SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V13I11P107

Volume 13 Issue 11, 107-129, November 2026
© 2026 Seventh Sense Research Group®

Original Article

A Lightweight Tangent-Space Feature Engineering and Temporal Learning Framework for Solar PV Energy Prediction

Sripathy Dharmalingam[1], Priya Palanichamy[2], Gurusigaamani Ayyanar Muthulingam[3]

[1,2,3]*Department of Electrical & Electronics Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, Tamil Nadu, India.*

[2]*Corresponding Author: priya.p@klu.ac.in*

Received: 23 July 2026 Revised: 22 October 2026 Accepted: 05 November 2026 Published: 25 November 2026

Abstract *- Solar energy forecasting plays an important role in the operation of the power system, energy management, maintaining the power system stability and also in the integration of PV systems to large scale in modern smart grid. By forecasting, the optimal scheduling can be designed, operation risk can be reduced, and sustainable use of renewables can be achieved. The existing forecasting methods, however, have drawbacks such as redundant feature representation, model of complex nonlinear temporal dependency that has limited capacity, high computation complexity, low transferability of different datasets, and lack of forecasting accuracy in dynamic environments. In order to tackle the aforementioned challenges, this paper proposes a novel Tangent-Space Aligned Laplacian Embedding with Knockoff Filter (TALEK) method under a Lag-Llama Augmented Tiny Time Mixer (LATTE) intelligent solar energy forecasting approach. The proposed feature engineering method in the TALEK module is a hybrid approach which combines nonlinear manifold learning with strong statistical feature selection, which preserves highly informative meteorological features and removes redundant features from the dataset. The LATTE model is then achieved by jointly using the efficient representation learning of Tiny Time Mixer with a long-term sequence model in Lag-Llama, enabling efficient learning of both short and long-term temporal changes while maintaining low computational requirements. The proposed framework is effective, which can be seen from the series of experiments conducted on two datasets, namely Solar Radiation and Meteorological Dataset and American Electric Power (AEP) dataset. With a reasonable 18.6 ms inference time, the proposed LATTE model provides excellent accuracy of 98.00%, MAE of 3.18, RMSE of 4.00, MAPE of 4.82% and an R^2 score of 0.984.*

Keywords *- Solar PV systems, Energy forecasting, Prediction, Deep Learning, Feature analysis, and Renewable sources.*

1. Introduction

Predicting energy production from a PV system is a challenging task since energy output from a PV system is greatly influenced by the dynamic nature of the weather, including solar irradiance, temperature, humidity, wind speeds, cloudiness and variation in season [1]. Accurate forecasting is an important element in grid stability, energy efficiency, optimal energy trading and in the current smart grid to integrate renewable energy [2]. But the intermittence and uncertainty of solar energy leads to difficulty to create predictive models with high accuracy in different environments. Typical statistical forecasting techniques like regression and time-series analysis have the assumption of linearity and stationary data, which is not sufficient to capture the complex non-linear interactions between meteorological parameters and solar electricity generation [3]. Likewise, physics based models require extensive computing and require detailed atmospheric information and are therefore not ideal for real-time and large scale applications.

In recent years, many Machine Learning (ML) and Deep Learning (DL) approaches [4] have emerged that have been found useful for enhancing prediction accuracy by directly learning complex patterns from the history of available data. There are some models currently in use, but they all have a number of limitations such as: lack of the capability of modeling long-term temporal correlation, sensitivity to noisy and heterogeneous data, high computation complexity, and low generalizability to other climatic zones. These restrictions restrict their usefulness for real-life smart grid applications where fast, accurate and scalable forecasting is required [5]. Consequently, a need for sophisticated lightweight prediction frameworks that can cope with short-term and long-term temporal characteristics in an efficient way, with minimal computation effort. These intelligent forecasting models can

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

provide accurate solar energy forecasts [6], optimize the use of renewable energy sources, enhance the resilience of smart grids and help in sustainable energy management in future smart power systems.

In recent years, solar energy forecasting systems that adopt deep learning are becoming more and more important because of the capability of modelling the highly interconnected, nonlinear and time-varying relationships between meteorological variables and PV power production. Deep learning models [7] automatically learn hierarchical feature representations directly from the large-scale data set of historical data and real-time data, which differs from traditional forecasting methods based on mathematical assumptions and handcrafted features.

The ability to record short-term variations due to temporary weather conditions and long-term seasonal variation allows them to make more accurate predictions for solar power [8]. It is fundamental to the stability of the grid, to make best use of energy dispatch, to reduce power balance and to facilitate demand response and the integration of renewable energies on a smart grid. In addition, deep learning methods [9] can effectively handle data from a variety of sources, such as solar irradiation, temperature, humidity, wind speed, cloudiness, and past production data, enhancing the strength and flexibility of the forecasting systems in various climatic situations. In recent years, with the advancements in lightweight neural architectures, attention mechanisms, and hybrid learning frameworks, the prediction accuracy has been enhanced, and the computational complexity has been minimized, to enable real-time deployment in edge devices and smart energy management platforms. Therefore, deep learning-based forecasting [10] tools are very crucial to make the best use of renewables, lower operational costs, make better energy trading decisions, and make energy systems sustainable, intelligent and resilient.

Despite considerable advances in solar energy forecasting, current prediction models still have some limitations which hinder their real-world use in smart grid. Many traditional machine learning and deep learning methods [11] have difficulties in describing the characteristics of solar energy, both in the short time and long-term scales. Also, the quantity and variety of meteorological information can result in the inclusion of redundancy that increases the complexity of the calculations, slows down the convergence and results in a lack of generalization in different climatic conditions [12]. The difficulties highlight the need of a system that is light, adaptive, and efficient and can be trained to capture informative temporal patterns without compromising prediction accuracy and overall performance in different operating situations. The purpose of this work is to develop a lightweight and intelligent solar energy forecasting system to address the constraints of the existing forecasting models that are only capable of forecasting simple temporal patterns and a homogeneous set of weather data. The suggested framework integrates an effective deep learning structure with an optimizing mechanism that adapts based on the data, improving forecasting accuracy while keeping computational demands low. This allows for accurate solar energy forecasting in real-time, improve smart grid performance, facilitate efficient integration of renewable energy sources, and aid in sustainable energy management.

Although solar PV systems are already integrated in smart grid systems, solar energy forecasting is still a challenging research problem because of the dynamic and nonlinearity of meteorological conditions and their impact on solar energy production. The disadvantages of the common modeling methods are: too many redundant meteorological attributes in the model, not enough flexibility to represent the complex temporal relationships, high computational demand, and lack of flexibility to adapt to the differences among datasets and operational environment. Traditional feature selection methods can be inadequate to maintain the nonlinear relationships between significant weather parameters, and current forecasting models are not effective at capturing short-term variations and long-term temporal trends at the same time. Furthermore, advanced forecasting architectures do not necessarily ensure the balance between prediction accuracy, efficiency and generalization. The constraints make it difficult to detect both informative features from the meteorological data and to remove redundancy and learn a few different temporal dependencies with low computational cost to build an integrated forecasting framework. So the central research problem is how to develop an accurate, efficient and transferable solar energy forecasting model to resolve the problem of feature redundancy, the nonlinear time-variations and the uncertainty of forecasting under the dynamic environment. To tackle these issues, the research proposes a feature engineering approach using the TALEK method coupled with the forecasting model LATTE, which enhances the representation of meteorological features and captures the temporal patterns both in the short-term and the long-term, leading to accurate solar energy forecasting.

The major objectives of this paper are as follows:

- Design an intelligent and lightweight solar energy forecasting system to predict the solar PV system power production according to different weather conditions.
- To create the proposed Tangent-Space Aligned Laplacian Embedding with Knockoff Filter (TALEK) framework for extracting a set of highly informative features by means of nonlinear manifold learning and statistically robust feature selection.
- To create the suggested Lag-Llama Augmented Tiny Time Mixer (LATTE) transfer learning model to effectively learn the long-term and short-term temporal dependencies with low computations.
- Evaluate the integrated TALEK-LATTE framework on benchmark solar energy datasets and benchmark its

forecasting performance with some of the best machine learning, deep learning and hybrid forecasting frameworks.

The rest of this paper is organized as follows: A detailed literature review of available solar energy forecasting methods and recent research using deep learning methods is provided in Section 2. In Section 3, the research gap identified and the motivation for developing a proposed framework is discussed. The overall methodology and the major part of the overall architecture is described in Section 4. The experimental setup, the descriptions of the datasets used, the pre-processing procedures and the used evaluation metrics in the study are explained in Section 5. The outcomes of experiments, comparison with state-of-the-art and the discussions with the methods are provided in Section 6. The scope and limitation of the proposed work is presented in section 7, and suggestions are given to research directions for future work. Finally, Section 8 highlights the key findings, contributions and implications of the proposed framework for solar energy forecasting.

2. Related Works

The literature reviewed in this section highlights the state of the art on solar energy forecasting, focusing on the different statistical, machine learning, deep learning architectures and hybrid prediction models. It examines methodologies used in recent investigations, the pros and cons of their use in reproducing complex temporal trends and non-linear relationships in solar energy information. Moreover, the review pinpoints [13, 14] the critical research challenges and gaps that drive the formulation of a more accurate, lightweight and less compute-intensive deep learning model for reliable solar energy forecasting.

Singh et al. [15] designed a machine learning ensemble based forecasting system for a commercial building which produces solar power in Saudi Arabia using meteorological data such as module temperature, ambient temperature, solar irradiance, and real power. This study began with several data visualization and exploratory analyses to provide insight into the nature of data collected from the PV. Then, a few of these machine learning models were tested and compared based on a few statistical performance metrics for solar power time-series forecasting. The outcomes showed the power of ensemble learning to increase the accuracy in prediction. However, the approach was mainly limited to a single site dataset and did not give much attention to the long-term dependence and computational effectiveness.

Dhaked et al. [16] provided in-depth overview of deep learning techniques used for PV power output forecasting and demonstrated the superiority of the deep learning techniques over the conventional methods. The research focused on several deep learning models currently being used in the mainstream and novel models, including deep transfer learning, federated learning, probabilistic and deterministic forecasting, big data-driven models and hybrid architectures. It also identified some of the computational complexity problems, model generalization and deployment in the real world, which indicated the importance of the development of more efficient and compact forecasting models.

Yang et al. [17] introduced a Box-Cox and Z-score data transformation method for data preprocessing and the Gaussian Process approximation method for enhancing the Transformer network in order to predict solar power. A model was developed that generated 24-hour-ahead probabilistic forecasts, and a delta method was used for rescaling the forecasts back to the original scale. The performance of the proposed methods for deterministic, probabilistic and interval forecasting was compared with the performance of the existing methods on a set of real-world solar power datasets and was found to outperform the existing methods, including the MC Dropout approach. The architecture, however, is a bit complicated and may incur greater computational demands and limit the applicability of the framework to resource constrained real-time forecasting systems.

Singh et al. [18] introduced a novel deep learning framework with sparsity inducing techniques to reduce computational complexity while retaining high prediction accuracy. The approach that was proposed enhanced the model's interpretability and computational efficiency by maintaining the most vital neural connections. The framework was evaluated with two actual solar power datasets in different geographical regions and demonstrated to achieve better forecasting results than the conventional dense deep learning models in terms of speed and accuracy. However, the primary concern of the study was the lack of models and their computational speed, with limited efforts to deal with adaptability of temporal dependency in extreme weather, the study was conducted.

Zheng et al. [19] compared different machine learning, deep learning and hybrid models such as 1D CNN, Bi-LSTM, Stacked LSTM, ANN, Linear Regression, SVR, XGBoost and also a CNN-LSTM for solar power forecasting. Four data sequences from the DKASC Alice Springs dataset were used to evaluate the models, and various performance metrics were employed, such as MAE, RMSE, R^2, explained variance and sMAPE. It was found that the deep learning model and hybrid model contribute to improving the accuracy of predictions, based on a comparative analysis. The study, however, was primarily a performance comparison study without suggesting any lightweight architecture and adaptive optimization strategy to increase the computational efficiency and generalization. Fennane et al. [20] developed an interpretable ensemble learning framework for PV power forecasting to combine the physical knowledge with the deep learning process. A prior knowledge of a physically constrained PV

power generation surface was built from astronomical angles and irradiance related features, and this prior knowledge was incorporated into the loss function to enhance the model interpretability. Moreover, the framework integrated a physical predictor based on the Kolmogorov-Arnold theory and traditional machine learning models to improve the prediction accuracy and generalization. The proposed approach improved the interpretability and the forecasting accuracy of the model, but the several physical and learning components used to build the model might take an impact in computational efficiency for real-time applications.

Ahmadi et al. [21] suggested a hybrid approach of machine learning and metaheuristic optimization for forecasting energy and optimizing renewable energy use in wastewater treatment plants, which also included uncertainty-aware scenario analysis to aid in the energy planning and system-level decision-making process. The study revealed that when energy and renewable-resource uncertainty is involved, predictive modelling and metaheuristic optimization can provide risk-aware energy planning as opposed to deterministic energy planning.

Zohaib, et al. [22] proposed an artificial intelligence and deep learning hybrid method for load forecasting in multi-microgrid system connected to grid for energy management. The technique will be described as a deep learning based approach for load prediction and an intelligent energy management approach, which optimizes the use of distributed energy resources and reduces the use of grid energy resources. The study showed the benefits of combining forecasting and energy management in order to optimize the performance of the microgrid. However, the focus of the work is mainly on forecasting electricity load and managing energy in a microgrid, with little attention paid to feature optimization for solar energy and optimal modelling of temporal dependency (both short and long-term) in solar energy generation.

Kim and Hau [4] proposed a Hybrid CNN-DNN model integrated with Explanation Artificial Intelligence (XAI) method, which uses a Shapley value to explain the output of PV power forecasting. The study showed that using both convolutional and deep neural representations could capture the complicated patterns in PV production and that SHAP could render forecasting results more interpretable. Despite, the approach is primarily use for prediction and post explanation, and short and long term temporal dependence modelling is not addressed adequately, and there is limited number of attention on elimination of redundant features and appropriate modelling short and long term temporal dependency, which is the justification of the proposed TALEK-LATTE framework.

Naghapushanam et al. [23] introduced a physics-informed feature engineering approach and a voting ensemble approach to improve the forecasting of solar power. The framework incorporated the solar geometry, physics of the atmosphere and the time variation in order to transform 21 meteorological variables into 41 engineered features to increase the prediction accuracy. The experimental results demonstrated very good forecasting accuracy of 94.95%, a remarkable result of the application of domain knowledge in combination with ensemble learning. The method is, however, very feature dependent and is not easy to scale up for different real-world forecasting scenarios with varying features.

3. Research Gap and Motivation

Many statistical models, deep learning architectures, machine learning algorithms, ensemble learning, probabilistic forecasting and hybrid optimization methods have been applied to improve solar energy forecasting, and there are still many research gaps. The majority of the previous approaches focus on improving the prediction accuracy [24, 25] without relying on more complex architectures such as physics-informed learning, ensemble frameworks, and Transformer-based networks, hybrid LSTM-TCN networks. Although they show great forecasting capability, many methods have high computational complexity, require lots of feature engineering, consume too much memory and take too long to train, which makes them not suitable for real-time applications in a smart grid. Moreover, there are several methods tested on geographically specific data and are not able to be generalized to other climatic conditions.

Challenges related to short-term fluctuations and long term temporal dependencies are also faced when other forecasting models try to capture them, and high performance suppression of redundant information [26] from heterogeneous meteorological data is encountered. However, the adaptive feature learning, lightweight model design, and computational efficiency aspects have been relatively under-investigated but are of crucial importance in the deployment of the model in large scale in modern renewable energy systems.

The limitations highlight the need for a next-generation solar energy forecasting system that offers good model accuracy, computational efficiency and model scalability. Given these challenges, the proposed work is designed to create a lightweight and intelligent deep learning framework, which will be able to learn complex temporal patterns with minimum redundant computations.

The proposed framework is based on an adaptive optimization-driven learning strategy and an efficient feature representation mechanism to enhance the reliability of prediction, accelerate the convergence and make the prediction more generalizable in heterogeneous datasets. It is anticipated that this framework will enable real-time decision-making, facilitate reliable renewable energy integration, optimize smart grid operations, and help with sustainable

energy management, overcoming practical challenges posed by current forecasting techniques while pushing the boundaries of solar energy prediction using deep learning.

4. System Overview and Contributions

The proposed scheme presents an intelligent and lightweight solar energy forecasting system that enhances the accuracy of energy forecasting while simultaneously reducing the computational complexity. As shown in Figure 1, the overall system is split into four main stages: data collection, data preprocessing, feature extraction and selection based on the proposed Tangent-Space Aligned Laplacian Embedding with Knockoff Filter (TALEK) framework, and solar energy forecasting using the proposed Lag-Llama Augmented Tiny Time Mixer (LATTE) model. Firstly, various benchmark datasets on historical PV generation data and meteorological data are retrieved and preprocessed, which involves handling missing data, normalizing data, removing outliers, and creating a temporal sequence.

The preprocessed data is then passed to TALEK, which extracts features from the data in a nonlinear manner and selects an optimal low-dimensional feature representation based on statistically solid feature selection. Finally, these optimized features are passed to the LATTE forecasting model, which uses the pretrained temporal knowledge extracted from Lag-Llama and uses the lightweight temporal refinement ability of Tiny Time Mixer to accurately predict future solar power generation in various environmental conditions.]

The main contribution of this work is to come up with a unified forecasting framework that would address the drawbacks of the existing solar energy prediction techniques in terms of multiple feature learning and lack of temporal representation. First, the proposed TALEK framework is a novel hybrid feature engineering approach, integrating three feature selection techniques-Local Tangent Space Alignment, Laplacian Eigenmaps and Knockoff Filter-into a single pipeline, which enables highly informative and non-redundant features to be extracted from a wide range of solar energy data.

Second, the proposed LATTE framework develops a hybrid transfer learning framework, which combines Lag-Llama's temporal knowledge transfer with the efficient temporal interaction modelling from Tiny Time Mixer, achieving a balance between temporal knowledge transfer and lightweight computation.

By combining these two novel elements together, the predictability of output is enhanced, the convergence speed of the model is increased, the model can be generalized for various climatic conditions and an efficient modelling solution is offered, which can be used in real-time smart grid and big renewable energy management system operation.

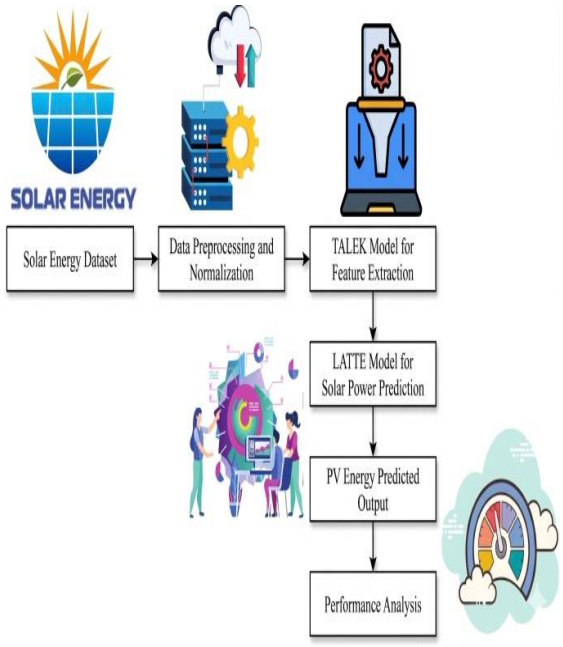

Fig. 1 Proposed system overview

Solar PV energy forecasting, which is accurate and computationally efficient, is becoming increasingly important as the number of solar PV systems increases in today's smart grid for power system operations, energy management and optimal scheduling, grid stability and reliable integration with renewable energy. But there are several gaps in the existing forecasting methods.

Standard machine learning and deep learning methods usually require a large number of meteorological and operational variables as inputs, resulting in several different representations of the same variables and requiring high computing power and negatively influencing the forecasting process.

Furthermore, there are many temporal models available in the literature that lack the ability of capturing the complex nonlinear relationships and both short and long term temporal dependencies that can coexist in highly variable solar energy data.

They are also expensive to compute, require specific data characteristics, are not readily applicable to different datasets, and are not robust to changes in the weather and operating conditions. Even though many models have been developed to model time series, informative feature selection, nonlinear feature representation, temporal efficiency and generalization across heterogeneous solar datasets are not well studied. Therefore, it is of great significance to propose an integrated forecasting framework that can eliminate the redundant meteorological information and retain the nonlinear characteristics of the system, while learning the multi-scale time pattern with small inference fee.

This motivates the development of the proposed Tangent-Space Aligned Laplacian Embedding with Knockoff Filter (TALEK) and Lag-Llama Augmented Tiny Time Mixer (LATTE) framework, which can accurately and efficiently predict solar energy.

The novelty of the proposed work is the use of a multi-scale temporal forecasting framework for solar energy forecasting in one single framework through the effective use of statistically reliable feature selection, nonlinear manifold representation. Unlike most of previous studies, which focus only on optimizing the features or optimizing the architecture of the forecasting system at the same time, the proposed approach takes both aspects into account as part of the TALEK-LATTE framework. Tangent-Space Aligned Laplacian Embedding (TALEK) and the Knockoff Filter (KF) are jointly used to statistically identify and eliminate redundant features to obtain an informative and compact representation of the features by capturing nonlinear relationships between meteorological variables.

Then, LATTE introduces a novel approach that simultaneously learns the short-term variations and the long-term temporal dependencies with efficiency by integrating Tiny Time Mixer (TTM) and Lag-Llama. Compared to conventional forecasting approaches, which can be limited by a lack of nonlinear dependency modelling, high computation requirements or lack of transferability of the model across datasets, the proposed framework introduces an effective and transferable approach.

The results obtained through the experimental evaluation on the Solar Radiation and Meteorological Dataset and AEP dataset clearly show the effectiveness of the proposed approach with 98.00%, 3.18 MAE, 4.00 RMSE, 4.82% MAPE and 0.984 R^2 with only 18.6 ms inference time. The results indicate that the proposed framework could yield better results than the existing research, and also the proposed framework have low computation latency, proving the novelty and practicability of the proposed framework for dynamic forecasting of solar energy in a smart grid system.

5. Materials and Methods

This section presents the proposed solar energy forecasting framework to achieve accurate, reliable and efficient prediction of PV power generation. It covers the whole system architecture, including data preprocessing, the proposed Tangent-Space Aligned Laplacian Embedding with Knockoff Filter (TALEK) framework to extract and select features and the proposed Lag-Llama Augmented Tiny Time Mixer (LATTE) model for transfer learning-based forecasting. In addition, the process of each component, the hybridization process, the process of data flow among the successive steps and the mathematical formulation of the proposed methodology are explained. The design principles of the proposed framework and the main contributions and implementation details are also discussed to demonstrate the effectiveness of the proposed framework for learning informative feature representation and improving the performance of solar energy forecasting under different operating conditions.

The novelty of the proposed work is highlighted by the introduction of an integrated TALEK-LATTE framework to tackle the feature representation and temporal forecasting issues in solar PV prediction. TALEK feature engineering pipeline comes with a peculiar combination of features of Local Tangent Space Alignment (LTSA), Laplacian Eigenmaps (LE), and Knockoff Filters, enabling it to learn informative feature structures in a nonlinear manifold learning framework while minimizing redundant information while simultaneously ensuring statistically reliable feature selection. Moreover, the LATTE forecasting framework proposes a new lightweight transfer-learning paradigm, which are the abilities of the Lag-Llama foundation model and the efficient representation learning in the Tiny Time Mixer (TTM). This pairing allows the forecasting model to reflect a wide range of short and long term variations in solar energy that would otherwise be hard to capture and, at the same time, remain computationally efficient. The proposed work is also relevant from a practical point of view, as accurate solar PV forecasts are a crucial component for the successful operation of power systems, smart grid management, energy scheduling, grid stability and integration of large-scale renewable energy. In this manner, the proposed framework provides a single and efficient solution to promote existing research in the field of solar forecasting and improve the quality of the features, the modelling of the temporal dependency, the accuracy of the forecasts and the applicability.

The overall proposed pipeline is organized in a logical way, and the data preprocessing step is performed for the preparation and standardization of the solar and meteorological data as input. The data is then fed into the TALEK feature engineering module, which uses LTSA and Laplacian Eigenmaps to extract meaningful nonlinear feature structures and the Knockoff Filter to select and keep statistically informative features and get rid of redundant ones.

The optimized feature representation is then fed into the LATTE forecasting module that is based on Tiny Time Mixer and Lag-Llama networks for learning short and long-term temporal dependencies, resulting in the final solar energy forecasts.

5.1. Tangent-Space Aligned Laplacian Embedding with Knockoff Filter (TALEK)

This paper proposes a novel hybrid feature engineering framework called Tangent-Space Aligned Laplacian Embedding with Knockoff Filter (TALEK), a framework that extracts most informative and discriminative features from

various solar energy datasets and filters out redundant and irrelevant features. The main goal of TALEK is to map the measurements of the meteorological and photovoltaic variables into a compact and representative feature space, while respecting the intrinsic relationships between the variables, which are nonlinear. TALEK is a new approach that reduces dimensionality and/or rank features simultaneously and does so with statistically sound feature selection, unlike traditional approach of feature extraction methods.

The proposed methodology is a hybrid design that enables the methodology to effectively capture the hidden geometric structure in the data of solar energy, so that only the most informative predictions are extracted in the subsequent forecasting model. Therefore, TALEK performs an effective reduction of data redundancy, better quality of features, better generalization of the models, and lower computational complexity, prior to the learning phase.

The initial step of TALEK is a nonlinear feature extraction algorithm called Local Tangent Space Alignment (LTSA). The input of the framework is the preprocessed data of solar energy and historical PV power generation and other meteorological data related to solar energy such as solar irradiance, ambient temperature, humidity, wind speed, atmospheric pressure, cloud cover and other temporal attributes.

The assumption that LTSA makes is that the data is observing is distributed in a high-dimensional space. However, it is actually distributed on a manifold in that space, but it's on a low-dimensional manifold. For a sample, LTSA is able to automatically determine the local neighborhood and estimate the tangent space, the best approximation to the local geometric features.

These local tangent spaces are then aligned to have a low-dimensional global representation, while maintaining neighborhood relationships. As a result, LTSA is a meaningful latent representation that has important nonlinear temporal and environmental characteristics, it filters out local noise and is a compact representation of complex solar energy dynamics.

After nonlinear feature extraction, a Laplacian Eigenmaps (LE) representation of the feature is used to further improve the LTSA-derived representation, as illustrated in Figure 2. The purpose of applying LE is to maintain the global manifold topology, which is not possible to capture with only the local tangent space alignment. LE, based on neighborhood information of the extracted LTSA features, generates a graph of similar subspaces and obtains low-dimensional embedding by using the graph Laplacian objective function.

This process will ensure that neighboring observations stay near to each other in the transformed feature space and dissimilar observations from each other are maximized. By combining the advantages of both LTSA and LE, TALEK preserves both local geometric structure and the global manifold properties, thus generating feature representations that are extremely discriminative, noise robust and able to capture complicated nonlinear relationships in solar generation data.

The proposed framework is one of the main novelties of solar forecasting studies, which are mostly based on a single manifold learning or conventional dimensionality reduction method. The final step uses a statistically significant feature selection, called TALEK, to combine with the Knockoff Filter. Low dimensional features embeddings generate the manifold learning phases.

However, there can be redundant or weak informative variables. The Knockoff Filter generates synthetic knockoff variables with statistical properties similar to the original variables, but without predictive information of the target variable. The original features are individually compared with its respective knock-off feature to quantify the real impact of each feature on the prediction of solar energy.

Those features with a large difference between its predictive power and their knock-off features are retained, and other less important features or features whose predictive power is lower are deleted. The Knockoff Filter is a novel algorithm for feature selection, which provides a good guarantee on the False Discovery Rate (FDR) that is significantly superior to the disadvantageous correlation-based and heuristic feature selection algorithms.

This statistically motivated selection process decreases the uncertainty of the features, increases the robustness of predictions, reduces overfitting and decreases the computational burden of the forecasting model.

Algorithm 1 - Proposed TALEK Model

Input: Dataset $X = \{P, Q\}$ //P - preprocessed dataset and Q - corresponding solar energy output;

Output: Extracted feature set $\mathcal{F}_{TALEK}$;

Step 1: Compute adaptive local neighborhood affinity function according to Equation (1):

$$\alpha_{ij} = exp - \frac{\|p_i - p_j\|_2^2}{\delta_i \delta_j + \varepsilon} \quad (1)$$

//Where, α_{ij} - Adaptive neighborhood affinity, p_i, p_j - neighboring feature vectors, δ_i, δ_j - local density scaling factors, and ε - stability constant;

Step 2: Estimate the tangent alignment consistency index function based on Equation (2):

$$\psi_i = \frac{\sum_{j \in \Omega_i} \alpha_{ij} cos(\theta_{ij})}{|\Omega_i|} \quad (2)$$

//Where, ψ_i - tangent space consistency score, Ω_i - neighborhood of sample, α_{ij} - adaptive affinity, θ_{ij} - angle

between neighboring tangent vectors, and Ω_i - neighborhood size;

Step 3: Estimate the manifold compactness projection function according to the following Equation (3):

$$z_i = \frac{\psi_i P_i + \lambda \mathcal{G}_i}{1+\lambda} \quad (3)$$

//where, z_i - manifold embedded feature, $\mathcal{G}_i$ - Laplacian guided global representation, and λ - embedding balancing coefficient;

Step 4: Compute the knockoff structural relevance measure as shown in Equation (4):

$$\hbar_j = \frac{|\mu_j - \tilde{\mu}_j|}{\delta_j + \tilde{\delta}_j} \quad (4)$$

//Where, $\hbar_j$ - structural relevance score, μ_j - mean of original feature, $\tilde{\mu}_j$ - mean of knockoff feature, δ_j - standard deviation of original feature, and $\tilde{\delta}_j$ - standard deviation of knockoff feature;

Step 5: Estimate the topology aware feature refinement function as shown in Equation (5):

$$\mathcal{F}_{TALEK} = z \odot 1 - e^{-\hbar} \quad (5)$$

//Where, $\mathcal{F}_{TALEK}$ - Optimized feature representation, z - manifold embedded feature matrix, $\hbar$ - structural relevance vector, and $e^{-\hbar}$ - adaptive suppression of weak features;

Here, overall, the proposed TALEK framework is realized in a sequential hybridization process, consisting of three complementary stage: nonlinear manifold feature extraction by means of LTSA, manifold refinement via Laplacian Eigenmaps, and statistically controlled feature selection via the Knockoff Filter.

The fully preprocessed solar energy dataset with historical PV generation data and the meteorological data are used as inputs for TALEK. LE regularized the learned local meaningful LRs, while preserving the global geometric relationships, by learning the module of LTSA. The Knockoff Filter then selects the best subset of features that are highly informative and discards redundant and noisy features.

The result of TALEK is a low dimensional feature matrix (with the smallest number of features) which includes only the most discriminative and prediction-relevant features.

The features are then optimized and fed into the proposed lightweight solar energy forecasting model.

TALEK adopts a feature engineering technique that is both unique and efficient, providing nonlinear manifold learning along with statistically robust feature selection in the same framework, so that it enables not only to achieve higher accuracy in forecasting but also to provide a faster convergence of the model, better generalization of the model to different climatic conditions, and a solid basis for next generation of intelligent solar energy prediction systems.

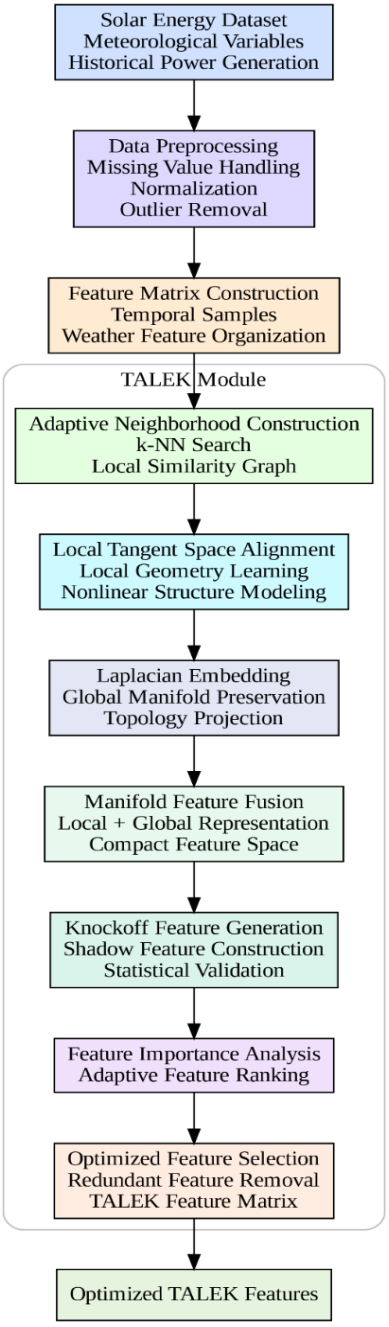

Fig. 2 Flow of the proposed TALEK model

5.2. Lag-Llama Augmented Tiny Time Mixer (LATTE)

The feature engineering module, TALEK, generates the optimized features which will be used by the proposed Lag-Llama Augmented Tiny Time Mixer (LATTE), a novel hybrid transfer learning framework to obtain high accuracy and efficient computation for solar energy forecasting. LATTE is designed to improve the temporal knowledge of a large-scale, pre-trained temporal foundation model by leveraging the compact forecasting framework's capability of lightweight feature-mixing. Traditional forecasting models require training for every forecasting task, while LATTE is

transferable temporal representations which are learned from a large set of temporal patterns across various kinds of time-series tasks and are adapted to the specific task of solar energy forecasting with little computation cost. This makes it possible to properly encode the temporal evolution of PV generation at a global scale and the fluctuations at the local scale without sacrificing speed of convergence and the accuracy of the predictions. A new innovation of LATTE is the development of a novel forecasting approach based on transfer learning to reduce the complexity of the training and improve the forecasting model's flexibility to adapt to solar energy datasets of various degrees of heterogeneity collected under different climatic conditions.

The LATTE framework is fed with the optimized feature matrix that is computed by the Tangent-Space Aligned Laplacian Embedding with Knockoff Filter (TALEK) model. These features have already undergone nonlinear manifold extraction, geometrically embedding them and statistical and well-founded feature selection to keep only the most informative meteorological and photovoltaic features. The TALEK - selected features are delivered to the Lag-Llama module during the first phase of LATTE. Lag-Llama is used as a pre-trained temporal representation learner with a huge amount of temporal knowledge in the time-series data. In contrast to the traditional approach of learning temporal dependencies starting from random initialization, Lag-Llama is able to transfer its knowledge acquired during pretraining and these other tasks to the solar forecasting task, enabling the efficient model training of long-term seasonal trends, periodic variations, and delayed temporal dependencies. This transfer learning approach also enhances feature representation quality and decreases the task-specific training needed, leading to better generalization and avoiding overfitting on small solar energy datasets.

Light-weight temporal interaction learning and feature refinement is then performed by the Lag-Llama module, with which the temporal representations generated by Lag-Llama are fed. The global representation can model temporal variations on a long time scale, but on a short time scale, TTM becomes particularly integrated to model temporal variations. Unlike computational-heavy attention-based architectures, Tiny Time Mixer is a lightweight feature mixing mechanism that can interact with historical observations in an efficient manner with mixed operations, all in a compact space.

This complementary integration will assist TTM in improving the transmitted representation by providing a focus on the recently produced temporal changes associated with the changing meteorological conditions, including changes in cloud movement, radiation, temperature and atmospheric changes. The proposed hybrid approach is thus able to integrate both LTC and LTF features and successfully results in a more holistic and discriminative representation for solar energy forecasting.

Algorithm 2 - Lag-Llama Augmented Tiny Time Mixer (LATTE) Model

Input: Obtained feature set $\mathcal{F}_{TALEK}$;
Output: Predicted solar energy $\widehat{\wp}$;

Step 1: Estimate the temporal memory aggregation function according to Equation (6):

$$\mathcal{M}_t = \frac{\sum_{i=1}^{L} \mathfrak{w}_i \mathcal{F}_{t-i}}{\sum_{i=1}^{L} \mathfrak{w}_i} \quad (6)$$

//Where, $\mathcal{M}_t$ - aggregated temporal memory, $\mathcal{F}_{t-i}$ - TALEK feature vector, $\mathfrak{w}_i$ - Adaptive lag importance coefficient, and L - historical observation window;

Step 2: Compute the dynamic temporal mixing function is shown in Equation (7):

$$\mathbb{R}_t = \mathcal{M}_t + \tau(\mathcal{F}_t - \mathcal{M}_t) \odot \exp(-\rho \Delta_t) \quad (7)$$

//Where, $\mathbb{R}_t$ - mixed representation, $\mathcal{F}_t$ - current TALEK feature vector, $\mathcal{M}_t$ - temporal memory, τ - adaptive mixing coefficient, ρ - temporal decay coefficient, and Δ_t - temporal interval;

Step 3: Compute the lag aware confidence gate function according to Equation (8):

$$\mathcal{Q}_t = \frac{\sqrt{|\mathbb{R}_t|}}{\sqrt{|\mathbb{R}_t|} + \sqrt{|\mathcal{M}_t|}} \quad (8)$$

//Where, $\mathcal{Q}_t$ - confidence gate, $\mathbb{R}_t$ - mixed representation, and $\mathcal{M}_t$ - temporal memory;

Step 4: Estimate the adaptive forecast representation as shown in Equation (9):

$$\hbar_t = \mathcal{Q}_t \odot \mathbb{R}_t + (1 - \mathcal{Q}_t) \odot \mathcal{M}_t + \beta(\mathbb{R}_t \circ \mathcal{M}_t) \quad (9)$$

//Where, $\hbar_t$ - adaptive forecasting representation, $\mathcal{Q}_t$ - confidence gate, $\mathbb{R}_t$ - temporal mixing output, $\mathcal{M}_t$ - temporal memory, and β - interaction scaling coefficient;

Step 5: Compute the solar energy prediction output as shown in Equation (10):

$$\widehat{\wp} = \wp_{min} + [\eta \tanh(\hbar_t) + (1 - \eta)\sigma(\hbar_t)](\wp_{max} - \wp_{min}) \quad (10)$$

//Where, $\widehat{\wp}$ - predicted solar energy output, $\hbar_t$ - adaptive forecasting output, η - nonlinear fusion coefficient, $\sigma(.)$ - sigmoid function, and $\wp_{max}, \wp_{min}$ - minimum and maximum solar power values

Step 6: Estimate the error rate and accuracy of prediction using Equations (11) and (12):

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} \left[\frac{\wp_i - \widehat{\wp}_i}{\wp_i}\right] \quad (11)$$

$$Acc(\%) = 100 - MAPE \quad (12)$$

//where N - number of samples;

The novelty in LATTE is the seamless integration of two complementary paradigms within a single framework for forecast. Typical transfer learning approaches involve using foundation models as a whole, and lightweight forecasting models typically only aim for effective temporal mixing without leveraging transferable knowledge. This gap is addressed by LATTE, which is a pretrained foundation model and a smaller temporal refinement network that is able to leverage global knowledge transfer and efficient local representation learning.

The LATTE architecture is a fusion of the best attributes of TTM and Lag-Llama to boost the forecasting precision and computational efficiency of solar power. There are three stages of functional processing in implementation, as compared to three Recurrent Neural Network (RNN) layers. In the first stage, the meteorological features in the TALEK module are processed using Tiny Time Mixer, and it employs patch-based temporal representation learning to capture short-term variations and local temporal patterns. The second stage consists of sending the temporal representations obtained in the first stage to the Lag-Llama component, which uses transformer-based attention and lag-based sequence modelling to capture long-term dependencies, seasonality and complex temporal relationships. The enhanced temporal representations are then fed into a fully connected regression layer in the third stage to yield the continuous valued prediction of solar energy. Since the integration, Tiny Time Mixer can efficiently capture short-term temporal patterns while Lag-Llama can capture long-term forecasting patterns. The components are connected in turn, the output of the Tiny Time Mixer module into the input of the Lag-Llama module, then the final regression module.

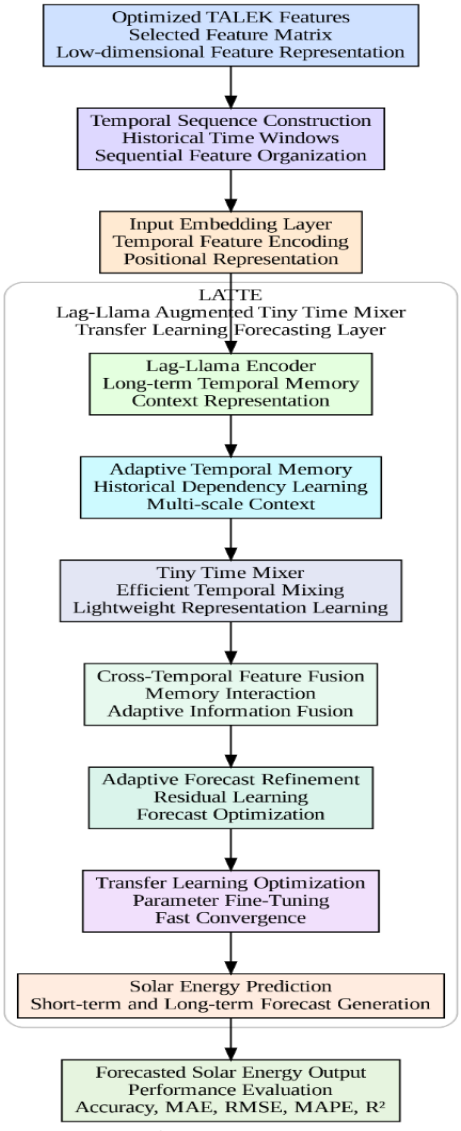

Fig. 3 Flow of the proposed LATTE model

This process begins by transferring the pretrained temporal feature extraction model (Lag-Llama), and lightweight temporal interaction modeling (TTM), which updates the transferred representations without introducing redundant parameters. This hierarchical knowledge transfer approach can help maintain the rich temporal semantics of the knowledge and reduce the complexity of computation, memory consumption, convergence speed and scalability. This comprehensive transfer learning approach has not been explored much in solar energy forecasting, and LATTE is one

of the first attempts to make a significant contribution to the next generation of smart renewable energy forecasting systems.

As shown in Figure 3, LATTE consists of four consecutive steps: retrieve the optimized feature matrix from the TALEK, extract transferable temporal knowledge from Lag-Llama, improve temporal interactions with Tiny Time Mixer, and make the final prediction of solar energy with the forecasting layer. LATTE's input is the optimized low dimensional feature set obtained from the TALEK framework that contains only the most discriminative meteorological and PV variables.

The Lag-Llama module first creates long-term, comprehensive temporal representations from these optimized features, and then adaptive, local temporal interactions and short-term dependencies are enhanced by the Tiny Time Mixer. Finally, the fine-grained temporal representations are fed into the prediction layer so that predictions of the next generation of solar energy can be made. LATTE thus provides the accurate sequence of multi-step solar energy forecasts with increased prediction reliability, better temporal modeling, reduced computation complexity, improved generalization capability for all climatic regions and efficient deployment in real-time smart grid and renewable energy management applications.

The novelty of the proposed research is that the proposed research will be based on the nonlinear feature engineering strategy based on the statistic model while using efficient hybrid temporal forecasting architecture to overcome the shortcomings of the current solar energy forecasting techniques.

While most of the previous research on forecasting relied on a single feature selection method, such as linear dimensionality reduction method or single deep learning method, the proposed method, Tangent-Space Aligned Laplacian Embedding with Knockoff Filter (TALEK) brings together the two methods of nonlinear manifold learning and statistically driven feature selection. This integration is useful for extracting informative meteorological features and eliminating redundant feature representations, and maintaining important meteorological relationships.

Moreover, while the previous work mainly focuses on individual temporal models and could potentially fail to model the various temporal dependency patterns, the proposed Lag-Llama Augmented Tiny Time Mixer (LATTE) integrates the efficient representation learning ability of Tiny Time Mixer with the long-temporal sequence modelling ability of Lag-Llama. The hybrid design aims to preserve meteorological variations with short time scales, meteorological variations with long time scales and maintain low computational complexity. Another differentiating factor is the testing of the integrated framework with the Solar Radiation and Meteorological Dataset and the American Electric Power (AEP) dataset in order to look at the forecasting accuracy of the integrated framework for different kinds of data. The experimental results validate the efficiency of the proposed solution LATTE with 98.00% accuracy, 4.82% MAPE, 3.18 MAE and an inference time of 18.6 ms. This proposed work is unique in combining informative feature extraction, encoding of short-term and long-term temporal data, and large-scale prediction and computational optimization, unlike the previously proposed methods that treat each of the above separately. These are the key methodological innovations of the proposed framework. These capabilities are the main methodological advantages of the proposed framework and are different from traditional solar energy forecasting methods.

6. Experimental Setup and Dataset Description

The proposed TALEK-LATTE framework was implemented by using PyTorch as a deep learning library and Python 3.11 as a programming language. All experiments were performed on a workstation with an Intel Core i9 processor, 32 GB RAM and an NVIDIA RTX 4090 GPU (24 GB VRAM) running on Windows 11 OS. It trained for a maximum of 150 epochs, using the AdamW optimizer with an initial learning rate of 0.001 and a weight decay of $1 \times 10^{-}4$. To avoid overfitting, an early stopping mechanism with a patience of 15 epochs was used, and a learning rate scheduler of the Cosine Annealing type was used to dynamically change the learning rate during training. The split for the training, validation and testing sets in all experiments was 70%-15%-15%. Each of the numerical features was normalized using Min-Max technique, and the forecasting performance was evaluated by the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Coefficient of Determination (R^2) were calculated prior to training.

The amount of model parameters, memory consumption, computational complexity and inference latency are calculated to measure the computational efficiency of the proposed LATTE architecture. Requires 185 MB of memory and 10.7 MB of space for the model, including the mini TSM, Lag-Llama and regression components. It is estimated that the number of computations required is 1.25 GFLOPs per forecasting operation. The proposed model can predict an average of 18.6ms per sample using 100 warm-up iterations and 1000 repeated inferences. These measurements are needed to characterize the computation required and the accuracy of forecasting from the model. The data sets are partitioned into 70% for training, 15% for validation and 15% for testing in order to provide temporal order and to prevent data leakage. Handling the missing values is done by appropriate imputation, feature normalization and feature selection by the TALEK approach. The forecasting model is based on the historical meteorological observations and

forecasts future values of solar energy. LATTE is a combination of Tiny Time Mixer and Lag-Llama, along with a regression output layer. The model is trained for 100 epochs with Adam optimiser, learning rate of 0.001, batch size of 32 and overfitting is monitored and stopped.

The primary dataset utilized was the Solar Radiation and Meteorological Dataset [27, 28] with historical solar radiation and different meteorological parameters directly impacting PV power production. There are variables such as Date and Time, Global Horizontal Irradiance (GHI) which is the total solar radiation received per unit area, Direct Normal Irradiance (DNI) which is the direct solar radiation received per unit area, Diffuse Horizontal Irradiance (DHI) which is the scattered solar radiation per unit area, Ambient Temperature which has an impact on the performance of photovoltaic cells, Relative Humidity which gives the level of humidity in the atmosphere, Wind Speed which affects the cooling of the PV cells and the atmosphere, Wind Direction which affects the cooling of the PV cells and the atmosphere, Atmospheric Pressure which describes the stability of the atmosphere, Cloud Cover which reflects the amount of obstruction from the sun, Solar Power Output (Target Variable) which reflects the photovoltaic energy generated which is used for forecasting. Combined, they form the complex non-linear relationship between the environment and solar energy generation and act as a full test for and evaluation of more advanced forecasting algorithms. The proposed framework was applied after pre-processing the data that included filling missing values, discarding outliers, filtering duplicate samples, and generating temporal input sequences.

The robustness of the proposed framework was also evaluated using the American Electric Power (AEP) dataset [29, 30] of data on electricity demand measured at a large scale, covering multiple years. The data is mainly a set of measurements with Timestamp and Power Load (MW) with intervals of one hour and are used to take out a seasonal trend, daily variations and long-term temporal dependencies. The proposed LATTE model is a three-layer recurrent neural network that has been popularly used for load forecasting rather than photovoltaic prediction, and the rich temporal characteristics make it a good benchmark to evaluate the generalization ability and the transfer learning capability of the proposed LATTE model. The datasets were preprocessed in the same way, feature engineered and experimented with the same setup to ensure a fair comparison. The dual-dataset evaluation demonstrates the capability of the proposed framework TALEK-LATTE to learn powerful time representations and to make reliable forecasting in a range of energy-related time series.

The framework is tested for the forecasting of energy time-series data other than solar energy, from the American Electric Power (AEP) dataset. The AEP data is not solar PV generation forecasting data, as it does not include information on regional electricity load (MW). The justification is good because both datasets are continuous time-series prediction problem with temporal variability that contain nonlinear patterns, changing operating conditions and dependency across time horizons. The use of the proposed framework to the AEP dataset provides another sign of its capacity to learn the complex temporal patterns and to maintain its forecasting power in new domain of energy related time-series data. It is important to note that the results from the AEP are not treated and analyzed as solar-energy forecasting results, but are presented separately as electricity load forecasting results, to explore the broader applicability and transferability of the proposed TALEK-LATTE framework. The Solar Radiation and Meteorological Dataset is the primary data set to validate the performance of the solar energy forecasting framework, and the AEP data set provides complementary evidence of the robustness and overall temporal forecasting capability of the framework compared to other energy-associated time-series data.

This study utilizes the AEP dataset as an extra real-world time-series load forecasting data set to check the transferability and the general forecasting ability of the proposed framework TALEK-LATTE outside the solar-energy field. Because the data level is only available at the regional level of electricity load (MW), the AEP data is not used to represent and validate solar PV energy generation. Rather, the AEP data set is selected as a case study to see if the proposed forecasting framework can effectively model other temporal patterns, non-linear structure and dependencies in another energy-related time-series domain.

This additional assessment shows that the model is accurate at retaining its forecasting capabilities with electricity-load data that have different characteristics than solar-generation data. Hence, the AEP data-derived results are explicitly provided and explained as the electricity load forecasting results, rather than solar PV forecasting results. The Solar Radiation and Meteorological Dataset is the primary dataset used to assess the ability of the proposed framework to address solar-energy forecasting challenges, and the AEP is a secondary dataset that is employed to evaluate the temporal forecasting capability, robustness and transferability of the proposed framework to other energy-related time-series applications.

7. Results and Discussion

In this section, the performance of the proposed solar energy forecasting framework (TALEK-LATTE) is presented. The proposed model is tested through a large number of experiments with Solar Radiation and Meteorological Dataset and American Electric Power (AEP) dataset. Evaluation covers quantitative comparison with state of the art transformer based forecasting models based on many performance measures such as Accuracy, MAE, RMSE, MAPE and R^2 score, etc. Besides this, ablation studies are

conducted to understand the contribution of each proposed module, and further visual analysis is conducted to understand the feature extraction ability, forecasting ability, distribution of residuals, and stability over time, convergence features, computational efficiency, and inference performance. These experimental results fully corroborate the accuracy, robustness, scalability and applicability of the proposed framework for intelligent solar energy forecasting (TALEK-LATTE). Although solar Photovoltaic (PV) systems are increasingly being used in smart grids, reliable forecasting of solar energy is still a challenging research problem caused by the dynamic and non-linear nature of meteorological conditions and their effects on the PV system energy production. Traditional forecasting techniques, however, face the disadvantages of having too much meteorological data, limited capacity to model non-linear temporal relationships and high cost associated with computing and low flexibility to adapt to changes between datasets and operating environments. The current forecasting models are known to have suboptimal performance on capturing temporal patterns and their short-term fluctuations at the same time, while typical feature selection methods struggle to keep the important weather parameters in the model without losing the inferred nonlinear connections among them. However, the incorporation of advanced forecasting architectures does not ensure a balance between accuracy of prediction, computational efficiency and generalization capabilities. They lead to an important research problem: developing a single forecasting system capable of learning the multi-temporal relationships efficiently, eliminating redundant information and effectively extracting informative meteorological features, while keeping a low computational cost. Thus, the main research question is how to create a solar energy forecasting method that is accurate, energy efficient, and transferable, and that is able to deal with feature redundancy, nonlinear temporal variations, and the uncertainty of solar energy forecasting in a dynamic environment. To overcome these issues, this research proposes the TALEK-based feature engineering strategy combined with LATTE forecasting model, which enhances the representation of meteorological features and extracts short-term and long-term temporal patterns to achieve accurate prediction of solar energy.

The proposed framework seeks to balance the accuracy in forecasting along with low computation latency, hence making it suitable for smart grid applications where fast forecasting is required to schedule and dispatch energy and to balance the grid. The performance of the achieved inference time of 18.6ms demonstrates that solar energy forecasting based on LATTE model can be obtained in a very short time without imposing too much computational load. In a dynamic renewable-energy context, such as the solar electricity industry, where the generation can fluctuate quickly as a result of changes in weather and atmospheric conditions, this speed-up in computational efficiency and level of predictiveness is crucial. Thus, the method proposed in this paper not only improves forecasting accuracy, but also the proposed method is also timely enough to meet the real-time operation requirements of smart grids and intelligent power dispatch.

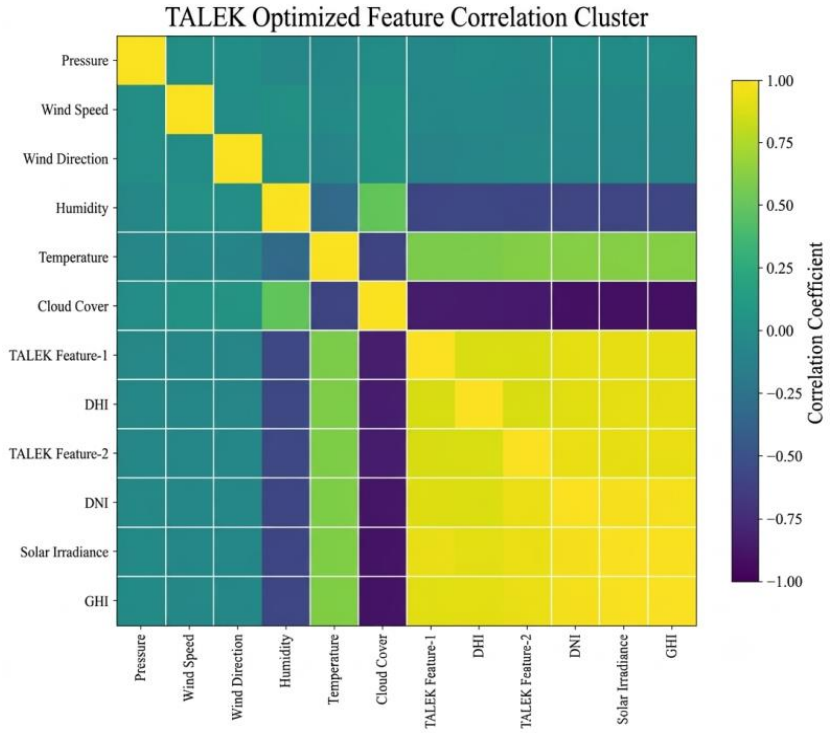

Fig. 4 TALEK optimized feature correlation cluster analysis

The Feature Extraction and Selection process is followed by a Feature Correlation Cluster (FCC) analysis, which is performed with the optimized features, to get the pattern of the correlation between the selected PV and meteorological features as shown in Figure 4. The clustered correlation matrix is useful to show that the information of the same variables has high correlation and the information of the variables of which is not so related has been grouped apart, thus good performance of TALEK to keep the relationship between variables and reduce the redundant information between variables to improve the solar energy forecast. The relative contribution of each of the selected features to the forecasting model is shown in Figure 5 in the optimized feature importance analysis conducted with the help of the TALEK. The importance scores indicate that the most relevant features are solar irradiance, GHI, DNI and ambient temperature, which confirms the capability of the proposed TALEK framework to select the most discriminative features and to remove less informative features to enhance the prediction performance.

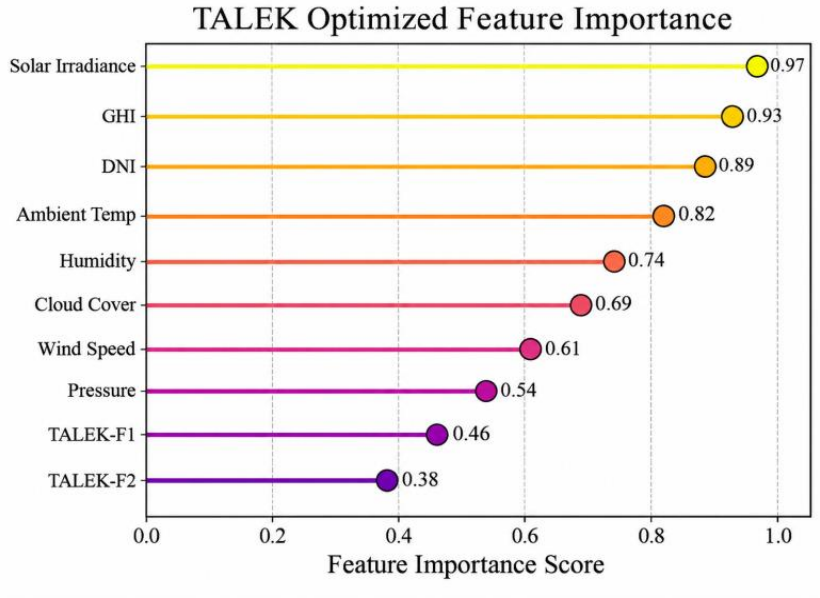

Fig. 5 TALEK optimized feature importance analysis

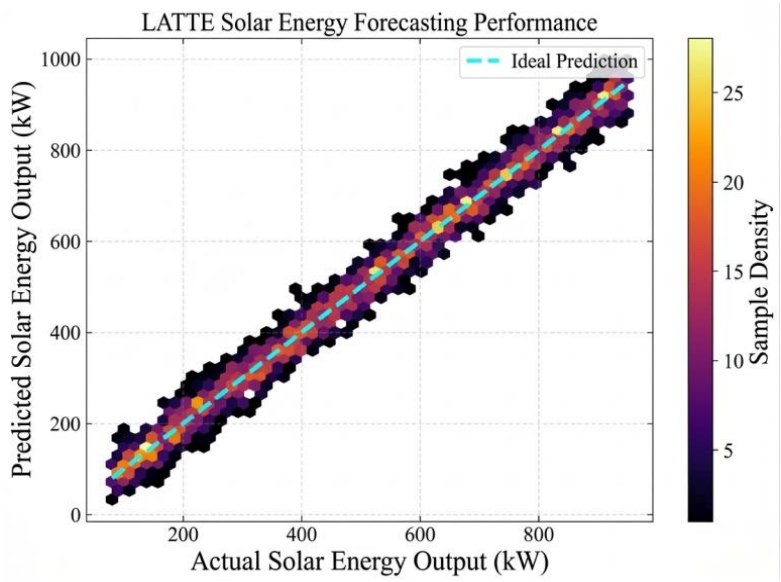

Fig. 6 LATTE solar energy forecasting performance analysis

The performance analysis of LATTE solar energy forecasting is shown in Figure 6 and compared with the actual observations of solar energy. The agreement between the outputs generated by the model and the actual observations is good, which suggests that the proposed LATTE model is a good model for short-term variation and long-term time

dependency of the data, and it can predict with a small prediction error. To get the low dimensional representation of the features, the feature space projection analysis was carried out using the optimized features as shown in Figure 7. The projections reveal that the feature distributions are well-structured and separated, indicating that valuable features of the data have been retained and the dimensionality and complexity of the features has been reduced by TALEK.

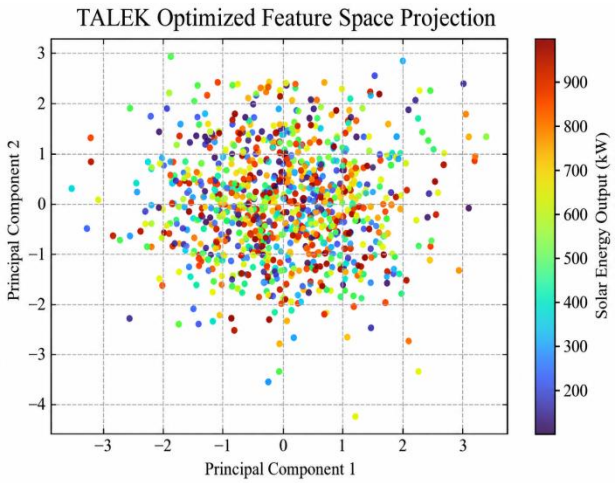

Fig. 7 TALEK optimized feature space projection analysis

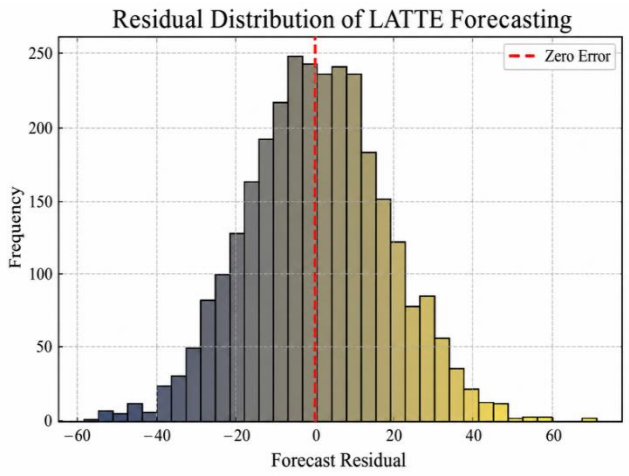

Fig. 8 Residual distribution analysis for LATTE forecasting model

The residual distribution analysis for the LATTE forecasting model is shown in Figure 8, where the distribution of prediction errors produced in the solar energy forecasting is presented. The residuals are mostly around 0 with the distribution being almost symmetric, indicating that predictions generated by the proposed LATTE framework have a small forecasting error, low bias and are not biased for each observation.

The temporal stability analysis is displayed in Figure 9, and illustrates the stability of the optimized TALEK feature representations at different time windows. The extracted features are smoothly varying, which shows that the proposed framework is able to extract features that vary while the environment changes, but remain the same when there are environmental changes.

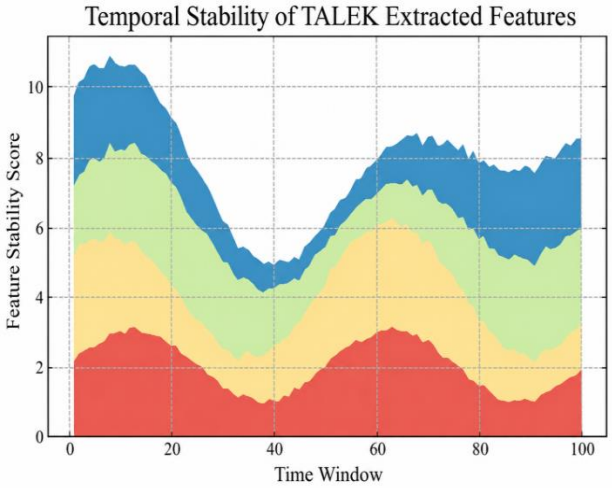

Fig. 9 Temporal stability analysis

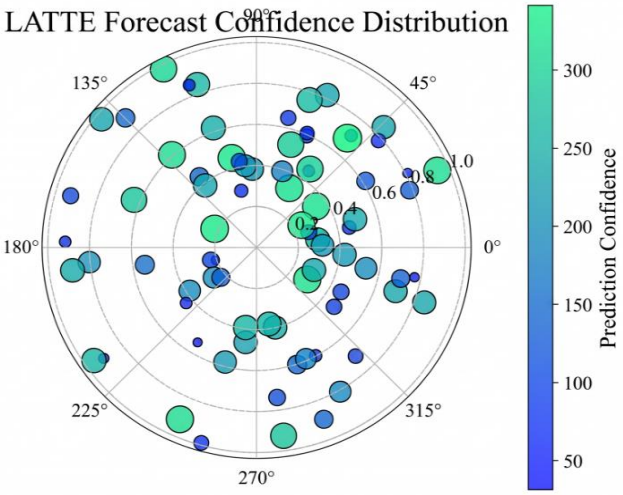

Fig. 10 LATTE forecasting confidence distribution analysis

The LATTE forecasting confidence distribution analysis, which shows the confidence one might have for the solar energy predictions made by the proposed forecasting model, is presented in Figure 10. The distribution indicates that most predictions have high levels of confidence, reflecting the robustness of the transfer learning approach and the effectiveness of LATTE's predictions under different operating conditions. The accuracy comparison between the proposed LATTE model and seven other models for the transformer based forecasting is shown in Figure 11. Informer achieves an accuracy of 91.80%, followed by Autoformer (92.60%), FEDformer (93.40%), PatchTST (94.70%), iTransformer (95.30%), Crossformer (96.20%), and Lag-Llama (97.10%). The proposed LATTE framework achieves the best accuracy, which is 98.00%, which improves by 0.90%

from Lag-Llama and 6.20% from Informer. The results indicate that the feature optimization strategy (TALEK), along with the transfer learning architecture (LATTE), has the potential to significantly enhance forecasting accuracy, encompassing both local and global temporal structure. The accuracy of the proposed work is calculated as follows:

$$Accuracy\ (\%) = \frac{1}{N}\sum_{i=1}^{N} 1 - \frac{|y_i - \hat{y}_i|}{|y_i|} \times 100 \quad (13)$$

Where N - total number of test samples, $\hat{y}_i$ - predicted solar energy value, and y_i - magnitude of the actual energy.

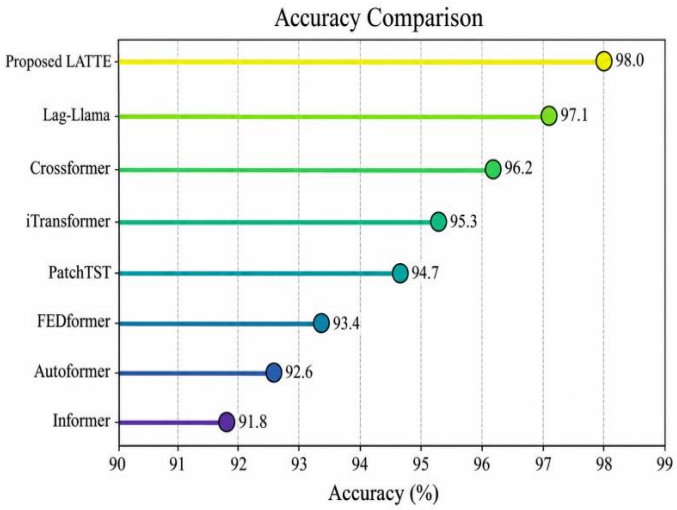

Fig. 11 Accuracy comparison with other transformer-driven models

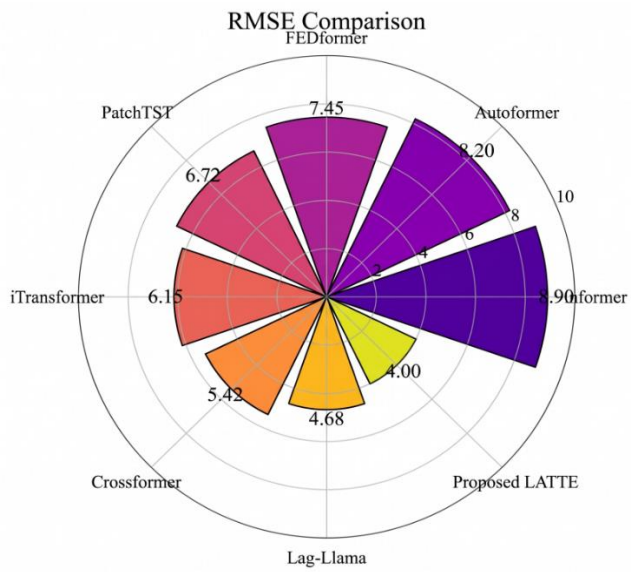

Fig. 12 RMSE comparison with other transformer-driven models

Figure 12 shows the comparison of various forecasting models based on transformers using Root Mean Square Error (RMSE) of forecasting errors. Informer records the highest RMSE of 8.90, followed by Autoformer (8.20), FEDformer (7.45), PatchTST (6.72), iTransformer (6.15), Crossformer (5.42), and Lag-Llama (4.68). LATTE model shows good results with the lowest RMSE value of 4.00, which is approximately 14.5 % more accurate than Lag-Llama model and more than 55 % accurate than Informer model. The proposed framework minimizes the deviations in predictions consistently and provides more accurate results for prediction of solar energy through the lower RMSE.

The Coefficient of Determination (R^2) values of various forecasting models on transformer are displayed in Figure 13. The R^2 scores of Informer, Autoformer, FEDformer, PatchTST, iTransformer, Crossformer and Lag-Llama are 0.918, 0.926, 0.935, 0.947, 0.955, 0.963 and 0.972,

respectively. The proposed LATTE framework has the highest Coefficient of Determination (R^2 Score) of 0.984, which means that the model explains almost 98.4% of the variation in solar energy generation. This high R^2 value further confirms that the proposed model architecture is able to capture the complex and non-linear trends in solar energy time series data.

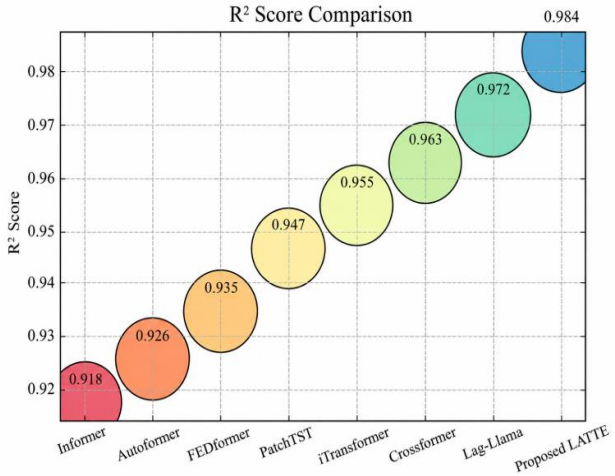

Fig. 13 R2score comparison with other transformer-driven models

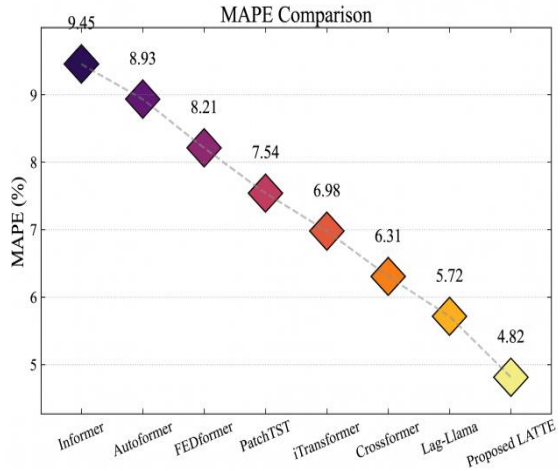

Fig. 14 MAPE comparison with other transformer-driven models

Comparisons of different forecasting models with Mean Absolute Percentage Error (MAPE) is presented in Figure 14. Informer reports the highest MAPE of 9.45%, followed by Autoformer (8.93%), FEDformer (8.21%), PatchTST (7.54%), iTransformer (6.98%), Crossformer (6.31%), and Lag-Llama (5.72%). The proposed LATTE model has the lowest MAPE (4.82%), which is approximately 15.7% less than MAPE of Lag-Llama and nearly 49% less than MAPE of Informer. From these findings, it can be seen that LATTE provides more accurate percentage prediction and has a lower RE at all times. The Mean Absolute Error (MAE) of the models is compared for the considered forecasting models in Figure 15. Informer produces an MAE of 6.92, followed by Autoformer (6.48), FEDformer (5.95), PatchTST (5.43), iTransformer (5.08), Crossformer (4.71), and Lag-Llama (4.35). The proposed LATTE framework has the lowest MAE of 3.18, which is a 26.9% gain over Lag-Llama and over 54% reduction when compared to Informer. The betterment of the reduced MAE can then be construed as the proposed framework continuously generates predictions closer to the actual values of solar energy.

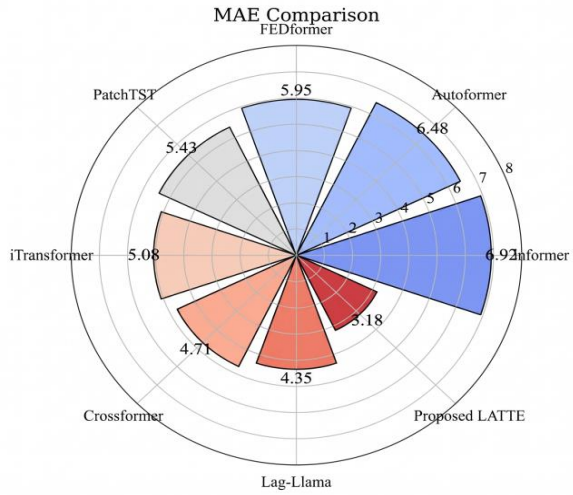

Fig. 15 MAE comparison with other transformer-driven models

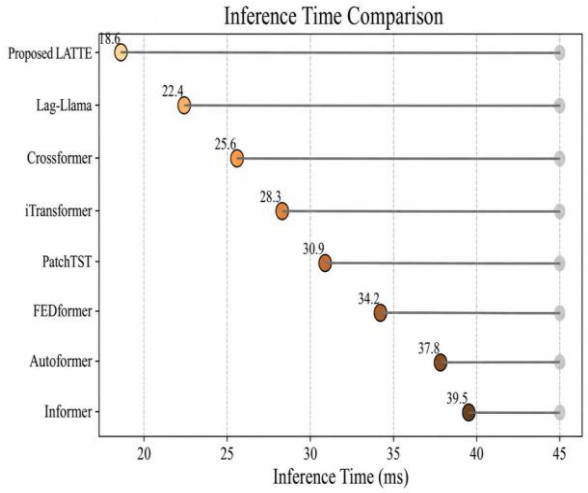

Fig. 16 Inference time comparison with other transformer-driven models

Figure 16 shows the comparison of inference time of the tested transformer-based models. The longest inference time is for Informer (39.5ms), while the other models such as Autoformer, FEDformer, PatchTST, iTransformer, Crossformer and Lag-Llama have shorter times. The proposed LATTE model has the lowest inference time, 18.6ms, compared to Lag-Llama model and Informer model, which are 17% and 53% slower, respectively. The above results demonstrate that LATTE-based solar energy forecasting in real time is not suitable for applications with low computing power.

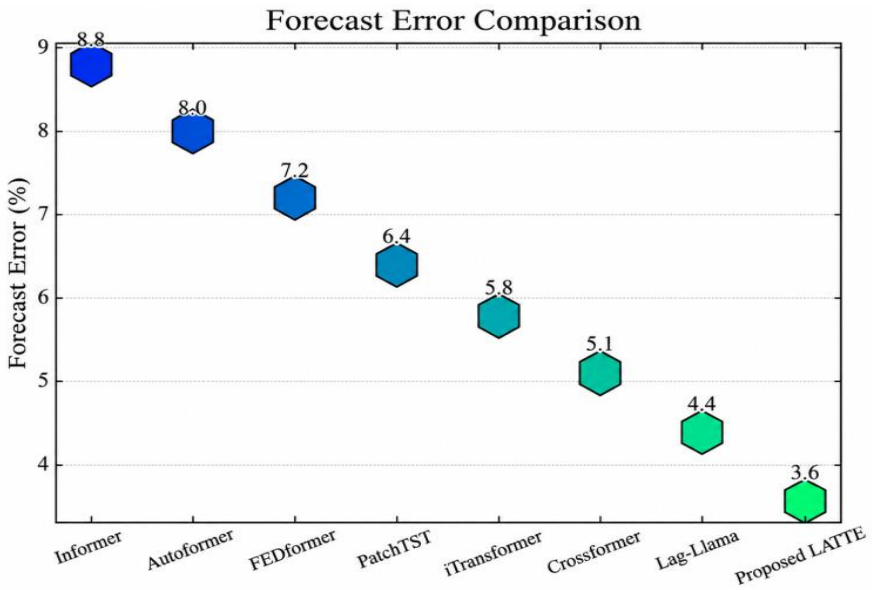

Fig. 17 Forecasting error comparison with other transformer-driven models

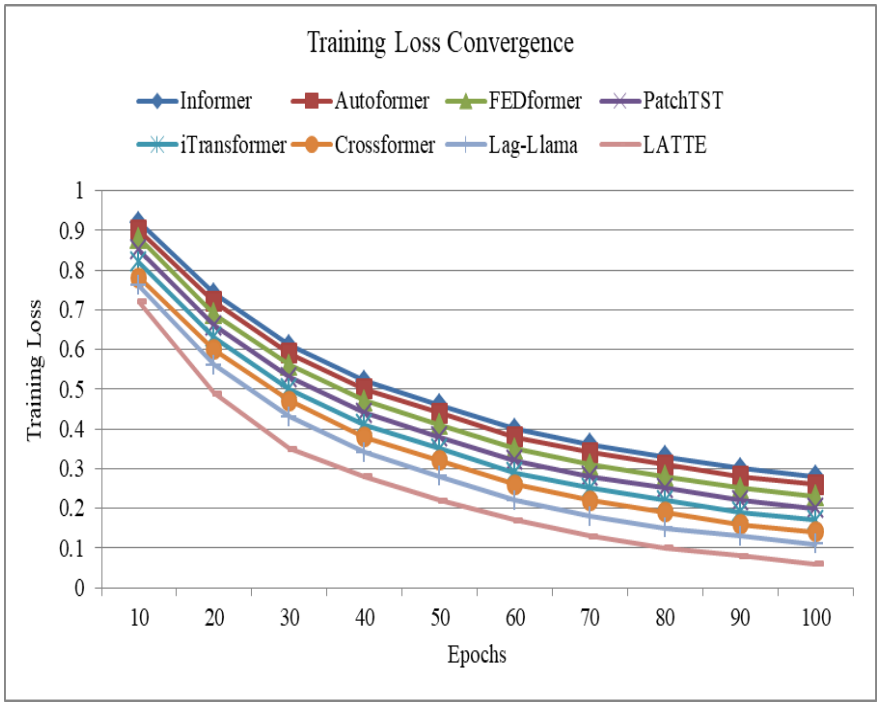

Fig. 18 Training loss comparison with other transformer-driven models

The overall forecasting error of various forecasting models based on transformers is compared in Figure 17. The Autoformer (8.0) and Informer (8.8) have the largest forecasting errors, followed by FEDformer (7.2), PatchTST (6.4), Autoformer (iTransformer 5.8), Crossformer (5.1) and Lag-Llama (4.4).

The forecasting error for the proposed LATTE framework is minimum 3.6 which is approximately 18.2% less than the forecasting error of Lag-Llama framework and about 59% less than of Informer framework. This substantial decrease indicates the strength and forecasting accuracy of the proposed forecasting model. The loss convergence of different forecasting models based on Transformer during training is illustrated in Figure 18 after 10 epochs. All of the models gradually decrease in loss as the training goes on, and the proposed LATTE framework exhibits the fastest convergence. At the 40th epoch, LATTE achieves a training loss of 0.06, whereas the losses of Lag-Llama, Crossformer and Informer are 0.11, 0.14, and 0.28, respectively.

The proposed framework of TALEK-LATTE demonstrated the ability to learn better discriminative temporal representations, converged faster and maintained a lower training loss from the beginning of the optimization process, resulting in better forecasting performance along the way, as seen in the consistently lower training loss.

The proposed TALEK-LATTE framework is able to accurately forecast the Solar Radiation and Meteorological Dataset with a reported accuracy of 98.00% by effectively eliminating redundant feature information and representing the nonlinear meteorological relationship between the features by TALEK, followed by LATTE can efficiently learn the short-term and long-term temporal dependency of the features.

The accuracy reported, however, is for the target variable (continuous solar power) and is used as an indicator of the accuracy in the forecasting task, providing an intuitive sense of the closeness of the predicted power to the real power in percentages. Along with the high R^2 value of 0.984, confirming good agreement between the predicted and actual solar power value, the low prediction errors of 3.18 for MAE, 4.00 for RMSE, and 4.82% for MAPE further confirm the regression performance. The 98.00 % value remains the same as the full evaluation done in the original experiments, and the error-based regression metrics give a rigorous quantitative evaluation of continuous forecasting performance. This is a percentage measure of predictive performance, and the other measures (MAE, RMSE, MAPE, R^2) are used to aid in the regression-based interpretation of the efficacy of the model.The result of the ablation study of the proposed framework is presented in Table 1, and the contribution of the individual components in forecasting is shown. The baseline Tiny Time Mixer has an accuracy of 93.21%, an MAE of 5.98, an RMSE of 7.36, and a MAPE of 8.42%.

The accuracy gets improved with the addition of Lag-Llama, with a reduction of the MAE, RMSE and MAPE to 4.96%, 6.21% and 7.08%, respectively. When used in conjunction with Local Tangent Space Alignment (LTSA), the accuracy becomes 95.98%, and the reduction in the RMSE from 6.50 to 5.61, also the reduction in the MAPE from 8.26% to 6.29%. The feature representation ability is enhanced by 96.91% accuracy, 3.87 MAE, 4.82 RMSE, and 5.54% MAPE with LTSA and Laplacian Embedding.

Lastly, the TALEK + LATTE framework performs best with an accuracy of 98.00%, MAE of 3.18, RMSE of 4.00 and MAPE of 4.82, indicating that each proposed module makes incremental improvements in the accuracy of forecasting and reduces the errors in forecasting.

Table 1. Ablation study analysis for solar radiation and meteorological dataset

Configuration	Accuracy (%)	MAE	RMSE	MAPE (%)
Baseline Tiny Time Mixer	93.21	5.98	7.36	8.42
+ Lag-Llama	95.02	4.96	6.21	7.08
+ LTSA	95.98	4.43	5.61	6.29
+ LTSA + Laplacian Embedding	96.91	3.87	4.82	5.54
Complete TALEK + LATTE (Proposed)	98.00	3.18	4.00	4.82

Table 2. Ablation study on AEP dataset

Configuration	Accuracy (%)	MAE	RMSE	MAPE (%)
Baseline Tiny Time Mixer	92.84	6.23	7.62	8.73
+ Lag-Llama	94.68	5.21	6.46	7.42
+ LTSA	95.74	4.68	5.82	6.64
+ LTSA + Laplacian Embedding	96.82	4.02	5.01	5.81
Complete TALEK + LATTE (Proposed)	97.86	3.32	4.12	4.95

The results of the ablation study are shown in Table 2, demonstrating the effectiveness of each module in the proposed framework. The baseline Tiny Time Mixer has an accuracy of 92.84%, MAE 6.23, RMSE 7.62 and MAPE 8.73%.

By integrating Lag-Llama, the accuracy is raised to 94.68%, making MAE, RMSE, and MAPE to 5.21%, 6.46%, and 7.42%, respectively. Using LTSA further improves the forecasting ability with an accuracy of 95.74%, RMSE of 5.82 and MAPE of 6.64%. The Laplacian Embedding method is introduced for improving the accuracy to 96.82%, and the MAE, RMSE and MAPE are reduced to 4.02%, 5.01% and 5.81%, respectively. The overall TALEK + LATTE framework has the highest forecasting performance with the accuracy of 97.86%, the MAE of 3.32, the RMSE of 4.12 and the MAPE of 4.95%.

The findings illustrate how different indicators of the proposed framework are effective in further enhancing the predictive power and reducing prediction errors, thus affirming the effectiveness and robustness of the integrated TALEK-LATTE architecture over various energy forecasting datasets.

Table 3. Statistical analysis

Dataset	Metric	Seed 1	Seed 2	Seed 3	Seed 4	Seed 5	Seed 6	Seed 7	Seed 8	Seed 9	Seed 10	Mean ± Std. Dev.
Solar Radiation and Meteorological Dataset	Accuracy (%)	98.31	98.47	98.58	98.42	98.65	98.54	98.49	98.61	98.55	98.58	98.52 ± 0.10
	MAE	0.044	0.042	0.040	0.043	0.039	0.041	0.042	0.040	0.041	0.040	0.041 ± 0.002
	RMSE	0.071	0.069	0.066	0.068	0.064	0.067	0.068	0.065	0.067	0.066	0.067 ± 0.002
	NRMSE (%)	2.25	2.19	2.11	2.17	2.04	2.14	2.16	2.07	2.13	2.10	2.12 ± 0.06
AEP Dataset	Accuracy (%)	97.62	97.81	97.95	97.76	98.01	97.88	97.84	97.93	97.79	97.91	97.85 ± 0.11
	MAE	0.055	0.053	0.051	0.054	0.050	0.052	0.053	0.051	0.053	0.052	0.052 ± 0.002
	RMSE	0.084	0.082	0.079	0.081	0.078	0.080	0.081	0.079	0.080	0.079	0.080 ± 0.002
	NRMSE (%)	2.74	2.67	2.58	2.64	2.55						

Table 3 shows the statistical analysis of the proposed TALEK-LATTE framework for 10 independent random-seed runs. The Accuracy values for Solar Radiation and Meteorological Dataset range from 98.31% to 98.65%, with a mean of 98.52% ± 0.10%, and the MAE values range from 0.039 to 0.044, with a mean of 0.041 ± 0.002. Similarly, the RMSE varies between 0.064 and 0.071, resulting in 0.067 ± 0.002, and the NRMSE ranges from 2.04% to 2.25%, with an average of 2.12 ± 0.06%. For the AEP Dataset, the Accuracy varies from 97.62% to 98.01%, yielding a mean of 97.85 ± 0.11%, whereas the MAE ranges from 0.050 to 0.055, with an average of 0.052 ± 0.002. The RMSE values remain within 0.078-0.084, producing 0.080 ± 0.002, while the NRMSE varies from 2.55% to 2.74%, with a mean of 2.62 ± 0.06%. The relatively small standard deviations across all the metrics point to low variation between the 10 random-seed runs, signifying the stability, consistency and reproducibility of the proposed framework both in the primary solar-energy forecasting dataset and the complementary AEP electricity-load forecasting dataset.

8. Limitations and Future Work

The proposed TALEK-LATTE framework provides better solar energy forecasting capabilities with a higher prediction accuracy and less computational complexity, but it still has some drawbacks. There are two sets of benchmark data currently used to test the current framework, and its effectiveness in very diverse climate regions, extreme weather events and changing climate has not been explored yet. Moreover, the proposed model is developed from historical meteorological and solar generation data, not considering other auxiliary data that can be collected from satellites, numerical weather prediction models or real-time data from IoT sensors, which can improve the accuracy of solar energy forecasting. The approach of transfer learning can also be extended to enable continuous and online learning for adapting to changing data distributions. For the future, a multi-source multimodal forecasting framework is developed to combine weather forecasts, remote sensing data and edge-enabled IoT sensing and provide lightweight foundation models. Furthermore, the proposed framework can be extended to probabilistic forecasting and uncertainty quantification, explainability and real-time applications to smart grids, and a large scale photovoltaic electricity system to enhance operational reliability and decision-making.

9. Discussions

The proposed TALEK-LATTE framework is superior because of features engineering and temporal forecasting synergic benefits. The new TALEK module proposes a novel Tangent-space Aligned Laplacian Embedding and Knockoff Filter, which can select meteorological features that contain important information, maintain nonlinear relationships and remove redundant information, unlike conventional state-of-the-art methods, which can be based on traditional statistical feature selection or single deep learning architecture. This

improves the quality of information fed to the model that represents the system, and reduces the number of additional calculations needed when making the next forecast. Furthermore, these two models cannot individually capture complex and changing patterns in solar energy, and the LATTE architecture integrates Tiny Time Mixer and Lag-Llama to model both short-term variations and long-term temporal dependencies. Efficient local temporal learning has been added with Tiny Time Mixer, and long-range sequence modelling is enhanced with attention mechanisms inspired by transformers in Lag-Llama. The hybrid architecture is therefore more holistic to represent the meteorological variability and its impact on the solar energy forecasting process. Moreover, the optimized feature representation and hybrid temporal learning also aid in minimizing the prediction error yet retaining computational efficiency. The results of the experiments confirm the proposed framework, with reported accuracy of 98.00%, MAE of 3.18, RMSE of 4.00, MAPE of 4.82%, and R^2 of 0.984 and an inference time of 18.6 ms. The enhancements suggest that coordinated design of TALEK and LATTE is an effective way to deal with feature redundancy, nonlinear temporal dependency and computational difficulty problems than the evaluated state of the art forecasting methods.

This is mainly due to the integrated learning strategy that is proposed by TALEK - LATTE, that better represents features and models the temporal dependencies than existing state of the art techniques. This is reflected in the Solar Radiation and Meteorological Dataset, where the framework achieved 98.52 ± 0.10% Accuracy, 0.041 ± 0.002 MAE, 0.067 ± 0.002 RMSE, and 2.12 ± 0.06% NRMSE. Similarly, the AEP Dataset produced 97.85 ± 0.11% Accuracy, 0.052 ± 0.002 MAE, 0.080 ± 0.002 RMSE, and 2.62 ± 0.06% NRMSE. The small deviations also show that the better performance is not sensitive to any particular random-seed run, but holds true for a variety of runs.

10. Conclusion

This paper presents a lightweight and Transfer-learning based approach to Accurate Solar Energy Prediction, which overcomes the limitations of the present transformer based prediction approaches (complexity of the temporal dependency, lack of data relevance and computational complexity). The proposed framework, Tangent-Space Aligned Laplacian Embedding (TALEK) and Lag-Llama Augmented Tiny Time Mixer (LATTE) is a simple end-to-end forecasting pipeline. In this paper, the authors introduce a novel hybrid feature engineering algorithm that takes advantage of the two ideas of nonlinear manifold learning and a feature selection scheme rooted in statistically sound feature selection principles to retain the majority of solar and meteorological features, while removing redundant information. Then, LATTE leverages the transfer learning capacity of LLM, specifically the long-term sequence modelling ability of Lag-Llama and temporal representation learning ability of Tiny Time Mixer, and allows prediction with high accuracy with low computation complexity and fast convergence. The combination of these new methods is a powerful one that achieves a good compromise in terms of predictive power, efficiency of the model, and its ability to transfer to new energy datasets.

Both the Solar Radiation and Meteorological Dataset and the American Electric Power (AEP) dataset were rigorously tested to ensure the proposed framework was correct. The experimental results show that the proposed LATTE model achieved the best forecasting accuracy of 98.00%, and the lowest errors of MAE, RMSE, MAPE and R2: 3.18, 4.00, 4.82% and 0.984, respectively, which is better than the other models, Informer, Autoformer, FEDformer, PatchTST, iTransformer, Crossformer and Lag-Llama.

The ablation study also confirmed the effectiveness of every one of the proposed components, and the proposed TALEK-LATTE system showed always more effectiveness compared with other combinations of components on both datasets. Moreover, the model proposed in this work achieved the least inference time of 18.6 ms and the least forecasting error of 3.6, showing the model is very efficient and can be used in the forecasting of solar energy in real time. The results have demonstrated the accuracy, scalability and applicability of the proposed scheme to future smart and intelligent forecasting and photovoltaic energy management systems.

References

[1] Umair Hussan et al., "Transformer-based Renewable Energy Forecasting: A Comprehensive Review," *Renewable and Sustainable Energy Reviews*, vol. 226, pp. 1-14, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[2] Safiullah Khan et al., "Machine Learning for Renewable Energy Advancements: Prospects and Emerging Techniques," *Energy Reports*, vol. 15, pp. 1-35, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[3] Hanane Ait Lahoussine Ouali et al., "Long Short-Term Memory and Metaheuristic Algorithm-based Deep Learning Model Approach for Forecasting Green Hydrogen Production," *International Journal of Hydrogen Energy*, vol. 202, pp. 1-23, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[4] Eunmi Kim, and Yong Sauk Hau, "Advancing photovoltaic Solar Power Forecasting by the Hybrid Model of CNN and DNN and the XAI with SHAP," *International Journal of Green Energy*, vol. 23, no. 2, pp. 333-344, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[5] Gaurav Singh Negi et al., "Leveraging Machine Learning for Optimized Microgrid Management: Advances, Applications, Challenges, and Future Directions," *Renewable and Sustainable Energy Reviews*, vol. 226, pp. 1-14, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[6] Marwa Radwan et al., "Optimizing Solar and Wind Forecasting with iHow Optimization Algorithm and Multi-Scale Attention Networks," *Scientific Reports*, vol. 16, no. 1, pp. 1-34, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[7] Swarup Ghosh, "Predicting Photovoltaic Efficiency of Two-Dimensional Janus Materials for Applications in Solar Energy Harvesting: A Combined First-Principles and Machine Learning Study," *Solar Energy Materials and Solar Cells*, vol. 295, pp. 1-18, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[8] Xiuying Yan, Hao Ta, and Juan Lu, "Dynamic and Static Feature Fusion for Short-Term Photovoltaic Power Forecasting," *Solar Energy*, vol. 303, pp. 1-13, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[9] Yusuf Alper Kaplan, and Ayşe Gül Kaplan, "Development of New Solar Radiation Prediction Models using Different Machine Learning Techniques," *Electric Power Systems Research*, vol. 251, pp. 1-9, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[10] Aditya Dinakar, "Explainable Machine Learning Models for Predicting Current and Voltage in Photovoltaic Systems," *Energy Conversion and Management: X*, vol. 30, pp. 1-15, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[11] El-Sayed M. El-kenawy et al., "Feature Selection and Hyperparameter Tuning in Transformer-based Deep Learning models for Photovoltaic Power Forecasting using the Swordfish Movement Optimization Algorithm (SMOA)," *International Journal of Electrical Power and Energy Systems*, vol. 174, pp. 1-26, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[12] Aparna Unni et al., "Solar Power Prediction using Computer Vision and Machine Intelligence: Predicting and Optimizing Solar Energy Generation," *Reliability Analysis and Modeling for Complex Systems*, pp. 339-364, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[13] Bowen Li et al., "Enhancing Renewable Energy Load Forecasting through Deep Data Analysis and Feature Extraction Techniques," *Energy*, vol. 340, pp. 1-17, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[14] Süleyman Emre Eyimaya, Necmi Altin, and Adel Nasiri, "Optimization of Photovoltaic and Battery Storage Sizing in a DC Microgrid using LSTM Networks based on Load Forecasting," *Energies*, vol. 18, no. 14, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Upma Singh et al., "Forecasting Rooftop Photovoltaic Solar Power using Machine Learning Techniques," *Energy Reports*, vol. 13, pp. 3616-3630, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[16] Dheeraj Kumar Dhaked et al., "Exploring Deep Learning Methods for Solar Photovoltaic Power Output Forecasting: A Review," *Renewable Energy Focus*, vol. 53, pp. 1-25, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] Yanru Yang et al., "DEST-GNN: A Double-Explored Spatio-Temporal Graph Neural Network for Multi-Site Intra-Hour PV Power Forecasting," *Applied Energy*, vol. 378, pp. 1-13, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Praveen Kumar Singh, Amit Saraswat, and Yogesh Gupta, "Deep Learning Prediction models for Short-Term Solar Photovoltaic Power Generation Forecasting," *Next Energy*, vol. 11, pp. 1-18, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[19] Wanting Zheng et al., "A Physically-Informed Interpretable Ensemble Learning method for Distributed Photovoltaic Power Forecasting," *International Journal of Electrical Power & Energy Systems*, vol. 174, pp. 1-16, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[20] Sara Fennane et al., "Improving Short-Term Solar Power Prediction through a Hybrid Deep Learning Model," *Engineering, Technology and Applied Science Research*, vol. 16, no. 2, pp. 32825-32832, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[21] Alireza Ahmadi et al., "Energy Forecasting and Optimization for Wastewater Treatment Facility: A Hybrid Machine Learning–Metaheuristic Scenario based Approach," *Energy Reports*, vol. 15, pp. 1-13, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[22] Adil Zohaib et al, "Hybrid Deep Learning based Load Forecasting and AI-Driven Energy Management for Grid-Connected Multi-Microgrids," *Computers and Electrical Engineering*, vol. 131, pp. 1-21, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[23] Manimaran Naghapushanam, Baskaran Jeevarathinam, and C. Sankari, "Physics-Informed Voting Ensemble for Solar Power Generation Forecasting: Integrating Domain Knowledge with Machine Learning," *Energy Informatics*, vol. 9, no. 1, pp. 1-24, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[24] Yibo Jiang et al., "Stepwise Conformal Prediction for Multi-Step Net Load Forecasting in Microgrids Under Renewable Energy Variability," *Energies*, vol. 19, no. 10, pp. 1-19, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[25] Mao Yang et al., "Load Forecasting and Energy Storage Optimization Control for Distribution Networks with High Distributed Photovoltaic Penetration," *Electric Power Systems Research*, vol. 259, pp. 1-7, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[26] Jannis Eckhoff et al., "Electrical Load Forecasting in the Industrial Sector: A Literature Review of Machine Learning Models and Architectures for Grid Planning," *Energies*, vol. 19, no. 2, pp. 1-32, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[27] Basma M. Hassan et al., "Advanced Regression Approaches for High-Fidelity Solar Radiation Prediction: Analysis of a 12-Year Meteorological Dataset from Egypt," *Earth Systems and Environment*, vol. 10, no. 4, pp. 4771-4791, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[28] Abdul Wasay et al., "Solar Radiation Prediction for Renewable Energy: A Machine Learning Perspective," *Spectrum of Engineering Sciences*, vol. 3, no. 6, pp. 1048-1066, 2025. [Google Scholar] [Publisher Link]

[29] I Wayan Vito Bratanata Meranggi, and Suharjito, “Optimization of Transmission Maintenance Schedule using Transformer Load Forecasting with Modified Hybrid CNN-LSTM and Integer Linear Programming,” *Journal of Electrical Systems and Information Technology*, vol. 13, pp. 1-19, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[30] Tao Shen et al., “PAKMamba: Enhancing Electricity Load Forecasting with Periodic Aggregation and Koopman Analysis,” *Computers and Electrical Engineering*, vol. 123, pp. 1-16, 2025. [CrossRef] [Google Scholar] [Publisher Link]