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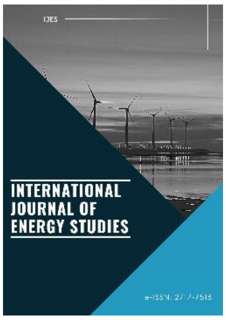

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Short-term photovoltaic power forecasting in Çanakkale, Türkiye: A comparative study of machine learning, deep learning, and hybrid models

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Highlights

- Short-term PV power forecasting is analyzed using real field data.
- Forecast horizons of 15 and 60 minutes are comparatively evaluated.
- The LSTM model achieves the best performance for 60-minute-ahead forecasting.
- The performance of the VMD-based hybrid model is sensitive to the number of modes.
- The hybrid approach does not consistently outperform the standalone LSTM model.

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ABSTRACT

This study investigates the short-term photovoltaic (PV) power forecasting problem using real field data and comparatively evaluates the performance of different forecasting approaches. The study utilizes active power and meteorological data from a 1 MW installed capacity PV plant located in Çanakkale province, northwest Turkey, with a 15-minute sampling interval. The dataset covers the period from August 2022 to August 2024, and only daytime data with solar irradiance above 20 W/m² were considered to minimize the negative impact of zero production on the model. Forecasting performance was analyzed for 15-minute (h = 1) and 60-minute (h = 4) forward forecasting horizons.In the comparative analysis, the persistence method was used as the basic reference model; Ridge regression, support vector regression (SVR), and LSBoost model were used as machine learning-based methods; Long-short-term memory (LSTM) and gated recurrent unit (GRU) networks were evaluated as deep learning-based methods. Additionally, a hybrid VMD+LSTM model combining Variational Mode Decomposition (VMD) with an LSTM network was investigated as a current signal decomposition-based approach. The models were evaluated using RMSE, MAE, normalized RMSE (nRMSE), and coefficient of determination (R^2) metrics on a dataset separated by 70% training, 15% validation, and 15% testing ratios without time-order distortion.The results showed that the persistence model offered competitive performance at a very short prediction horizon (h = 1), but the accuracy of this approach decreased significantly as the prediction horizon increased. For 60-minute forward prediction, deep learning models produced more successful results; the optimized LSTM model achieved the best performance with 9.69% nRMSE and an R^2 value of 0.884. In contrast, while the VMD+LSTM hybrid model produced promising results during the validation phase, it exhibited poor generalization performance on the test set. This finding reveals that decomposition-based hybrid approaches are not superior in all conditions.

Keywords: Photovoltaic power forecasting, Short-term forecasting, LSTM, GRU, Variational mode decomposition, Machine learning.

1. INTRODUCTION

Rising energy demand, dwindling fossil fuel reserves, and environmental concerns stemming from climate change have led to a rapid increase in the share of renewable energy sources in electricity production. Among these sources, photovoltaic (PV) systems are widely used globally due to their flexibility in installation, low maintenance costs, and scalability [1]. According to reports from the International Energy Agency (IEA), the share of PV-based electricity generation in the energy portfolio is expected to increase significantly in the coming years [2]. However, because the production capacity of PV systems depends directly on solar radiation and meteorological conditions, the output power is inherently variable and uncertain. This situation poses critical challenges for grid operators, including load balancing, frequency control, and energy planning [3]. In particular, the accuracy of short-term power forecasts is vital for safe and economical operation in distribution and transmission systems [4]. PV power forecasting is generally classified in the literature as very short-term, short-term, medium-term, and long-term. Very short-term and short-term forecasts (minutes–hours) play a critical role in real-time grid control, energy storage management, and market operations [5]. Therefore, studies on short-term PV power forecasting have intensified in recent years. In early studies, statistical time series models such as autoregressive (AR), moving average (MA), ARIMA, and SARIMA were widely used [6]. However, these methods cannot adequately model the nonlinear structure and abrupt changes observed in PV generation. These limitations have encouraged the use of machine learning-based methods in PV forecasting. Support vector regression (SVR), random forests (RF), and gradient boosting-based methods can more successfully capture nonlinear relationships using meteorological variables [7–9]. In addition to machine learning methods, deep learning approaches that can directly model temporal dependencies have come to the forefront in recent years. Long short-term memory (LSTM) and gated recurrent unit (GRU) networks, in particular, have yielded successful results in PV power forecasting [10,11]. These models can achieve higher accuracy in short-term predictions than classical methods, thanks to their ability to learn long-term relationships among past time steps. Recently, hybrid approaches that separate different frequency components of the signal to facilitate learning have been proposed for PV power prediction studies. In this context, methods such as empirical mode decomposition (EMD), complementary EMD (CEEMDAN), and variational mode decomposition (VMD) have been combined with deep learning models [12–14]. These studies show that decomposition-based hybrid models can improve prediction performance in some datasets. However, a generally accepted conclusion that these approaches are superior in all conditions has not been reached in the literature. In this context, this study aims to compare classical machine learning, deep learning, and decomposition-based hybrid approaches fairly and systematically within a common experimental framework. While most studies in the literature report only positive hybrid results, this study evaluated all models using the same data preprocessing steps, the same training-validation-test split, and the same performance metrics. Furthermore, using current, high-resolution real-world field data from Çanakkale, Turkey, it was explicitly investigated whether VMD-based hybrid models truly provide a consistent superiority across different prediction horizons.

2. LITERATURE REVIEW

Research in photovoltaic (PV) power forecasting has focused particularly on the effective use of machine learning and deep learning methods in recent years. Advances in model architectures and hybrid strategies have enriched it.

2.1. Deep Learning-Based PV Power Forecasting Studies

In a review by Yu et al., deep learning models for PV power estimation were systematically examined, and architectures such as LSTM, CNN, RNN, and GNN were compared, highlighting the advantages of each model family. For example, RNN-based structures are strong in capturing long-term dependencies, while CNNs offer advantages in auto-learning local features [14].

Xiang et al. proposed a hybrid model that combines a TCN (Temporal Convolutional Network) and an Efficient Channel Attention (ECANet) with a GRU. This model reported that enriching the TCN's convolutional feature-extraction capabilities with ECANet yielded significant performance improvements in short-term PV estimation [15]. The GA-AMODE-BiLSTM model proposed by Wang et al. improved short-term estimation accuracy by optimizing BiLSTM hyperparameters with a genetic algorithm. This study evaluated the contribution of hyperparameter optimization to classical deep learning models using statistical tests and reported successful results, with a high correlation ($R^2 \approx 0.99$) [16]. The application of transformer architectures to PV prediction has also intensified: Piantadosi et al. predicted PV power generation across different datasets using a transformer-based framework, achieving lower error rates than other machine learning models [17]. Zhou showed that the transformer model achieved better MSE and R^2 performance for both short-term and long-term predictions than traditional models such as BP, LSTM, and Bi-LSTM [18]. In general, these studies have revealed that deep learning models have a superior capacity to capture nonlinear and temporal relationships in PV power time series compared to classical models. Furthermore, Transformer-based models demonstrate significant advantages, particularly in learning long sequences and variable interactions.

2.2. Hybrid and Multimodal Approaches

Hybrid models have gained popularity during the 2024–2025 period. The combination of signal separation, convolutional feature extraction, and attention mechanisms is particularly noteworthy. Hou et al. proposed a hybrid PV forecasting model that combines VMD with the Whale Optimization Algorithm (WOA) and LSTM; this approach improves forecasting accuracy by leveraging VMD's signal separation capabilities and meta-heuristic optimization [19]. Research also shows that multi-stage hybrids, such as VMD-SSA-Transformer-LSTM, can reduce data requirements and achieve high performance while incurring lower computational costs [20].

Hu et al. (2024) developed a short-term forecasting method that integrates information from surrounding PV stations and employs the Conv-LSTM-Attention model. This approach achieved higher accuracy than single-station models by accounting for common meteorological effects and spatial relationships [21]. These hybrid approaches represent successful examples of efforts to combine the strengths of different model components. However, despite the growing popularity of hybrid forecasting models that combine signal decomposition techniques with deep learning architectures, recent studies have reported that such approaches do not consistently outperform standalone deep learning models. El Robrini et al. [22] demonstrated that while Variational Mode Decomposition (VMD) can enhance the performance of classical machine learning models, its integration with deep learning architectures does not necessarily lead to superior results and, in some cases, may even be outperformed by non-decomposed deep learning models. Similarly, Zhang et al. [23] emphasized that hybrid decomposition-based models are highly sensitive to parameter selection, particularly the number of modes and penalty coefficients in VMD, and that suboptimal configurations can significantly degrade forecasting accuracy. Moreover, Khelifi et al. [24] reported that increasing the number of decomposed components does not guarantee performance improvement, as overly fine-grained signal decomposition can introduce redundancy and limit the forecasting model's learning capability. These findings collectively suggest that decomposition-based hybrid models are not universally superior and that their effectiveness strongly depends on data characteristics, decomposition settings, and forecasting horizon.

2.3. Multiple Data Sources and Large-Scale Models

In the current literature, there are studies on models that can learn from multi-site data, not just single-station data. Depoortere et al.'s study, SolNet, proposes a multi-site model trained with transfer learning on PV data from various geographic regions. This approach has shown better generalization even in systems with limited observational data [25]. Similarly, Gao et al.'s PV-Client model improved Transformer-based prediction performance by modeling the interactions of different weather and production inputs with an intervariable attention mechanism. Such advanced architectures offer much more flexible representation capabilities than classical single-model approaches [26]. The PV-VLM study proposed in 2025 presented a multimodal framework integrating time series, textual summaries, and sky images; this approach improved prediction accuracy by learning cloud motion and visual trends [27]. When the recent literature on short-term photovoltaic power forecasting is examined, it becomes evident that existing approaches can be broadly categorized into three main groups: classical machine learning methods, deep learning-based models, and signal decomposition-supported hybrid approaches. Classical machine learning studies commonly rely on linear and nonlinear regression techniques as well as ensemble learning algorithms, which often serve as robust and computationally efficient benchmarks. Deep learning approaches, on the other hand, primarily focus on modeling temporal dependencies using recurrent neural network architectures such as LSTM and GRU. More recently, hybrid models that combine signal decomposition techniques such as VMD or EMD with deep learning models have attracted growing attention. In this context, this study differs from existing literature by providing a systematic and fair comparison of classical machine learning, deep learning, and signal decomposition–based hybrid models using the same real-world dataset, identical preprocessing steps, and consistent evaluation metrics. Unlike many recent studies that primarily emphasize the superiority of hybrid approaches, this work explicitly investigates scenarios in which decomposition-based models do not yield performance gains over standalone deep learning architectures. Furthermore, the proposed analysis evaluates both short (15-minute-ahead) and medium (60-minute-ahead) forecasting horizons, highlighting how model effectiveness varies with prediction horizon. By demonstrating that a well-configured LSTM model can outperform a VMD-integrated hybrid approach under certain data and horizon conditions, this study contributes a more balanced and realistic perspective to the short-term PV power forecasting literature.

3. MATERIAL AND METHOD

This study addresses the short-term photovoltaic PV power-forecasting problem and compares the performance of different forecasting approaches using the same dataset and evaluation framework. This section describes the dataset, data preprocessing steps, forecasting models, and evaluation metrics used. The overall methodological flow of the study is presented in Figure 1.

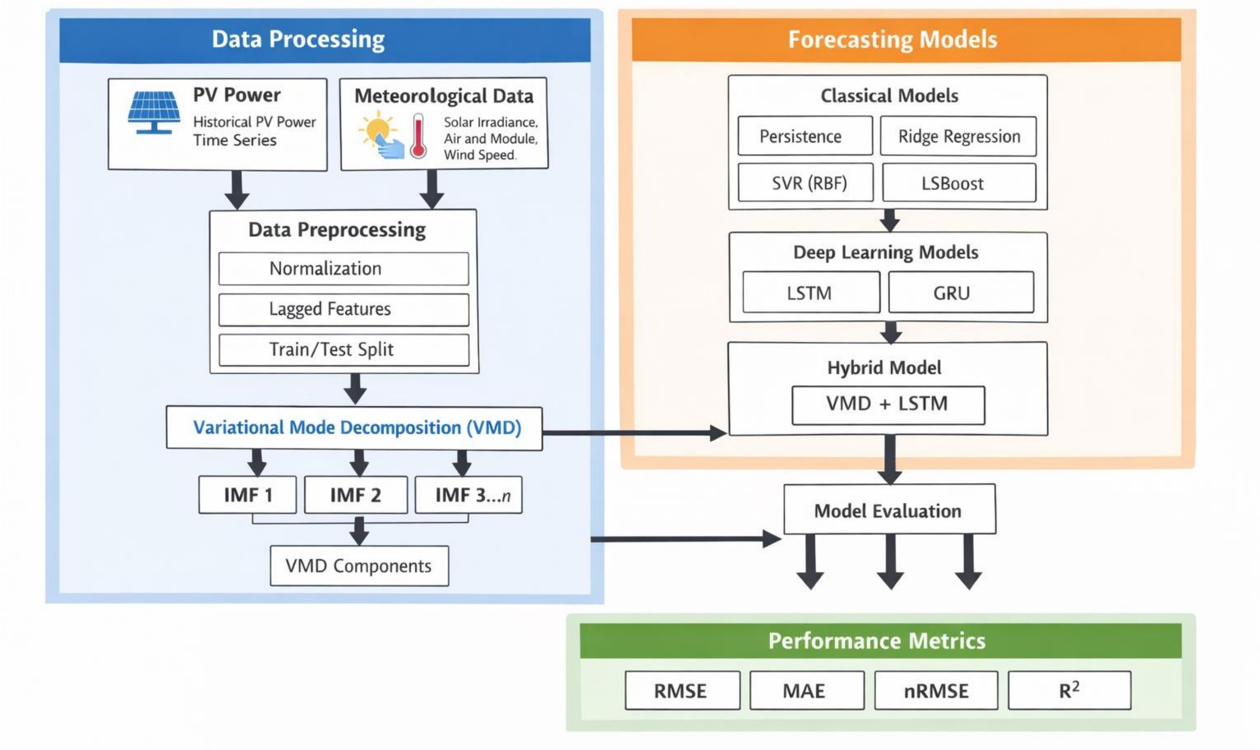

Figure 1. The overall methodological flow of the study

3.1. Data Description

In studies related to PV power forecasting, the importance of explainability, as well as methodological innovation, is increasingly coming to the forefront [28]. Therefore, the definition of the data used in the studies is also expected to be clear. The dataset used in this study was obtained from a 1 MW PV power plant in Çanakkale Province, northwestern Turkey. Çanakkale is largely located within the Marmara Region, situated between 25°40′–27°30′ east longitudes and 39°27′–40°45′ north latitudes. The region has favorable meteorological conditions for solar energy investments and hosts many PV power generation systems of varying scales.

In this study, a PV plant located at approximately 26°41′ east longitude and 40°12′ north latitude, which provides ideal conditions for data collection, was selected from among the PV systems in the region. The meteorological station integrated into the plant chosen provides reliable and real-time measurements. In this way, the fundamental meteorological variables affecting PV power generation were directly measured and included in the dataset. The dataset covers the period from August 1, 2022, to August 3, 2024, with a sampling interval of 15 minutes. The data obtained were taken from source [29]. The collected dataset includes active power (kW) values of the PV panels, as well as total solar radiation, wind speed, PV module temperature, and ambient temperature variables obtained from the meteorological measurement station within the plant.

3.2. Data Preprocessing

PV power generation can reach near-zero values at night, which could artificially improve the performance of short-term forecasting models. Only daytime data were considered in this study. For this purpose, the dataset was filtered to select time steps with total solar radiation above 20 W/m². The entire dataset was divided into 70% training, 15% validation, and 15% testing sets, without altering the temporal order. This approach was chosen to prevent data leakage in time series forecasting problems. Furthermore, all normalization processes were performed using only the training dataset, and the same transformations were applied to the validation and test data.

3.3. Definition of Forecast Problem

In this study, two different forecast horizons are considered: h = 1 (15-minute forward forecast) and h = 4 (60-minute forward forecast). The forecasting problem can be expressed mathematically by equation 1.

$$\hat{P}(t + h) = f\big(P(t), P(t - 1), \dots, X(t)\big) \tag{1}$$

Here, P^(t+h) represents the predicted PV power, P(t) represents past PV power values, and X(t) represents meteorological inputs.

3.4. Forecast Models Used

3.4.1. Persistence model

The persistence model is frequently used as a baseline in short-term forecasting problems. In this model, the forecast assumes the current value will not change in the future. Its mathematical expression is given in equation 2.

$$\hat{P}(t + h) = P(t) \tag{2}$$

3.4.2. Ridge regression

Ridge regression is a linear regression model regularized with the L2 norm. The objective function is defined by equation 3, where λ represents the regularization coefficient.

$$\min\|y - X\beta\|^2 + \lambda\|\beta\|^2 \tag{3}$$

In this formulation, $X \in \mathbb{R}^{N\times d}$denotes the input feature matrix composed of $d$explanatory variables and Nobservations, $y \in \mathbb{R}^{N}$represents the vector of observed output values (PV power), and $\beta \in \mathbb{R}^{d}$ is the vector of regression coefficients to be estimated.

3.4.3. Support vector regression (SVR)

The Support Vector Regression (SVR) model is an error-tolerant regression approach, and in this study, the radial basis function (RBF) kernel was employed. The kernel function is defined by equation 4.

$$K(xi, xj) = \exp(-\gamma\|xi - xj\|^2) \tag{4}$$

In this expression, $x_i, x_j \in \mathbb{R}^{d}$denote two input feature vectors in a d-dimensional space, and $\gamma > 0$ is the kernel width parameter that controls the influence range of each training sample. The RBF kernel enables SVR to capture nonlinear relationships between the input variables and the output PV power.

3.4.4. LSBoost (Gradient Boosting)

LSBoost is an ensemble learning method that successively trains decision trees. The model aims to minimize the root cause error function.

3.5. Deep Learning Models

3.5.1. LSTM and GRU

LSTM and GRU networks are recurrent neural network architectures designed to model long-term temporal dependencies in sequential data. In particular, LSTM networks address the vanishing gradient problem through a gating mechanism that controls the flow of information within the memory cell. The gate operations of an LSTM cell are expressed by equations 5,6,7.

$$ft = \sigma(Wf\ [h\{t-1\}, xt] + bf) \tag{5}$$

$$it = \sigma(Wi\,[h\{t-1\}, xt] + bi) \quad (6)$$

$$ot = \sigma(Wo\,[h\{t-1\}, xt] + bo) \quad (7)$$

In these equations, $x_t \in \mathbb{R}^d$represents the input vector at time step t, and $h_{t-1} \in \mathbb{R}^n$denotes the hidden state from the previous time step. The terms f_t, i_t, and $o_t$correspond to the activations of the forget gate, input gate, and output gate, respectively. The matrices W_f, W_i, and $W_o$are the weight matrices associated with each gate, while b_f, b_i, and $b_o$denote the corresponding bias vectors. The function $\sigma(\cdot)$represents the sigmoid activation function, which constrains the gate outputs to the range [0,1].

GRU networks employ a simpler gating structure than LSTM, reducing computational complexity while preserving the ability to capture temporal dependencies. In this study, both LSTM and GRU architectures are used to model the nonlinear and temporal characteristics of PV power generation.

3.6. VMD + LSTM Hybrid Model

In this study, the Variational Mode Decomposition (VMD) method was also examined as a hybrid approach based on signal decomposition. VMD aims to decompose a given signal into Kintrinsic mode functions (IMFs), each representing a narrow-band component centered around a specific frequency. The VMD optimization problem is defined by equation 8.

$$\min_{\{u_k\},\{\omega_k\}} \sum_{k=1}^{K} \parallel \partial_t\left[u_k(t)e^{-j\omega_k t}\right] \parallel^2 \quad (8)$$

In this formulation, $u_k(t)$denotes the k-th intrinsic mode function (IMF), $\omega_k$represents the center frequency associated with the k-th mode, and $K$is the total number of decomposed modes. The operator $\partial_t(\cdot)$indicates the time derivative, while $j$denotes the imaginary unit. The objective function minimizes the total bandwidth of all modes by enforcing compact frequency representations for each IMF.

By decomposing the original PV power signal into multiple frequency components, VMD enables the separation of low- and high-frequency dynamics inherent in PV power generation. In this study, the extracted IMFs are subsequently used as additional inputs to the LSTM model, forming a VMD+LSTM hybrid framework for short-term PV power forecasting.

3.7. Performance Evaluation Criteria

The performance of all prediction models developed and compared in this study was evaluated using four commonly used performance metrics in the literature: root mean square error (RMSE), mean absolute error (MAE), normalized root mean square error (nRMSE), and coefficient of determination (R^2). Root Mean Square Error (RMSE) is calculated by taking the square root of the average of the squares of the differences between the predicted and actual values, and it gives more weight to larger errors (Eq. 9).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{9}$$

Here, y_i represents the actual PV power value, $\hat{y}_i$ represents the predicted PV power value, and N represents the total number of samples. Mean Absolute Error (MAE) represents the average of the absolute values of the prediction errors and reflects the overall error level of the model (Eq.10).

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i | \tag{10}$$

Normalized Root Mean Square Error (nRMSE) is obtained by dividing the RMSE value by the power plant's rated power (P_{rated}) and is expressed as a percentage (Eq.11)

$$nRMSE = \frac{RMSE}{P_{rated}} \times 100 \tag{11}$$

This metric allows comparison of PV systems with different power levels. The Coefficient of Determination (R^2) indicates how much of the variance in the actual data the model explains and is calculated using equation 12.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{12}$$

Here, $\bar{y}$ represents the average of the actual PV power values. An R^2 value close to 1 indicates that the model has high explanatory power.

4. RESULTS AND DISCUSSION

This section presents a comparative analysis of the short-term PV power-forecasting performance of different forecasting models and discusses the results within the context of the literature. All models were tested using the same dataset, training-validation-test split, and evaluation metrics. Quantitative results are summarized in Table 1. The VMD+LSTM model was evaluated only for the 60-minute-ahead forecasting horizon (h = 4), as signal decomposition-based approaches are typically designed to capture multi-scale temporal patterns and are therefore not effective for very short-term PV power forecasting, where persistence-based dynamics dominate.

Table 1. Models performance metrics.

Model	RMSE_h1	MAE_h1	R2_h1	nRMSE_h1	RMSE_h4	MAE_h4	R2_h4	nRMSE_h4
Persistence	89,028	50,114	0,91715	8,1861	167,29	138,06	0,70762	15,383
Ridge Regression	92,418	57,792	0,91072	8,4978	116,21	80,451	0,85892	10,685
SVR (RBF)	106,13	68,454	0,88225	9,7591	108,12	61,321	0,87788	9,9413
LSBoost	94,194	59,037	0,90725	8,6611	112,1	72,708	0,86872	10,308
LSTM	86,653	50,628	0,92164	7,9677	105,38	70,682	0,88436	9,6895
GRU	86,583	50,996	0,92176	7,9613	120,05	91,404	0,84991	11,039
VMD+LSTM (K=6)	-	-	-	-	214,44	186,16	0,5211	19,72

4.1. Short Prediction Horizon Results (h = 1)

When the results obtained for a 15-minute forecast horizon (h = 1) are examined, the persistence model exhibits very strong performance, as expected. According to the results presented in Table 1, the persistence model performed closely on many advanced models, with an nRMSE of 8.19%. This can be explained by the high temporal continuity of PV power generation in very short forecast horizons. Among machine learning-based models, the LSTM and GRU achieved the lowest error rates, with nRMSE values of 7.967% and 7.961%, respectively. These results show that deep learning models can learn nonlinear relationships even in the very short term. However, the limited difference between the persistence model and deep learning models reveals that the return of more complex models is relatively low for a forecast horizon of h = 1.

4.2. Long Prediction Horizon Results (h = 4)

The results obtained for a 60-minute forecast horizon (h = 4) show that performance differences between the models become apparent. According to Table 1, the error rate of the persistence model increased to 15.38% nRMSE, indicating that the persistence assumption, valid in the short term, loses validity at longer horizons. Among machine learning-based models, the SVR model achieved the best performance with an nRMSE of 9.94%, while the LSBoost and Ridge regression models had nRMSEs of 10.308% and 10.685%, respectively. These findings demonstrate that methods capable of modeling nonlinear relationships are advantageous for longer forecast horizons. When deep learning models were examined, the LSTM model achieved the best performance, with an nRMSE of 9.69% and an R^2 of 0.8844. The GRU model, with an nRMSE of 11.04%, achieved lower accuracy than the LSTM. This result indicates that the LSTM architecture is more effective than the GRU architecture for learning long-term dependencies.

4.3. Actual-Predicted Comparison and Error Analysis

The relationship between the actual and predicted PV power values obtained at a prediction horizon of h = 4 for the best-performing LSTM model is presented in Figure 2. It is observed that the points are largely concentrated around the 1:1 reference line, confirming the model's high explanatory power.

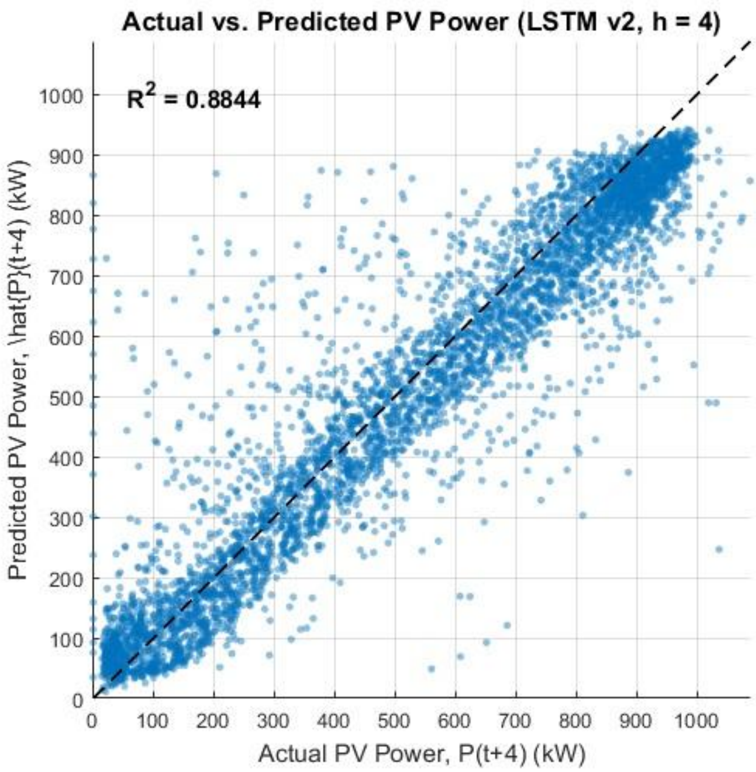

Figure 2. Actual vs. Predicted PV Power

Furthermore, when the residual analysis in Figure 3 is examined, it is observed that the errors are symmetrically distributed around zero and show no significant systematic deviation. This finding indicates that the LSTM model exhibits a balanced prediction performance at different production levels.

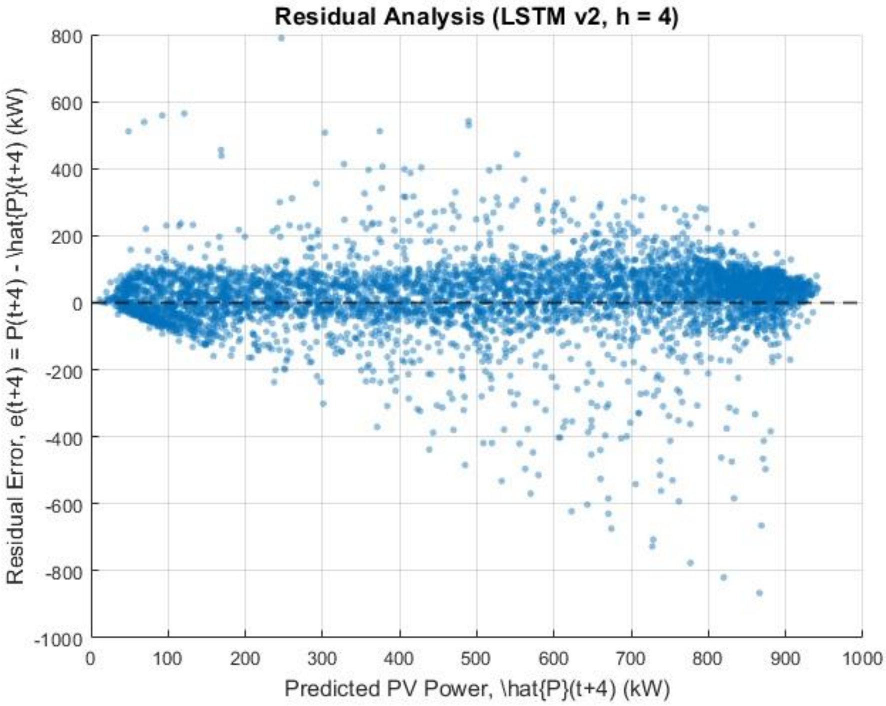

Figure 3. Residual analysis

4.4. Evaluation of the VMD+LSTM Hybrid Model

In this study, a hybrid model combining Variational Mode Decomposition (VMD), a current-signal decomposition-based approach, with a long short-term memory (LSTM) network was evaluated. Using the VMD method, the PV power time series was decomposed into components representing different frequency bands. The resulting intrinsic mode functions (IMFs) and residual term clearly reveal the low and high-frequency components in PV generation. Example results of the VMD decomposition process are presented in Figure 4.

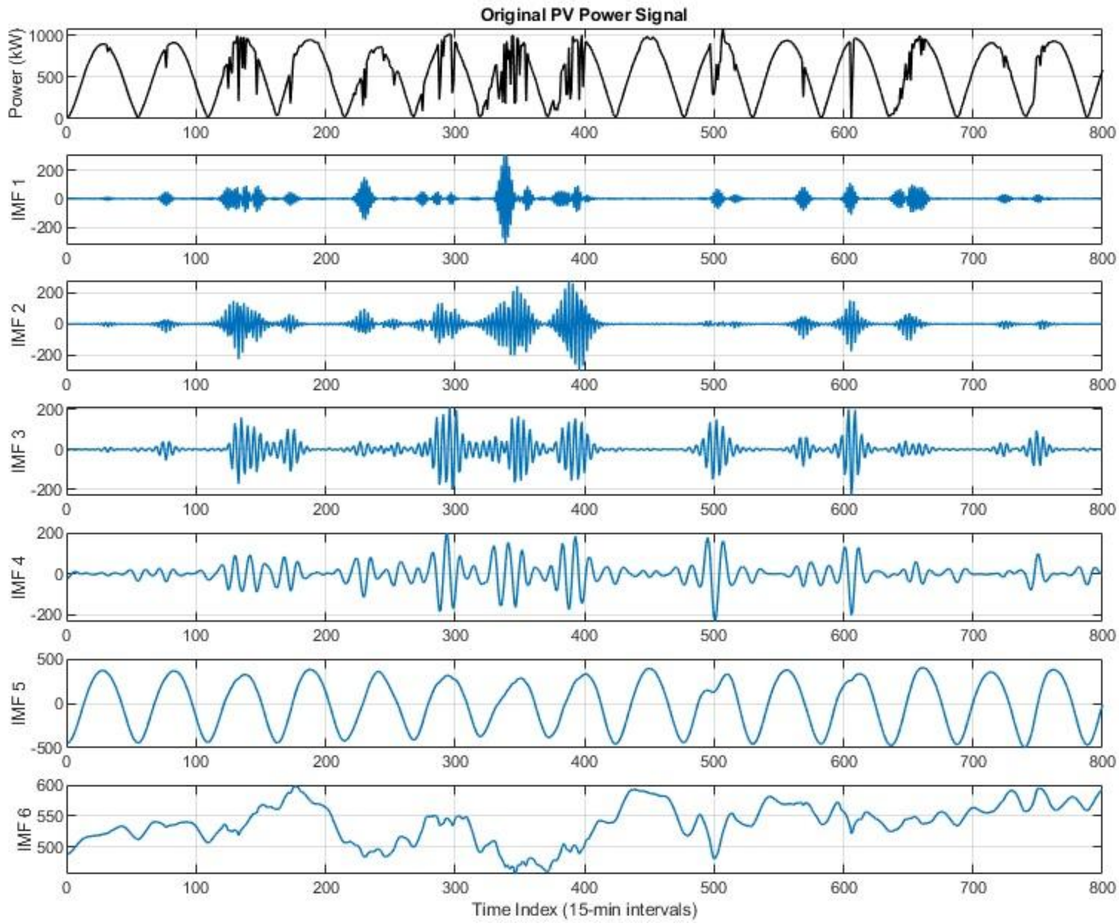

Figure 4. Example results of the VMD decomposition process

The IMF components and residual term obtained from VMD decomposition were given as additional input to the LSTM model to create a hybrid prediction structure. This approach aims to increase prediction accuracy by modeling different frequency components of the PV power time series separately. Although relatively promising results were obtained in the validation phase, the hybrid model's generalization performance decreased significantly on the test set. According to the results presented in Table 1, the VMD+LSTM model achieved an nRMSE of 19.72% and an R^2 of 0.5211 for a 60-minute forecast horizon (h = 4). This performance lagged behind the results of LSTM and other machine learning-based models obtained at the same forecast horizon. This indicates that decomposition-based hybrid models do not consistently deliver superior performance across datasets and conditions. Possible reasons for this finding include the strong periodic structure of the PV power time series, which the LSTM model can learn directly; information loss during VMD decomposition; and increased model complexity, leading to overlearning. It is considered that additional decomposition steps may negatively affect generalization capability, especially when the data length is limited. Therefore, this study reveals that decomposition-based hybrid approaches should be applied carefully depending on the conditions and data characteristics.

5. CONCLUSION

In this study, the short-term photovoltaic (PV) power estimation problem was addressed using real-world data, and the performance of different estimation approaches was compared. The study used measurements from a 1 MW installed-capacity PV power plant in Çanakkale province, sampled at 15-minute intervals. Estimation performance was evaluated for 15-minute (h = 1) and 60-minute (h = 4) forecast horizons.

The results showed that the persistence model provided a strong baseline reference at very short forecast horizons (h = 1), but this approach became insufficient as the forecast horizon lengthened. Machine learning-based methods produced more stable results than the persistence model, owing to their ability to model nonlinear relationships. However, deep learning-based approaches demonstrated a significant advantage, especially for the h = 4 forecast horizon.

Among all models, the LSTM model achieved the highest accuracy on the 60-minute forward forecasting problem, with an nRMSE of 9.69% and an R^2 of 0.8844. This finding demonstrates that the LSTM architecture can effectively learn the temporal dependencies and periodic structure in PV power generation. Despite its simpler structure, the GRU model exhibited lower performance than the LSTM.

The study also evaluated the VMD+LSTM hybrid model, a current signal decomposition-based approach. Although promising results were obtained during the validation phase, the model's generalization performance decreased significantly on the test set. This indicates that decomposition-based hybrid approaches do not consistently outperform other approaches across datasets and that performance is sensitive to data characteristics and model parameters.

In conclusion, this study systematically examines the strengths and weaknesses of various methods in short-term PV power forecasting. It emphasizes the effectiveness of deep learning-based models, particularly for long forecast horizons. Future studies aim to further improve forecasting performance by using data from multiple power plants, developing seasonal adaptive models, and integrating spatial meteorological data.

NOMENCLATURE

RMSE: Root Mean Square Error
MAE: Mean Absolute Error
nRMSE: Normalized Root Mean Square Error (%)
VMD: Variational Mode Decomposition
LSTM: Long Short-Term Memory network
GRU: Gated Recurrent Unit
SVR: Support Vector Regression
LSBoost: Least-Squares Boosting
PV: Photovoltaic

DECLARATION OF ETHICAL STANDARDS

The author of the paper submitted declares that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions.

CONTRIBUTION OF THE AUTHORS

Conceptualization, methodology, research, modeling, visualization, data analysis, article writing, and editing were all carried out by Vedat ESEN.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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