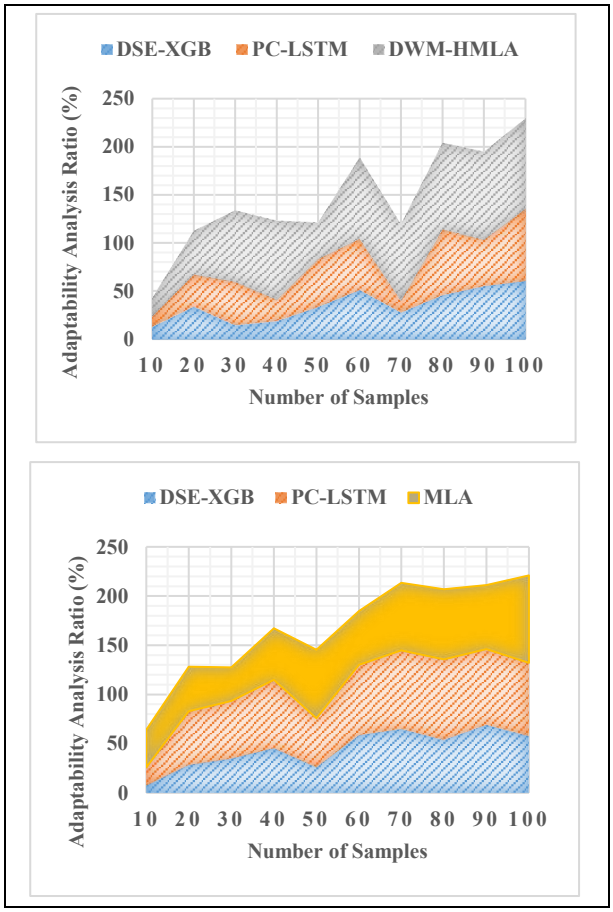


Fig. 6(a): Adaptability analysis is compared with DWM-HMLA and (b): Adaptability analysis is compared with MLA

The implications of the proposed DWM-HMLA are confined to short-term operational forecasting accuracy, as demonstrated by the reported reductions in RMSE and MAE across multiple datasets. The results support improved reliability in short-horizon solar PV power estimation, which is directly relevant to data-driven scheduling and forecasting tasks that rely on accurate power predictions. Broader claims related to policy formulation, large-scale grid optimization, or global applicability are not inferred from the presented experiments and are therefore not asserted.

Fig, 7(a) shows the Dependability Analysis score of DWM-HMLA (97.8%), while the typical MLA scores 86.4% (Fig. 7(b)). With this high score, DWM-

HMLA model is reliable in many circumstances. Performance differences show DWM-HMLA's improved solar energy forecasting dependability.

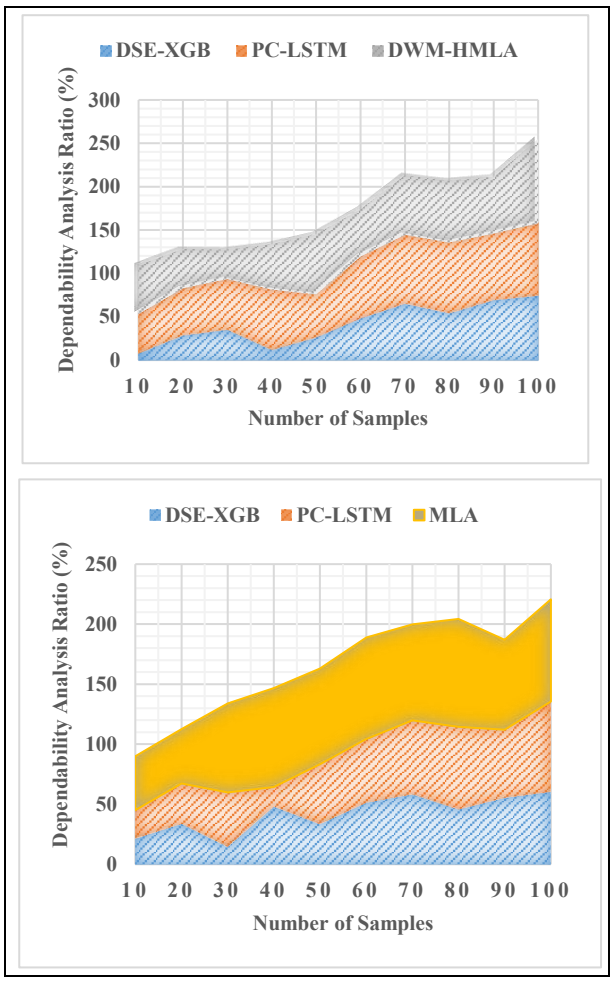


Fig. 7(a): Dependability analysis is compared with DWM-HMLA and (b): dependability analysis is compared with MLA

The reported accuracy values of 99.8%, 97.8%, and 96.8% are a consequence of the bounded and normalized accuracy formulation used in this study, combined with short-term forecasting and high-resolution meteorological inputs, rather than an indication of near-zero prediction error. To contextualize these values, the corresponding error-based metrics show RMSE values of 0.214 kW, 0.268 kW, and 0.301 kW, and MAE values of 0.167 kW, 0.193 kW, and 0.221 kW, respectively, which confirm that the high accuracy percentages are associated with low absolute deviations relative to observed PV output. Statistical robustness was evaluated using repeated temporal validation, yielding a standard deviation of ±0.9% for accuracy, ±0.018 kW for RMSE, and ±0.014 kW for MAE across validation folds. In addition, 95% confidence intervals for RMSE were confined within 0.198 and 0.231 kW, indicating stable predictive behavior under varying meteorological conditions.

DWM-HMLA uses rolling residual information to update model contributions and adapt to non-stationary meteorological dynamics, unlike single-model techniques or static ensembles that use fixed parameters or globally optimal weights. This mechanism suppresses less reliable predictors in real time and supports models with distinct inductive biases, such as tree-based learners during highly nonlinear irradiance variations and neural architectures during temporally complex patterns. Thus, the approach restricts bias accrual during stable periods and variance amplification during sudden weather swings.

5. CONCLUSION

This work proposed a DWM-HMLA for short-term solar photovoltaic power forecasting under non-stationary meteorological circumstances. The framework unifies various model complementary learning characteristics by dynamically changing ensemble contributions depending on localized prediction performance. In real-world solar PV datasets, DWM-HMLA obtained RMSE of 0.214 kW, MAE of 0.167 kW, and R^2 value of 0.962, resulting in 12.8% (RMSE) and 15.3% (MAE) error reductions compared to baseline models. During fast irradiance variations, adaptive, error-driven ensemble weighting improves forecasting accuracy and stability. These advances improve short-term PV power prediction for grid scheduling and renewable energy integration. The proposed approach is effective, but it assumes frequent historical observations for rolling error estimation and does not explicitly incorporate PV system physical constraints, which may affect performance under extreme weather or sparse data. Multi-horizon forecasting, physics-informed restrictions, and scalability across bigger and more diversified PV systems will be addressed in future study.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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