Incremental Learning for Fast Shading Adaption in Solar Power Forecasting

Tim Kappler, Bernhard Schwarz, Nina Munzke, Marc Hiller
Institute of Electrical Engineering, Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany
tim.kappler@kit.edu

2025 IEEE Kiel PowerTech | 979-8-3315-4397-6/25/$31.00 ©2025 IEEE | DOI: 10.1109/PowerTech59965.2025.11180693

***Abstract*—This study presents a novel hybrid incremental learning approach for short-term solar power prediction under dynamic shading conditions, using time window-based incremental learning to adapt a pre-trained prediction model. The proposed approach rapidly adapts to changes in shading patterns without the need for full model retraining. The model is configured to use an estimation period, after which it requires three additional days to effectively compensate for shading effects. The results show that the proposed method significantly reduces forecast errors, improving the RMSE by up to 19.27% and the MAE by up to 31.81% in strong shading scenarios compared to transfer learning approaches. Moreover, the method requires only one tenth of the computation time. The proposed method provides a scalable, robust, and efficient solution for solar power forecasting, particularly in scenarios with frequent and strong shading.**

***Index Terms*—machine learning, solar power forecasting, incremental learning, shading**

I. Introduction

With photovoltaics (PV) emerging as the dominant renewable energy source, its share of global electricity is projected to rise from 6.8% in 2024 to 16.1% by 2030 [1], playing a crucial role in achieving carbon reduction targets. This will position it as the leading renewable energy source. This expansion underscores the key role of solar in meeting international carbon reduction targets and transitioning to sustainable energy systems. This surge underscores the critical role of PV systems in achieving a sustainable energy transition. However, the variability of solar power output, driven by factors such as cloud cover, precipitation, shading [2], [3], soiling [4] and fluctuating solar irradiance, poses significant challenges energy management and grid stability [5]. Accurate forecasting of solar power generation is essential to mitigate these challenges, ensure system reliability, and enable effective integration of renewable energy into the grid.

Traditional methods, including physical models, statistical approaches, and machine learning, have been employed to predict solar power generation. Among these, machine learning has gained significant attention due to its ability to generalize across different conditions [6]. In the recent years, the most notable methods are those based on long-short term memory (LSTM) [7] and those based on the self-attention mechanism [8], which have gained popularity in short-term PV power prediction. Nguyen et al. [9] demonstrated that Transformer networks, coupled with Convolutional Neural Networks and data pre-processing techniques like Variational Mode Decomposition, significantly outperform traditional approaches in capturing complex solar irradiance patterns. Similarly, Jailani et al. [10] highlighted the advantages of LSTM-based models in handling sequential solar energy data, particularly in hybrid setups combining LSTM with other architectures. Al-Ali et al. [11] further explored CNN-LSTM-Transformer hybrid architectures, demonstrating their ability to achieve state-of-the-art forecast accuracy by integrating complementary strengths of these methods.

Despite these advancements, forecasting models often struggle with unexpected changes, such as shading caused by tree growth or buildings. Shading dynamics, influenced by factors like irradiance, panel orientation, and obstacle geometry, remain challenging to model. Zhang et al. [12] discussed the limitations of transfer learning, noting that errors increase when models are applied to conditions that are significantly different from the domain in which they were trained. Other studies [13], [14] have incorporated external sensor data to address shading effects, but these solutions often add significant costs due to the requirement for additional hardware.

To overcome these limitations, incremental and online learning methodologies have emerged as promising alternatives. Incremental learning is particularly valuable in non-stationary environments, where models must adapt to changing conditions without retraining. Yang et al. [15] proposed a concept drift detection method for online extreme learning machines (OS-ELMs) that effectively identifies model dissimilarity, emphasizing the need for adaptation when retraining is computationally expensive. Similarly, Puah et al. [16] introduced the Regression Enhanced Self-Organizing Incremental Neural Network (RE-SOINN), which incrementally learns time-series data and predicts in real time, outperforming conventional models in highly fluctuating scenarios. Incremental learning frameworks, such as those by Zhang et al. [17], have successfully integrated concept drift detection with privacy-preserving methods, ensuring accurate PV power prediction in distributed settings. These methods aim to identify drifts, allowing for real-time model adaptation without expensive retraining.

While these incremental learning techniques show great promise, no prior work has attempted to combine the adaptive capabilities of incremental learning with the strong performance of traditional batch learning models. This paper introduces a hybrid approach that leverages the strengths of both paradigms. By combining incremental learning with high-performance models trained using large datasets, the proposed framework provides rapid adaptation to dynamic conditions like shading without the need of external radiation sensors, while still benefiting from the robust performance of established batch-learning techniques.

Building on this foundation in short-term power forecasting, this paper presents a hybrid framework that combines solar power prediction models using LSTM and Transformer networks with a windowed incremental learning approach for rapid adaptation to shading conditions. The proposed incremental learning algorithm dynamically adjusts the output of the prediction model, enabling faster adaptation, improved performance, and reduced computational cost compared to conventional transfer learning methods. This approach exploits the high performance of a model trained on a large dataset, while benefiting from the fast adaptation capabilities of incremental learning. Furthermore, the framework supports PV system monitoring based on the prediction error, providing valuable insights for condition-based maintenance and system optimization.

The contributions of this study are as follows:

- A hybrid approach combining LSTM and Transformer networks with incremental learning, enabling dynamic adaptation to shading conditions
- Efficient adaptation to shading effects with minimal computational cost
- Experimental validation of the proposed methodology across various shading scenarios and PV array configurations

The paper is organized as follows: Section II outlines the methodology, Section III presents the experimental setup, and Section IV discusses results and future directions.

II. Methodology

The structure of the work is divided into four steps. First, a model is trained on an unshaded PV system. In this study, both LSTM- and Transformer networks (Encoder) are investigated. Second, the forecasted power is compared to new PV systems with different levels of shading. Third, to adapt the method to the new environmental conditions, a new hybrid method is presented (see Fig. 1). This method combines a pre-trained network with an incremental support vector machine (iSVM) to adjust the prediction error. Finally, the performance of the proposed approach is evaluated and compared against conventional forecasting methods.

The proposed framework builds upon a pre-trained model that has been trained on extensive recorded PV data. This study employs two advanced deep learning architectures, Long Short-Term Memory (LSTM) networks and Transformer networks, to predict solar power generation.

The LSTM network is specifically designed to handle temporal dependencies in sequential data. By using memory cells controlled by the forget gate, input gate, and output gate, the network determines which information is stored, updated, or output at each time step. This mechanism enables the LSTM to effectively model long-term dependencies, which are essential for capturing the dynamics of solar power generation.

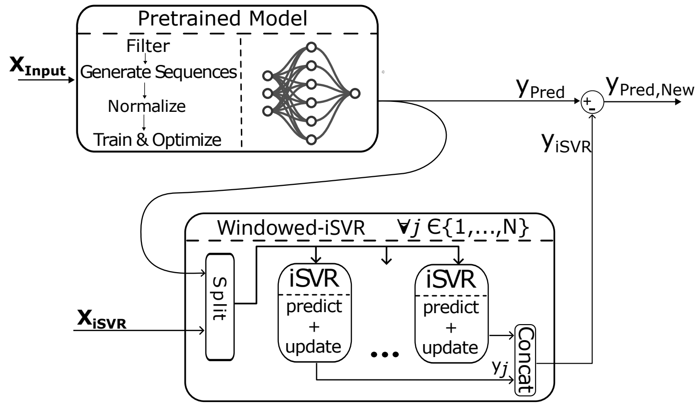

Fig. 1. Overview of the Proposed Approach

In contrast, the Transformer network leverages a self-attention mechanism to identify dependencies within time series data without relying on recurrent connections. This allows the model to process the entire input sequence in parallel, greatly enhancing computational efficiency. The Transformer encoder used in this study incorporates a position embedding layer, a self-attention mechanism, and feedforward layers to process the input data. These components work together to capture intricate patterns in solar power generation. The training procedure and parameters for the LSTM and Transformer networks are further detailed in Section III.

While the deep learning models provide accurate initial forecasts, they can benefit from refinement to account for local and recent variations in data. To achieve this, the predictions from these models are incrementally improved using a Window-Based Incremental Learning Support Vector Regression (W-iSVR) approach. This hybrid framework combines the global learning capabilities of deep learning models with the adaptability of incremental regression.

The W-iSVR method addresses the challenge of adapting to new data efficiently without requiring complete retraining. Instead of solving the optimization problem over the entire dataset repeatedly, the SVR model updates its parameters incrementally as new data arrives. Assume the model is trained on a dataset $\{\mathbf{X}_{\text{old}}, \mathbf{y}_{\text{old}}\}$ and new samples $\{\mathbf{X}_{\text{new}}, \mathbf{y}_{\text{new}}\}$.The variable $\mathbf{w}$ represents the weight vector of the model. The slack variables ξ and ξ^* account for deviations beyond the margin of tolerance ϵ. The parameter C is a regularization term that controls the trade-off between model complexity and the penalty for errors.

The updated SVR problem can be written as:

$$\min_{\mathbf{w},\xi,\xi^*} \frac{1}{2}\|\mathbf{w}\|^2 + C\left(\sum_{i=1}^{N_{\text{old}}}(\xi_i + \xi_i^*) + \sum_{j=1}^{N_{\text{new}}}(\xi_j + \xi_j^*)\right) \quad (1)$$

The slack variables ξ_i and ξ_i^* correspond to the old samples, while ξ_j and ξ_j^* are associated with the new samples. The optimization process focuses exclusively on the new samples, ensuring that the parameters remain consistent with what was learned from the old data. To enhance accuracy and adaptability, the framework incorporates hour-based time window splitting. The day is divided into distinct hourly windows, and for each time window, a separate incremental learner is constructed. This approach ensures that the specific characteristics and patterns of each hour are captured effectively. For instance, the early morning and late afternoon hours may have distinct behaviors compared to the midday hours as a result of variations in solar angles and weather conditions.

Let $T = \{t_1, t_2, \ldots, t_N\}$ represent the set of N hourly windows within a day. For each hourly window $t_k \in T$, a separate model M_k is incrementally trained and updated to account for specific characteristics observed during that hour. This ensures that temporal patterns, such as solar angles or weather conditions unique to that hour, are modeled effectively.

The training process for each hourly model can be described as follows: Let $\mathcal{D}$ represent the dataset containing input features $\mathbf{X}$ and corresponding target values $\mathbf{y}$:

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N} \tag{2}$$

where N is the total number of samples. The dataset is partitioned into subsets $\mathcal{D}_k$ for each hourly window t_k:

$$\mathcal{D}_k = \{(\mathbf{x}_i, y_i) : \text{hour}(t_i) = t_k, \forall i\} \tag{3}$$

where $\text{hour}(t_i)$ extracts the hour from the timestamp t_i of sample i. For each hourly window t_k, the corresponding model M_k is updated using the subset $\mathcal{D}_k$. The update step incorporates new data after a predefined period (e.g., 10 days), ensuring that the model adapts to changes without overfitting:

$$M_{\text{k,new}} \leftarrow \text{Update}(M_{\text{k}}, \mathcal{D}_{k,\text{new}}) \tag{4}$$

where $\mathcal{D}_{k,\text{new}}$ represents the new data collected for hour t_k. The W-iSVR model updates incrementally to adapt to new data efficiently, avoiding the computational overhead of full retraining. At each prediction step, the corrected forecast is computed as:

$$y_{\text{pred,new}} = y_{\text{pred,pretrained}} - y_{\text{iSVR}} \tag{5}$$

where $y_{\text{pred,pretrained}}$ is the output of the pre-trained model (LSTM or Transformer) and y_{iSVR} is the correction term provided by the W-iSVR model, accounting for recent data patterns and errors.

III. Case Study

To evaluate the robustness of the proposed forecasting approach three photovoltaic (PV) systems with varying shading conditions over a one-year period are used. The configurations of these systems are detailed in Table I. For System D, however, only data covering half a year is available. System A serves as the reference system without shading, while Systems B, C, and D represent scenarios with low, medium, and strong shading. First, the datasets used for both the pre-trained models and the W-iSVR model are described in detail. This is followed by a comprehensive explanation of the evaluation methodology.

TABLE I
Configurations for system A-D

	System A	System B	System C	System D
Azimuth	0°S	30°W	60°E	74°E
Tilt	30°	15°	30°	9°
Mounting	Ground	Ground	Ground	Roof
P_{STC} / kW	10	10	10	7.2
Shading	None	Low	Medium	Strong

A. Data Description

The dataset consists of weather forecasts and measured power data. The weather forecasts are obtained via OpenMeteo [18], based on the DWD ICON-D2 model [19], which provides numerical weather predictions with a spatial resolution of 2.2 km and a temporal resolution of 15 minutes. The ICON-D2 model generates short-term forecasts with lead times of up to 48 hours and is updated eight times per day, effectively providing forecasts 3 hours ahead. The data includes parameters such as air temperature, shortwave radiation, diffuse radiation, and direct normal irradiance. The geographic coordinates of the systems are used to compute solar angles (elevation and azimuth) via the `pvlib` library [20]. Data quality is ensured by pre-processing steps to remove corrupted or erroneous values caused by sensor or communication errors. Power output data is aggregated to match the temporal resolution of the weather forecasts. To forecast power, LSTM and Transformer models are pre-trained on one year of data from the unshaded System A. These models are tested on the shaded systems over a subsequent year. For validation, real shading data is utilized. Figure 2 presents a comparison of the mean predicted and actual power outputs for the shaded systems during the test period using a trained LSTM model. These shading effects are confirmed by comparing the data with PV systems with

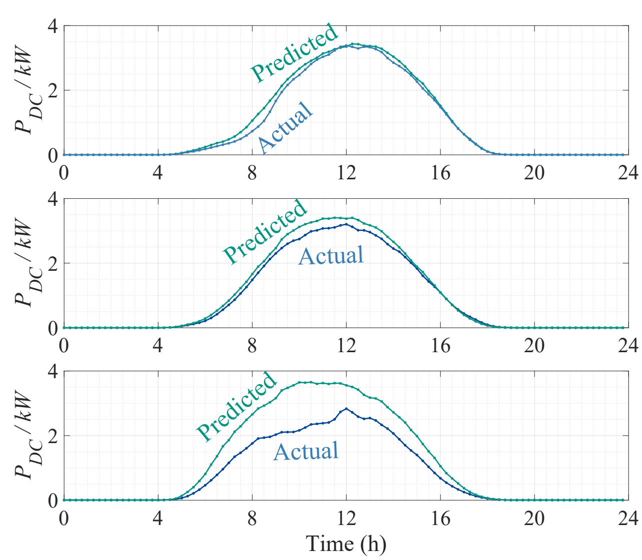

Fig. 2. Mean predicted and actual power outputs for shaded systems B (upper panel)-D (lower panel) over the test period.

identical tilt and azimuth angles but no shading. This shows the intensity of the different shadings. It should be noted, that shading does not occur at the same time or to the same extent throughout the year. It varies depending on the season and the type of weather (proportion of diffuse and direct radiation).

B. Benchmark

The W-iSVR uses lagged power outputs, forecast errors and weather forecasts of the last three days as input, as well as time-based features such as hour and month. To account for daily and seasonal variations, predictions are grouped into hourly time windows. This ensures that the models capture patterns specific to varying solar radiation levels throughout the day. The W-iSVR approach is compared to pre-trained models under shading conditions. Both the LSTM and Transformer models are trained using a 70/30 data split. Additionally, a grid search for hyperparameter optimization has been performed. The best configurations, summarized in Table II, include parameters such as hidden size, layers, learning rate, and attention heads for Transformers. The model trained on the unshaded system is used as a baseline for comparison. The retraining strategy involves periodically updating the pre-trained models with new data to ensure adaptability to changing conditions. Retraining cycles of 30 and 90 days are used to evaluate performance over different time periods. Performance is evaluated using several key metrics. Root Mean Squared Error (RMSE) measures overall performance, with a higher penalty for larger errors. Mean Absolute Error (MAE) quantifies the average magnitude of errors, treating all deviations equally. Mean Bias Error (MBE), on the other hand, highlights prediction bias, revealing whether the model tends to overestimate or underestimate power output. This metric is important in shading scenarios, where a low MBE close to zero indicates effective bias correction. Additionally, the Mean Computational Time per Prediction (MCTPP) is used to assess the scalability of the approach. It is calculated by dividing the total computation time by the number of predictions. Overall, this benchmark highlights the effectiveness of the hybrid approach in adapting to changing conditions and provides a comprehensive evaluation of its performance across multiple metrics.

TABLE II
SETTING FOR HYPERPARAMETER TUNING

Model	Parameter	Range	Best
LSTM	Hidden Size	$\{8, 16, 24, 32, 64\}$	24
	Learning Rate	$[10^{-4}, 10^{-2}]$	$1.5 \cdot 10^{-3}$
	Layers	$\{1, 2, 3, 4, 5, 6\}$	2
Transformer	Attention Heads	$\{1, 4\}$	1
	Feedforward Size	[16, 32, 64]	16
	Learning Rate	$[10^{-4}, 10^{-2}]$	$1 \cdot 10^{-3}$

IV. Results and Discussion

The performance of the proposed model is first analyzed using system D, which is characterized by a strong shade (see Fig. 2). This analysis demonstrates how quickly the model can adapt to abrupt changes in shading patterns. To highlight the model's response, the evaluation focuses on summer days with high levels of direct solar radiation, as such conditions are more likely to trigger shading effects. The model is configured with an estimation period of one day, during which it accumulates sufficient information to identify the shading pattern. Remarkably, the results show that the model requires just three additional days after the estimation period to fully adapt and compensate for the shading. This is evident from the significant reduction in forecast error observed after the estimation period, as illustrated in Fig. 3. The figure highlights the transition from baseline predictions to corrected predictions, demonstrating how the model learns and adjusts to the shading effects over time. The difference between predictions and actuals in the plot represents the high prediction error before adaptation, which diminishes rapidly as the model corrects its outputs. These results underline the effectiveness of the incremental learning approach in handling dynamic shading scenarios, ensuring robust and accurate power predictions under varying environmental conditions. The performance metrics for each system and approach are summarized in Table III. The metrics include RMSE, MAE, and MBE, providing a comprehensive view of the forecast error. The comparison focuses on the proposed approach and its improvements relative to transfer learning-based methods, as well as the impact of different

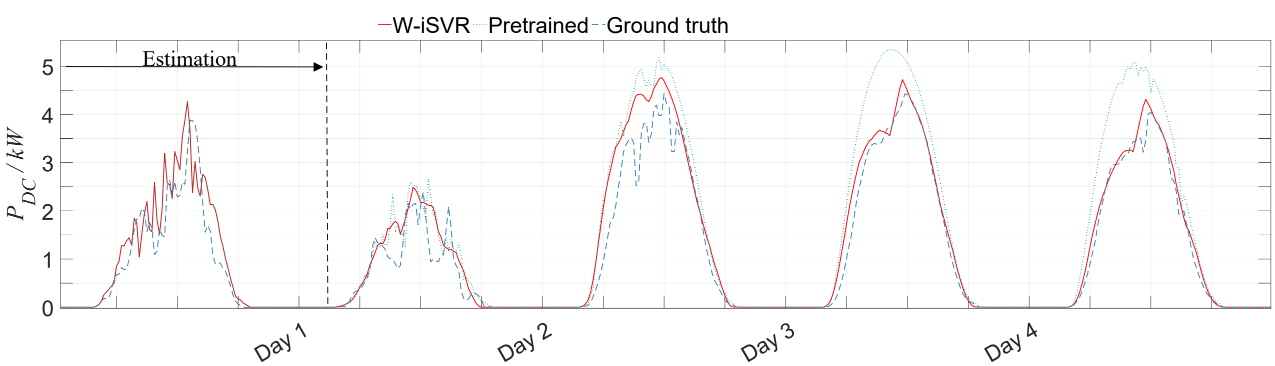

Fig. 3. Predictions of reference model and proposed model of system B after the estimation period

TABLE III
RESULTS AND METRICS (IN KW) FOR EACH SYSTEM OF THE LSTM AND TRANSFORMER MODELS

LSTM	Metric	Reference	Retrain 30 Days	Retrain 90 Days	Proposed
System B	RMSE	0.708	0.720	0.707	**0.680**
	MAE	0.325	0.327	0.323	**0.296**
	MBE	0.045	-0.026	0.047	**-0.019**
System C	RMSE	0.676	0.687	0.675	**0.627**
	MAE	0.310	0.315	0.307	**0.277**
	MBE	0.088	0.008	0.081	**-0.006**
System D	RMSE	0.702	0.519	0.632	**0.419**
	MAE	0.388	0.270	0.340	**0.208**
	MBE	0.327	0.086	0.247	**0.021**

TF	Metric	Reference	Retrain 30 Days	Retrain 90 Days	Proposed
System B	RMSE	0.714	0.729	0.707	**0.670**
	MAE	0.335	0.322	0.322	**0.295**
	MBE	0.071	-0.031	-0.028	**0.007**
System C	RMSE	0.755	0.690	0.722	**0.659**
	MAE	0.383	0.318	0.348	**0.293**
	MBE	0.228	-0.020	0.042	**0.017**
System D	RMSE	0.929	0.730	0.861	**0.608**
	MAE	0.591	0.415	0.528	**0.283**
	MBE	0.538	-0.099	0.359	**0.023**

retrain intervals (30 days vs. 90 days). The proposed approach outperforms both LSTM and Transformer retrain strategies across all systems. For System B, the Transformer achieves slightly greater improvements in RMSE (5.23%) and MAE (8.39%) compared to the LSTM (3.82% and 8.36%). For System C, both models demonstrate RMSE improvements (7.11% for LSTM and 4.49% for Transformer), while LSTM achieves a greater MAE reduction (9.77%) compared to Transformer (7.86%). These results highlight the effectiveness of the proposed approach in leveraging each model's strengths and addressing shading-induced variations. Comparing to the Baseline models, the proposed method demonstrates superior performance across most metrics. For RMSE, the improvements are more pronounced for LSTM models, with reductions of 7.11% and 9.77% in System C compared to the best retrain approach. However, for MAE, Transformer models achieves better improvements in Systems B and D, indicating a nuanced advantage depending on the metric. The retrain interval length (30 days vs. 90 days) significantly impacts the performance of retraining-based methods. Shorter intervals (30 days) generally result in better accuracy, as seen in lower RMSE and MAE values across the systems. In System D, the Transformer improves in MAE (31.81%) and RMSE (16.71%) compared to LSTM (22.96% and 19.27%). Additionally, the proposed approach eliminates most of the negative bias observed in the retrain methods, with an MBE of 0.02 kW. In contrast, transfer learning-based approaches struggle to fully correct shading, as the learned domains differ too significantly from the target domain. This is a common problem in transfer learning strategies, where retraining on new data is complicated because the target domain is too far apart from the trained domain. As a result, the retraining approach exhibits higher residual bias

TABLE IV
RELATIVE IMPROVEMENTS DES INKREMENTELLEN LERNENS GEGENÜBER DEM BESTEN 30-TAGE-RETRAIN

	Metric	System B	System C	System D
LSTM	ΔRMSE	3.82%	7.11%	19.27%
	ΔMAE	8.36%	9.77%	22.96%
Transformer	ΔRMSE	5.23%	4.49%	16.71%
	ΔMAE	8.39%	7.86%	31.81%

and less effective compensation for shading-induced errors. This highlights that the greater the extent of shading, the higher the expected benefit to the retrain approaches. However, this advantage diminishes when the shading impact is moderate, where the proposed approach already demonstrates superior performance in eliminating residual bias. As shown in Table IV, the proposed approach consistently outperforms the best retrain approaches across all systems. The relative improvements in RMSE range from 3.82% to 19.27%, with the most significant gains observed in System D. For MAE, the improvements are similarly notable, with a maximum of 31.81% for the Transformer model in System D. These results demonstrate the robustness and efficiency of the proposed method, particularly in scenarios with strong shading. For a more comprehensive study, the model pool is extended to XGBoost, yielding RMSE improvements from 2.39% to 7.74% and MAE improvements from 0.59 % to 13.51 %, further reinforcing the incremental approach's effectiveness in enhancing prediction quality.

Next, the computational time of the two methods is evaluated. The total execution time was calculated across all systems and divided by the number of predictions in a year to determine the Mean Computational Time Per Prediction (MCTPP). All tests were performed on an Intel(R) Core(TM) i7-12700H CPU @ 2.30GHz. These times reflect an average estimate for prediction on this specific CPU, but may vary on different hardware platforms. Table V summarizes the computational effort required for the different approaches in terms of MCTPP ratios. The ratios indicate how many times faster the proposed approach is compared to the retraining methods. For the Transformer model, the 30-day retraining window results in a ratio of 27.4, meaning it is approximately 27 times slower than the proposed approach. Extending the retraining window to 90 days reduces the ratio to 9.2, but it remains significantly slower than the incremental method. LSTM models have even higher computational demands. The

TABLE V
COMPUTATIONAL EFFORT FOR DIFFERENT APPROACHES

	Method	MCTPP / μs	Ratio
Transformer	Retrain 30 Days	764.6	27.4
	Retrain 90 Days	256.5	9.2
LSTM	Retrain 30 Days	905.8	32.5
	Retrain 90 Days	503.6	18.1
Proposed	-	**27.9**	**1**

30-day retraining window leads to a ratio of 32.5, making the LSTM approach over 32 times slower than the proposed method. Even with a 90-day retraining window, the LSTM model is still about 18 times slower. In contrast, the proposed incremental approach is the fastest and most computationally efficient method. By eliminating the need for retraining, it provides a significant advantage in terms of speed and scalability. This makes it especially superior for applications where forecasts are required for many different PV systems, as it minimizes the computational cost and time associated with frequent retraining.

V. Conclusion

This study proposes an incremental learning approach to improve solar power prediction under dynamic shading. The method outperforms traditional retraining, reducing RMSE by up to 19.27 % and MAE by 31.81 %, while being ten times more computationally efficient. Its rapid adaptability proves to be especially effective for fluctuating shading, as seen in System D with strong shading effects. Compared to LSTM and Transformer networks, the approach provides superior error reduction and computational efficiency by eliminating frequent retraining. In conclusion, the proposed method is a scalable, practical solution for solar power forecasting in PV systems, offering rapid adaptation and low computational overhead. However, this study has limitations, as the proposed method requires continuous availability of measured power data for model updates, which may not always be available. Furthermore, the systems studied are geographically close, and broader testing in varied locations is needed to evaluate the method's generalizability. Future work could explore the use of prediction errors from the W-iSVR output for monitoring and predictive maintenance of the PV system.

Acknowledgment

This work contributes to the research performed at KIT Battery Technology Center and CELEST (Center for Electrochemical Energy Storage Ulm-Karlsruhe). The results were generated within the "Solarpark 2.0" project (funding code 03EE1135A) funded by the Federal Ministry for Economic Affairs and Climate Action (BMWK). The authors thank the project management organization Julich (PTJ) and the BMWK. This work was supported by the Helmholtz Association under the program "Materials and Technologies for the Energy Transition".

References

[1] IEA, "Net zero by 2050," *International Energy Agency*, p. 16, 2024. [Online]. Available: https://www.iea.org/reports/renewables-2024

[2] R. Ahmad, A. Murtaza, H. A. Sher, U. T. Shami, and S. Olalekan, "An analytical approach to study partial shading effects on pv array supported by literature," *Renewable and Sustainable Energy Reviews*, vol. 74, p. 721, 2017. [Online]. Available: https://doi.org/10.1016/j.rser.2017.02.078

[3] Y. Chaibi, M. Malvoni, A. Chouder, M. Boussetta, and M. Salhi, "Simple and efficient approach to detect and diagnose electrical faults and partial shading in photovoltaic systems," *Energy Conversion and Management*, vol. 196, p. 330, 2019. [Online]. Available: https://doi.org/10.1016/j.enconman.2019.05.086

[4] A. Babatunde, S. Abbasoglu, and M. Senol, "Analysis of the impact of dust, tilt angle and orientation on performance of pv plants," *Renewable and Sustainable Energy Reviews*, vol. 90, p. 1017, 2018. [Online]. Available: https://doi.org/10.1016/j.rser.2018.03.102

[5] A. Salah Saidi, "Impact of grid-tied photovoltaic systems on voltage stability of tunisian distribution networks using dynamic reactive power control," *Ain Shams Engineering Journal*, vol. 13, no. 2, p. 101537, 2022. [Online]. Available: https://doi.org/10.1016/j.asej.2021.06.023

[6] K. Barhmi, C. Heynen, S. Golroodbari, and W. van Sark, "A review of solar forecasting techniques and the role of artificial intelligence," *Solar*, vol. 4, no. 1, pp. 99–135, 2024. [Online]. Available: https://doi.org/10.3390/solar4010005

[7] R. Asghar, F. R. Fulginei, M. Quercio, and A. Mahrouch, "Artificial neural networks for photovoltaic power forecasting: A review of five promising models," *IEEE Access*, vol. 12, pp. 90 461–90 485, 2024. [Online]. Available: https://doi.org/10.1109/ACCESS.2024.3420693

[8] J. Zhu, Z. Zhao, X. Zheng, Z. An, Q. Guo, Z. Li, J. Sun, and Y. Guo, "Time-series power forecasting for wind and solar energy based on the sl-transformer," *Energies*, vol. 16, no. 22, 2023. [Online]. Available: https://doi.org/10.3390/en16227610

[9] T. Nguyen Trong, H. Vu Xuan Son, H. Do Dinh, H. Takano, and T. Nguyen Duc, "Short-term pv power forecast using hybrid deep learning model and variational mode decomposition," *Energy Reports*, vol. 9, pp. 712–717, 2023. [Online]. Available: https://doi.org/10.1016/j.egyr.2023.05.154

[10] N. L. M. Jailani, J. K. Dhanasegaran, G. Alkawsi, A. A. Alkahtani, C. C. Phing, Y. Baashar, L. F. Capretz, A. Q. Al-Shetwi, and S. K. Tiong, "Investigating the power of lstm-based models in solar energy forecasting," *Processes*, vol. 11, no. 5, 2023. [Online]. Available: https://doi.org/10.3390/pr11051382

[11] E. M. Al-Ali, Y. Hajji, Y. Said, M. Hleili, A. M. Alanzi, A. H. Laatar, and M. Atri, "Solar energy production forecasting based on a hybrid cnn-lstm-transformer model," *Mathematics*, vol. 11, no. 3, 2023. [Online]. Available: https://doi.org/10.3390/math11030676

[12] D. N. M. V. e. a. Sarmas, E., "Transfer learning strategies for solar power forecasting under data scarcity," *Sci Rep*, 08 2022. [Online]. Available: https://doi.org/10.1038/s41598-022-18516-x

[13] Kappler, Tim, Starosta, Anna Sina, Munzke, Nina, Schwarz, Bernhard, and Hiller, Marc, "Detection of shading for short-term power forecasting of photovoltaic systems using machine learning techniques," *EPJ Photovolt.*, vol. 15, p. 17, 2024. [Online]. Available: https://doi.org/10.1051/epjpv/2024013

[14] D. Chen, J. Breda, and D. Irwin, "Staring at the sun: a physical black-box solar performance model," in *Proceedings of the 5th Conference on Systems for Built Environments*, ser. BuildSys '18. New York, NY, USA: Association for Computing Machinery, 2018, p. 53–62. [Online]. Available: https://doi.org/10.1145/3276774.3276782

[15] Z. Yang, S. Al-Dahidi, P. Baraldi, E. Zio, and L. Montelatici, "A novel concept drift detection method for incremental learning in nonstationary environments," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, no. 1, pp. 309–320, Jan 2020. [Online]. Available: https://doi.org/10.1109/TNNLS.2019.2900956

[16] B. K. Puah, L. W. Chong, Y. W. Wong, K. Begam, N. Khan, M. A. Juman, and R. K. Rajkumar, "A regression unsupervised incremental learning algorithm for solar irradiance prediction," *Renewable Energy*, vol. 164, pp. 908–925, 2021. [Online]. Available: https://doi.org/10.1016/j.renene.2020.09.080

[17] L. Zhang, J. Zhu, D. Zhang, and Y. Liu, "An incremental photovoltaic power prediction method considering concept drift and privacy protection," *Applied Energy*, vol. 351, p. 121919, 2023. [Online]. Available: https://doi.org/10.1016/j.apenergy.2023.121919

[18] P. Zippenfenig, "Open-meteo.com weather api," 2023. [Online]. Available: https://doi.org/10.5281/zenodo.7970649

[19] Deutscher Wetterdienst (DWD), "DWD Open Data: ICON-D2 Weather Model Data," https://opendata.dwd.de/weather/nwp/icon-d2/, n.d., accessed: 2025-01-15.

[20] K. Anderson, C. Hansen, W. Holmgren, A. Jensen, M. Mikofski, and A. Driesse, "pvlib python: 2023 project update," *Journal of Open Source Software*, vol. 8, no. 92, p. 5994, 2023. [Online]. Available: https://doi.org/10.21105/joss.05994