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Long-Term Prediction of Solar Panel Power Output with Artificial Intelligence Techniques

Melisa TÜRKER [1,2], Celal YELGEL [2,3], Övgü Ceyda YELGEL [*1,2]

[1] Department of Electrical-Electronics Engineering, Recep Tayyip Erdoğan University, Rize, Türkiye
[2] The Computational Science and Machine Learning Laboratory, Recep Tayyip Erdoğan University, Rize, Türkiye
[3] Department of Electricity and Energy, Recep Tayyip Erdoğan University, Rize, Türkiye
Corresponding Author Email: oceyda.yelgel@erdogan.edu.tr

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Abstract: The increasing global population and unsustainable energy consumption have led to a growing energy demand, making it imperative to predict future energy requirements and devise proactive strategies. Among renewable energy sources, solar energy stands out as a clean, eco-friendly, and readily accessible option, facilitating the integration of renewable energy into power grids. To ensure successful grid operation, efficient energy management, and economic planning, the development of an optimal solar photovoltaic (PV) power forecasting technique has become critical. Traditional forecasting methods, such as Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), Numerical Weather Prediction (NWP), Artificial Neural Networks (ANN), and hybrid artificial intelligence approaches, are often inadequate for long-term PV power output predictions. While short-term forecasting may suffice for small or standalone PV systems, large-scale PV systems integrated into power grids require reliable long-term predictions for effective management and operation. The increasing complexity of grid-integrated renewable energy systems further emphasizes the need for advanced forecasting methodologies capable of providing accurate and long-term predictions. This study addresses this critical challenge by employing a deep learning-based Long Short-Term Memory (LSTM) artificial intelligence model to forecast long-term PV power outputs. Unlike existing approaches, this research introduces a novel model utilizing the Nadam optimizer, which enhances performance on time-series data. In our study, we utilized single-layer, three-layer, and four-layer LSTM models to predict the power output of solar panels. Additionally, we experimented with ReLU and Leaky ReLU activation functions across all model configurations. To evaluate performance, we employed several metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error (SMAPE). By leveraging this innovative approach, the proposed LSTM model delivers improved accuracy and reliability in long-term solar PV power forecasting, offering valuable insights for grid operators and energy planners.

1. Introduction

Energy is a fundamental and conserved property of physical systems, which cannot be directly observed but can be quantified through its contextual state. In simple terms, it is defined as the capacity to perform work and manifests in various forms, including potential, luminous, thermal, kinetic, electrical, chemical, nuclear, and acoustic energy. Globally, as technology advances, the demand for energy continues to rise, and Türkiye is no exception. Currently, despite regional variations in energy resource utilization, a significant portion of global energy demand is still met through fossil fuels. To address evolving energy needs, governments are revising existing policies, driven by the finite reserves of fossil resources, their high depletion risks, and environmental degradation. This has led nations to seek alternatives to primary energy sources. Renewable energy refers to sources with continuous energy flows, such as solar, wind, biomass, geothermal, hydroelectric, and wave energy. Worldwide, interest in renewable energy sources including solar, wind, hydrogen, and geothermal has grown significantly, leading to increased adoption. Among these, solar energy stands out as one of the most critical and inexhaustible resources. Its advantages, such as being clean, noiseless, cost-effective, reliable, and environmentally friendly, make it a stronger alternative compared to conventional energy sources (Dandil and Gürgen, 2017). Figure 1(a) illustrates the global production of renewable energy sources; hydroelectric, wind, solar, and others (including biomass, geothermal, and wave energy) from 1965 to 2022. Notably, solar energy adoption has accelerated rapidly since the late 2000s, surpassing electricity generation from wind and hydropower. Figure 1(b) displays country-level electricity production (in TWh) from these renewable sources. China leads by a significant margin, followed by the United States, India, Germany, France, Türkiye, the United Kingdom, and Canada. Focusing on global solar energy production, Figure 2(a) maps worldwide electricity generation from solar sources in 2022. Figure 2(b) compares output across eight countries, with China again leading, followed by the United States, Germany, India, France, the United Kingdom, Türkiye, and Canada. Figure 2(c) highlights Türkiye's solar energy production trends from 1996 to 2022. Post-2015, the rapid expansion of solar conversion systems has driven sustained growth in solar energy output (Anonymous, 2025a).

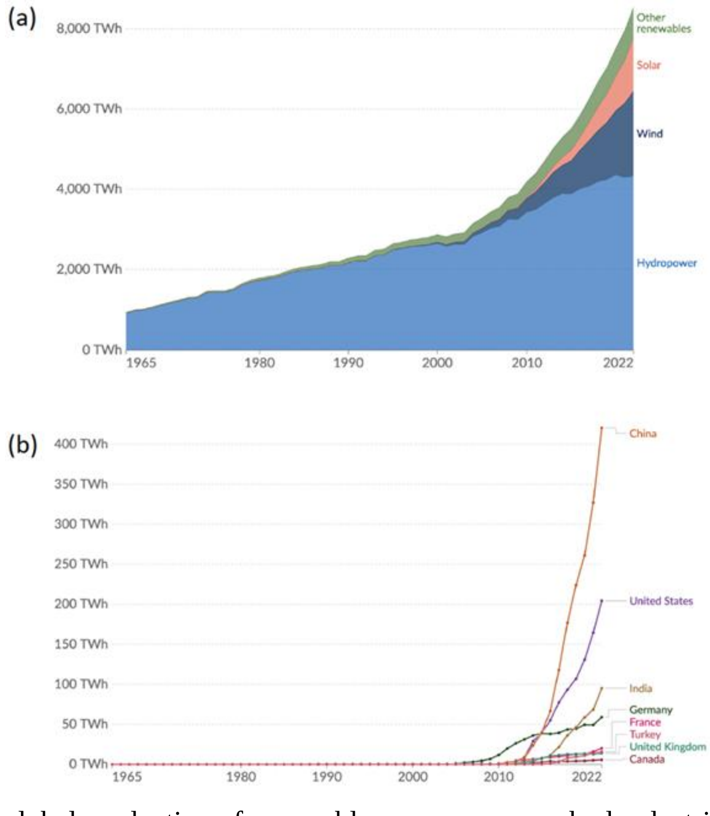


Figure 1. (a) The global production of renewable energy sources; hydroelectric, wind, solar, and others (including biomass, geothermal, and wave energy) from 1965 to 2022. **(b)** The country-level electricity production (in TWh) from these renewable sources.

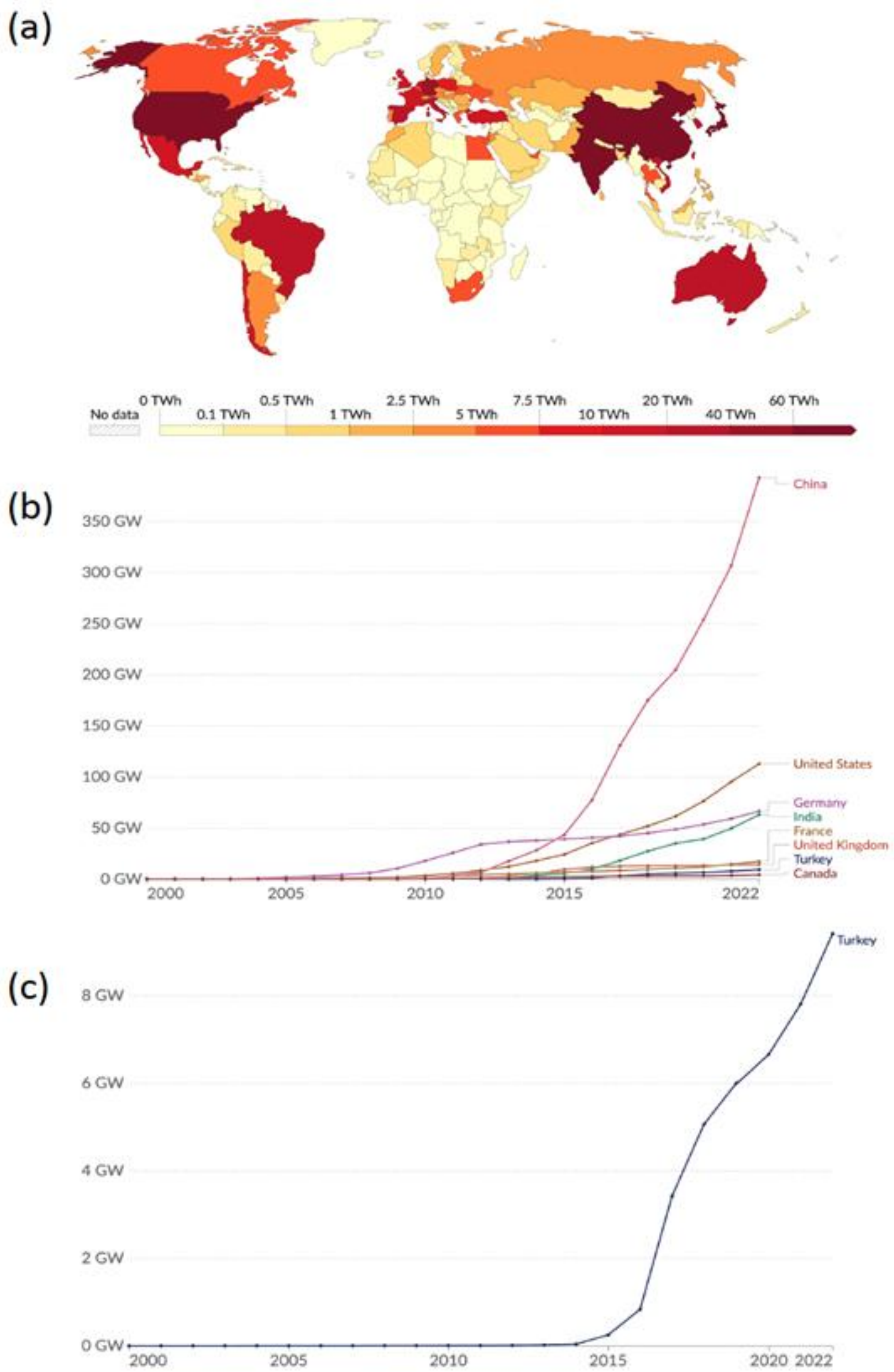
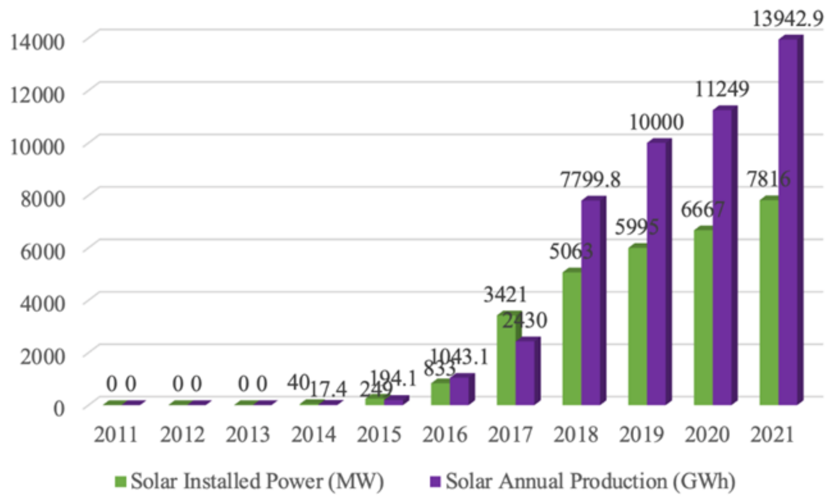


Figure 2. (a) In 2022, the global electricity generation levels from solar energy, **(b)** a comparison of the generated energy values across 8 countries, and **(c)** solar energy production levels in Türkiye between 1996 and 2022 (Anonymous, 2025a).



Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Solar Installed Power (MW)	0	0	0	40	249	833	3421	5063	5995	6667	7816
Solar Annual Power (GWh)	0	0	0	17,4	194,1	1043,1	2430	7799,8	10000	11249,0	13942,9

Figure 3. The installed solar power capacity and annual solar energy production values between 2011 and 2021 (TEİAŞ. "Turkey Electricity Generation Statistics"), (Anonymous, 2025b).

Figure 3 presents Türkiye’s installed solar capacity and annual energy production from solar conversions between 2011 And 2021. Ongoing research aims to optimize alternative energy utilization and enhance efficiency. Solar radiation levels, critical for electricity generation via photovoltaic (PV) panels, fluctuate with daily weather and seasonal variations. PV systems convert sunlight directly into electricity, playing an increasingly vital role in meeting energy demands.

PV panel output varies with geographic location, seasonal shifts, and environmental conditions. Adjusting panel tilt angles monthly, seasonally, or annually maximizes energy capture. Modern power systems require real-time, daily, weekly, monthly, and annual production planning to ensure secure and cost-effective operation. Consequently, forecasting output and load trends for renewable installations like PV plants has become essential. It is well-established that solar power station efficiency fluctuates with weather conditions (Lorenz et al., 2009).

The prediction of power output values generated by PV systems at different times is crucial for the efficient and economical use of solar panels as a reliable energy source. With the increasing per capita energy consumption, investments in power plants are being sustained to maintain the supply-demand balance in a healthy manner. The growing awareness of clean energy has been significantly increasing investments in environmentally friendly and long-lasting Solar Power Plants (SPPs) over time. The climatic conditions of the region where SPPs are established directly influence the output power obtained from PV panels and the cost of energy (Gök et al., 2019). For this reason, studies on predicting the power output values of PV panels have seen a remarkable increase in recent years. Accurate prediction of power output is critical to evaluating the true performance of PV panels; even a slight increase of a few degrees in the PV panel's temperature, coupled with lower solar irradiance, can significantly enhance the system's energy conversion efficiency and, consequently, its power output (Wang et al., 2011).

Until 2010, the research and development of PV panel production forecasting models were at a minimal level. Most models relied on predicting the radiation incident on the PV solar panel, and the generated electricity was calculated based on these values. Data sources included curves provided by PV solar panel manufacturers, a set of equations, or known empirical relationships (Vrettos et al., 2019). However, over the last decade, the exponential increase in PV systems worldwide and studies on the characteristics of this energy source have significantly boosted the development of new and accurate forecasting models. Prediction models typically depend on reviewing statistical data of production over time and long-term meteorological records, providing essential information for determining the expected behaviour of production systems through a variety of methods (Badwawi et al., 2015). There is substantial interest in predicting energy production in multi-source systems that evaluate the current power output of each component (Badwawi et al., 2015; Vrettos et al., 2019). These predictions, enabled by adequate modelling and analytical processes, allow for determining the amount of energy generated based on the system's climatic and operational conditions (Mellit and Pavan, 2010). Various methodologies for prediction in PV energy systems have been defined in the literature. In some studies, the energy generated by PV systems has been predicted using neural network methods (Bou-Rabee et al., 2017; Kumar and Saravanan, 2017; Abdel-Nasser and Mahmoud, 2019). This type of analysis has also been applied to predict the temperature of PV modules (Kim et al., 2017a). Solar radiation predictions have been determined using statistical tests for percentage errors, mean absolute bias, and squared errors. Today, thanks to the advancements provided by different models used for prediction, various classifications can be made depending on the criteria considered (McCulloch and Pitts, 1943; Hornik et al., 1989). Some criteria consider the linearity of the model, classifying them as linear and nonlinear. Others take into account the method used for the mathematical development of the model, categorizing them as models based on artificial intelligence techniques or regressive models (Mellit and Pavan, 2010). Figure 4 illustrates the classification of PV panel power output prediction models and techniques (Gutiérrez et al., 2021). The choice of prediction method primarily depends on the intended prediction horizon, which represents the time interval between the published forecast and the most recent observation (Voyant et al., 2017a). For intra-hour delivery times, statistical methods based on ground measurement time series provide excellent forecasts by projecting current conditions into the near future, as local weather patterns exhibit minimal changes over this time scale (Diagne et al., 2013). Regarding forecasts ranging from 6 hours to a few days, physical methods, such as numerical weather predictions, yield better results than statistical methods by indirectly understanding the local cloud probability through the dynamic modelling of the atmosphere and the transmittance of solar radiation (Voyant et al., 2012; Diagne et al., 2013). Intra-day solar radiation forecasts (1 to 6 hours) can be addressed using statistical and physical methods or their combinations. Statistical methods derive temporal evolution models from past time series and project the model into the time to be predicted (McCulloch and Pitts, 1943; Hornik et al., 1989; Voyant et al., 2012, 2017; Diagne et al., 2013; Kumar and Saravanan, 2017; Mirzapour et al., 2019; Abdel-Nasser and Mahmoud, 2019). These methods offer the advantage of simplicity but lack generalization. Physical methods have better generalization capabilities; however, their application is hindered by complexity and computational costs. Recently, with the rapid advancement of artificial neural network (ANN) models and the growing interest in their reliability, these techniques have also become widely used in PV power forecasting. An artificial neural network emulates the learning system of the human brain and can establish input-output relationships for both linear and nonlinear systems with less computational effort (McCulloch and Pitts, 1943; Hornik et al., 1989). Consequently, the extensive use of artificial neural networks for predicting various criteria such as irradiance and temperature in PV systems can yield reliable results (Mellit and Pavan, 2010b; Wang et al., 2011). If we are to explain the primary reasons why ANN models are increasingly preferred for PV power output forecasting today, it lies in the unique characteristics of neural networks. ANNs are composed of multiple simultaneously operating cells, allowing them to manage complex functions through these interconnected units. The information acquired is stored across the network in a distributed manner, ensuring that the failure of some cells does not result in the loss of information. They can function with incomplete data and handle previously unseen examples. Additionally, they excel at pattern association, completion, and classification. ANNs possess self-learning capabilities and error tolerance, meaning they can continue functioning even if some of their cells fail. Any issue arising in the network results in gradual and relative degradation over time. In summary, the advantages of artificial intelligence techniques in forecasting the power output of PV solar panels include their ability to define nonlinear relationships through robust data analytics and complexity management, enabling more precise predictions. These techniques can work with adaptive and continuously updated models due to their learning capabilities, provide fast processing and real-time forecasting, offer scalability and a broad range of applications, reduce human errors, and enable comprehensive analyses that account for environmental factors. With the development of new models based on artificial intelligence techniques and the growing number of PV plants worldwide, PV plant modelling, reliable energy power output forecasting, and efficiency have become active areas of research in recent years (Mellit and Kalogirou, 2008). Although numerous studies in the literature focus on predicting parameters such as temperature and solar radiation using ANN models, long-term comprehensive research on solar panel power forecasting is relatively scarce. However, accurate long-term PV power output forecasting plays a pivotal role in informed decision-making, efficient energy planning, grid stability, financial sustainability, and transitioning toward a sustainable and renewable energy future. To achieve long-term power output predictions for a solar panel, certain detailed data are required. However, such data are sometimes unavailable due to the lack of relevant databases (Mellit and Kalogirou, 2008; Khatib et al., 2012). Therefore, prediction techniques must also be applied to sizing and meteorological data inputs to improve efficiency and plan operations effectively (Hocaoğlu et al., 2008; Chen et al., 2011; Linares-Rodríguez et al., 2011).

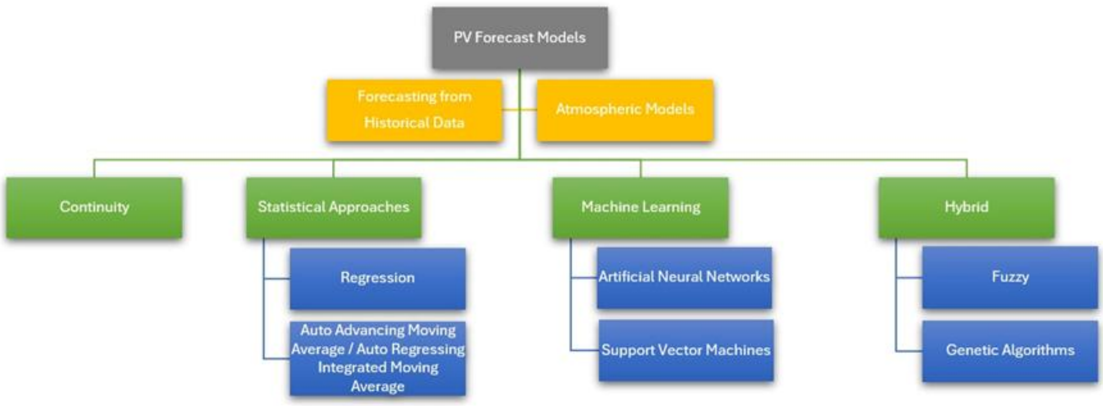


Figure 4. Classification of photovoltaic panel power output forecasting models

Various studies have been proposed in the literature to predict PV panel power outputs using ANN techniques. The relevant literature and the methodologies employed in these studies can be briefly summarized comparatively as follows: Lorenz et al. (2009) and Kudo et al. (2009) presented very short-term forecasts of solar irradiance predictions for a temporal range of up to a few hours. These forecasts were derived using multiple linear regression methods and ANN models, based on weather data to reveal PV panel power output characteristics (Kudo et al., 2009; Lorenz et al., 2009). Shi et al. (2012) conducted studies aimed at predicting next-day PV panel power outputs using support vector machines, a machine learning technique. However, classical SVM algorithms are better suited for binary classification problems, whereas PV power prediction is typically a multi-classification problem. Wang et al. (2011) demonstrated in their study that the most suitable method for predicting PV power outputs is ANN. They used an ANN trained with multivariate time series data of output power, average air temperature, and clear sky indices. The main drawback of predefined weather models is their reduced flexibility in dealing with changes in unpredictable weather conditions throughout the day. Furthermore, predictions based on air temperature are insufficient, as power generation is more closely related to the temperature of the PV module. Approximate equations exist for calculating PV module temperature from solar irradiance and air temperature, but these are typically adopted only for quantitative analyses during PV module performance evaluations (Wang et al., 2011). Kou et al. (2013) used an ANN structure trained with the backpropagation (BP) method, along with meteorological data, to predict daily solar panel output power. They argued that PV power prediction is a typical multi-classification problem and concluded that ANN, particularly BP neural networks, is the most promising method for PV forecasting due to its advantages in simulating complex nonlinear systems, strong learning ability, good approximation performance, and error tolerance. However, BP networks have inherent drawbacks such as slow convergence, susceptibility to local minima, and difficulty in achieving a global optimal solution. To improve convergence, enhancements to the BP network have been made. Zhang et al. (2013) integrated the PSO evolutionary algorithm into a hybrid method for training ANN, using irradiance values as inputs to derive solar radiation predictions. Qasrawi et al. (2015) designed an ANN trained with BP (Levenberg-Marquardt) using data from solar panels installed in different regions and satellite-derived measurements, presenting monthly forecasts. Inputs such as humidity, solar irradiance, daylight duration, and clear sky conditions were included in the system. Zhu et al. (2015) applied wavelet transform to reduce data and subsequently used a hybrid method to train ANN. After applying wavelet decomposition to restructure the data, they predicted solar panel output power for ultra-short time intervals with fewer mathematical operations compared to existing ANN studies (Zhu et al., 2015). Prokop et al. (2012) proposed a study for short- and medium-term PV plant output predictions using ANFIS and multi-layer perceptron (MLP) methods, achieving consistent results with an average accuracy of 2%. They reported that ANFIS provided more precise results compared to MLP. Paulin and Praynlin conducted a comparative study training BP-based ANN with inputs including average ambient temperature, panel temperature, inverter temperature, solar irradiance, wind speed, and power output (Paulin and Praynlin, 2016). Rana et al. (2015) compared the results of iterative and non-iterative methods using different ANN architectures, demonstrating that iterative methods yielded closer results for short-term power output forecasting. Kim et al. (2017) proposed a daily forecasting model based on weather predictions for PV system outputs, integrating it with a commercial PV monitoring system in Korea, and found it to outperform existing forecasting models. Cai et al. (2010) proposed a NARX network-based forecasting model for hourly PV system power output without relying on complex meteorological instrumentation. Yang et al. (2014) developed a forecasting model for energy production in PV systems using temperature and precipitation probability data from the day before, demonstrating good performance on sunny days. Su et al. (2012) developed new real-time forecasting models for PV system power output and energy efficiency, validating them with measured data from grid-connected PV systems in Macau. As listed above, studies in the literature predominantly focus on short- and medium-term solar panel output forecasting. However, very few studies have investigated the long-term data-driven forecasting of solar panel power output efficiency.

In this present study, Long Short-Term Memory (LSTM) network models were developed to predict the energy production of solar panels, utilizing daily data collected over a one-year period (January 2023 – December 2023). The data were gathered from the location where the solar panels were installed and began generating energy. The collected dataset includes one year of solar panel electricity production, daily measurement data, the measurement month, total operational hours, daily average temperature, and weather conditions. Using this dataset, the temporal modelling capabilities and forecasting performance of the LSTM models were analysed. In our study, we utilized single-layer, three-layer, and four-layer LSTM models to predict the power output of solar panels. Additionally, we experimented with ReLU and Leaky ReLU activation functions across all model configurations. To evaluate performance, we employed several metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error (SMAPE).

2. Materials and Methods

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) model. RNN is a class of artificial neural networks (ANN). ANN techniques offer various advantages over the techniques. However, RNN has a distinctive feature it can retain information. This allows it to learn short-term dependencies; however, as data grows, RNN may not be able to mitigate this issue. To address this problem and establish a long-term learning dependency, LSTM is used. Unlike the conventional neurons used in RNN, the primary advantage of utilizing an LSTM unit is that the cell state accumulates activities over time. Since derivatives are distributed over sums and their derivatives are propagated backward in time, errors do not vanish rapidly. This enables LSTM to perform tasks over long sequences and explore long-range features. One of the major challenges encountered when using a PV source is overcoming the nonlinear output characteristics. LSTM-based models are effective in understanding the nonlinear relationship between the input and output parameters of a given dataset. Therefore, LSTM models have been used for long-term analysis of the effects of meteorological parameters on PV panel output. Figure 5 illustrates the diagram of an LSTM cell. Various memory blocks or cells represented as blocks are used for memorizing information and can be utilized through three main mechanisms known as gates. A typical LSTM cell network consists of three gates: input, output, and forget gates. These gates are used not only to control and preserve the cell states transferred to the next cell but also to manage the hidden state and cell state. The role and mathematical representation of each LSTM gate are as follows:

Input gate: Determines the extent of information to be written into the internal cell state;

$$i_t = \sigma\ (w_i[h_{t-1}, x_t] + b_i)$$

Forget gate: Determines the extent to which previous data will be forgotten;

$$f_t = \sigma\ (w_f[h_{t-1}, x_t] + b_f)$$

Output gate: Determines which output will be generated from the current internal cell state;

$$o_t = \sigma\ (w_o[h_{t-1}, x_t] + b_o)$$

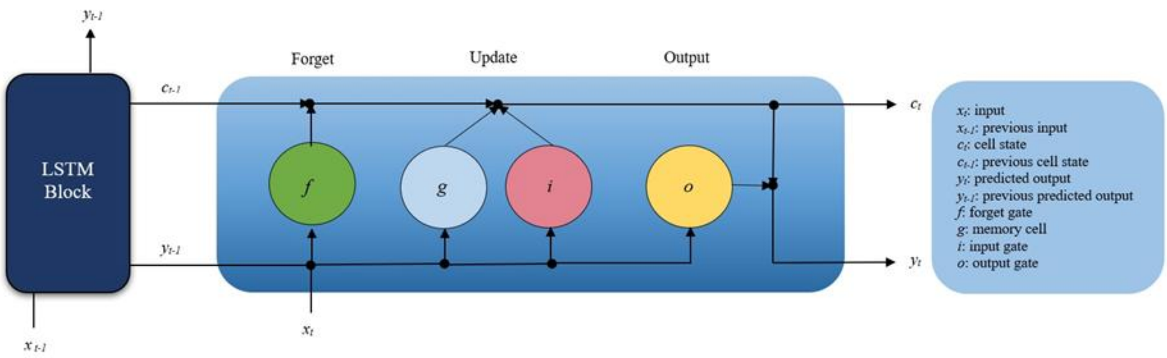


Figure 5. The diagram of an LSTM cell

While traditional techniques often rely on external data that is still inaccessible, uneconomical, or unreliable most of the time, LSTM can work quite well with intrinsic data. This quality of LSTM networks/models makes them stand out and the first choice for PV power predictions. MAE (Mean Absolute Error) will be used as a loss recovery method to account for the weights of the LSTM network and determined as

$$\text{MAE} = \sum\nolimits_{i=1}^{n} \frac{|\hat{y}_i - y_i|}{n} \quad .$$

Here, $\hat{y}_i$ represents the predicted value, y_i represents the actual value, and n defines the number of days for which the prediction is made. Mean Squared Error **(**MSE**)** is a fundamental error metric used to evaluate the performance of predictive models, particularly in regression and time-series forecasting. It quantifies the average squared difference between predicted values and actual observations, providing a measure of the model's accuracy. Mathematically, it is expressed as:

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

Additionally, by placing the validation data argument into the model, both training and testing losses were tracked throughout the training process. RMSE (Root Mean Square Error) is defined as follows:

$$\text{RMSE} = \sqrt{\sum\nolimits_{i=1}^{n} \frac{|\hat{y}_i - y_i|}{n}} \ .$$

The mean absolute percentage error (MAPE) is a commonly used metric for assessing prediction accuracy in terms of scale independence and interpretability. The MAPE and error variance may be computed as follows:

$$\text{MAPE} = \frac{1}{n}\sum\nolimits_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \text{x}100\% \ .$$

The Symmetric Mean Absolute Percentage Error (SMAPE) is a commonly utilized metric for assessing the accuracy of forecasting models, especially in time-series analysis. It is an improvement over traditional MAPE, addressing its asymmetry and sensitivity to scale variations. SMAPE is defined as:

$$\text{SMAPE} = \frac{100\%}{N}\sum_{i=1}^{N}\frac{|\hat{y}_i - y_i|}{(|y_i||\hat{y}_i|)/2}$$

where $\hat{y}_i$ represents the forecasted values, y_i denotes the actual values, and NNN is the number of observations. Unlike MAPE, SMAPE normalizes the error by the average of actual and predicted values, ensuring that it remains bounded between 0% and 200%, thereby reducing bias when dealing with small or zero values. Owing to its symmetric characteristics, SMAPE is especially appropriate for assessing renewable energy forecasting models, including solar photovoltaic (PV) power predictions, where data variations can be considerable.

The use of optimizers in prediction tasks with artificial intelligence methods provides several advantages, including improved model performance, faster and more efficient training, better generalization, the ability to work with less data, easier parameter tuning, and quicker training processes. However, selecting the correct optimizer and making appropriate parameter adjustments are crucial, as each problem is unique, and a chosen optimizer may not always deliver the best performance in every case. In our study, the LSTM model will be used in conjunction with the Nadam optimizer. Nadam optimization is a specialized algorithm designed for deep neural networks, offering unique features and advantages compared to other popular optimization algorithms. Nadam utilizes the Nesterov momentum method, which corrects momentum using a pre-computed gradient estimate, enabling faster and more stable updates than other optimizers. Nadam has an adaptive learning rate, which dynamically adjusts the learning rate based on the weights of each parameter. This allows different parameters to be updated at varying speeds during the training process, resulting in more effective learning. Momentum aims to accelerate updates by using a weighted sum of past gradients. Nadam leverages this momentum to estimate gradients more accurately, enabling faster and smoother convergence. Nadam performs particularly well on surfaces with narrow valleys by utilizing a gradient-based movement, making it more effective in advancing through non-convex optimization problems. Its structure resembles that of basic optimization algorithms like Stochastic Gradient Descent (SGD), making it easy to integrate with existing infrastructures. In addition to these superior features, Nadam combines the benefits of momentum and Nesterov momentum while simultaneously offering an adaptive learning rate, leading to more efficient training. This combination is particularly advantageous for non-convex optimization problems, as it reduces RMSE error and results in better overall performance.

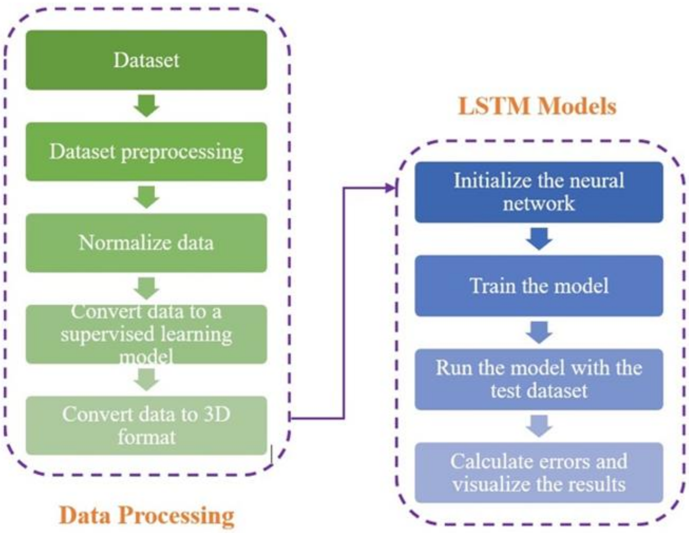


Figure 6. The flow diagram of the training model we proposed in our present study

The flow diagram of the training model we proposed in our study is presented in Figure 6. The flowchart outlines a structured process for time-series forecasting using Long Short-Term Memory (LSTM) networks. Initially, raw data undergoes preprocessing, including handling missing values, normalization, and conversion into a supervised learning format before being reshaped into a three-dimensional structure suitable for LSTM models. The training phase begins with initializing the neural network, followed by model training using the processed dataset. Once trained, the model is tested on an independent dataset, and its performance is evaluated through error calculations and visualized results. This systematic approach ensures the model effectively captures temporal dependencies, enhancing predictive accuracy.

Figure 7. The solar panel application we proposed in our present study. (a) A top-down and street view of the location where the solar panel installation was carried out. (b) An image of the residence where the solar panel installation was performed and a view of the rooftop installation.

The solar panel application we are focused on consists of 8 half-cut panels with a capacity of 470 W each (Topcon Monocrystalline model TT470 120TN10), placed as shown in Figure 7. Its location is specified as 38°34'38.5"N 43°16'13.8"E in Van, Türkiye. The data were measured between 1st of January 2023 and 31st of December 2023. The parameters monitored include daily total electricity production (kW), full-capacity operating hours, daily average temperature, and daily weather conditions (sunny, cloudy, heavy rain, and snowy).

3. Results

In our study, we employed single-layer, three-layer, and four-layer LSTM models to predict the power output of solar panels. Furthermore, we conducted experiments using ReLU and Leaky ReLU activation functions across all models. This enabled us to explore how varying the number of LSTM layers and types of activation functions influence the training of the model. Figure 8 illustrates the impact of ReLU and Leaky ReLU activation functions on error metrics for single-layer LSTM models. To assess performance, the metrics employed include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Our analysis revealed a consistent decline in error metrics during the training phase for both models. In the model utilising the ReLU activation function, it was noted that error rates were elevated, especially in the initial 50 epochs, but showed a consistent decline in the subsequent training phases. Conversely, in the model utilising the Leaky ReLU activation function, the error values were consistently lower from the outset and exhibited a more stable trend. Upon a detailed examination of the MAPE and RMSE metrics, it becomes clear that the model employing Leaky ReLU demonstrates reduced error values. A notable drawback of the ReLU function is the dead neurone issue, which may diminish the model's responsiveness to specific input values. Due to the fact that ReLU assigns a zero derivative for negative inputs, it can hinder weight adjustments, consequently impeding the learning rate. In contrast, the Leaky ReLU activation function features a minor yet consistent slope for negative inputs, addressing the dead neurone issue and facilitating improved generalisation within the model. It can be concluded that Leaky ReLU demonstrates enhanced stability and reduced error rates in comparison to ReLU. This benefit arises from Leaky ReLU's capacity to handle negative inputs and its enhanced weight adjustment efficiency. Consequently, in time-series analyses like long-term photovoltaic power forecasting, selecting the Leaky ReLU function can improve prediction accuracy by promoting a more balanced and generalised learning process.

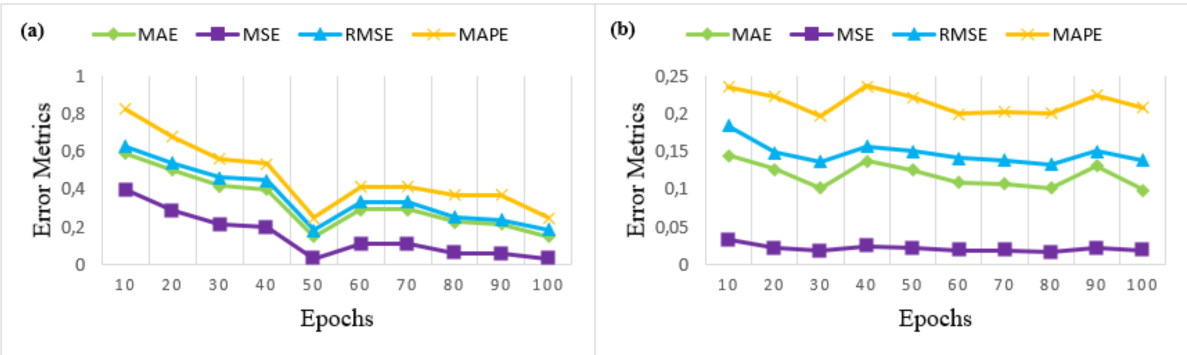


Figure 8. The effects of (a) ReLU and (b) Leaky ReLU activation functions on error metrics for single-layer LSTM models

Figure 9 compares the impact of ReLU and Leaky ReLU activation functions on error metrics in three-layer LSTM models. Upon a detailed examination of the MAPE and RMSE metrics, it becomes evident that Leaky ReLU results in reduced error values. This enhances the model's ability to generalise and aids in avoiding overfitting. Reduced MSE values signify that the model's predictions are more accurate and exhibit lower error rates. In summary, this analysis shows that in three-layer LSTM models, the Leaky ReLU activation function results in reduced error rates and a more consistent learning process when compared to ReLU. This can be attributed to the capability of Leaky ReLU to handle negative inputs effectively and its enhanced weight update mechanism. In scenarios where maintaining data continuity is essential, like in time-series forecasting, selecting the Leaky ReLU activation function can improve model accuracy, resulting in more dependable predictions.

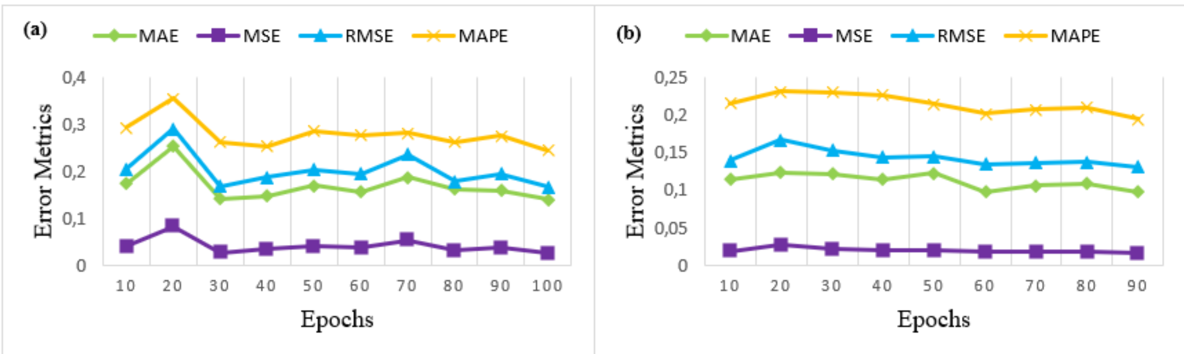


Figure 9. The effects of (a) ReLU and (b) Leaky ReLU activation functions on error metrics for three-layer LSTM models

Figure 10 represents the effects of ReLU and Leaky ReLU activation functions on error metrics for four-layer LSTM models. The examination of the graphs reveals that although both models show a trend of decreasing error during training, the one employing Leaky ReLU presents lower and more consistent error metrics. In summary, the model employing Leaky ReLU demonstrates reduced MAE, MSE, and RMSE values when contrasted with the model that utilises ReLU, resulting in a significant decrease in error rates. In deep architectures featuring four layers, the continuous gradient flow enabled by Leaky ReLU enhances weight updates, leading to improved generalisation of the model.

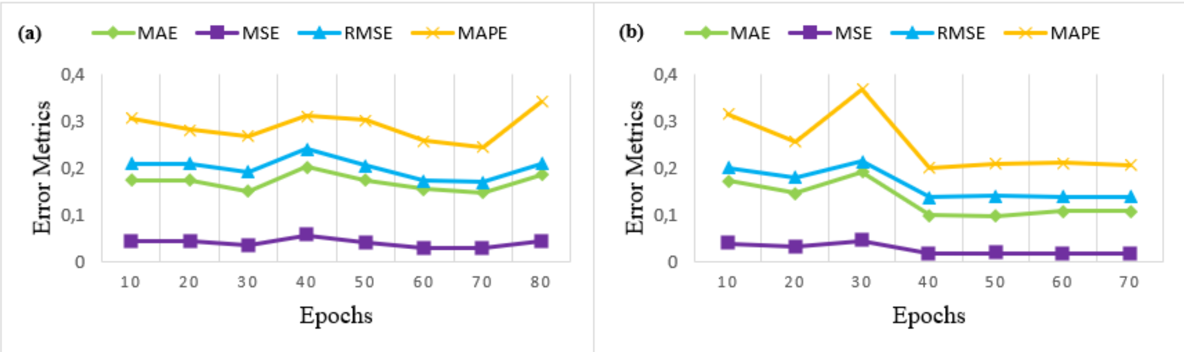


Figure 10. The effects of (a) ReLU and (b) Leaky ReLU activation functions on error metrics for four-layer LSTM models

As shown in Figure 11, we utilised the Symmetric Mean Absolute Percentage Error (SMAPE) metric to assess the forecasting performance of single-layer, three-layer, and four-layer LSTM models. The model architectures utilised both ReLU and Leaky ReLU activation functions to analyse the variations in error rates across the epochs. The graph shows that the single-layer ReLU-based LSTM model starts with the highest SMAPE values, which decline as the epochs advance. Nonetheless, the error rate is still considerably elevated when juxtaposed with more complex models. This can be linked to the limited learning ability of the single-layer LSTM. To effectively capture long-term dependencies in time series data, it is typically necessary to employ deeper architectures for LSTMs. The restricted capabilities of the single-layer model result in notably elevated prediction errors during the initial epochs. In the analysis of three-layer versus four-layer LSTM models, notable fluctuations in error levels are evident in the three-layer configurations, especially in the ReLU-based variant, across the epochs. These fluctuations could suggest a lack of consistency in weight adjustments. In comparison, the error metrics observed in four-layer models exhibit a more consistent trend. This indicates that more complex LSTM architectures improve the model's capacity to grasp long-term relationships in time series data. The finding that four-layer models, particularly those employing Leaky ReLU activation, attain the lowest error rates can be attributed to Leaky ReLU’s capacity to avoid gradient zeroing in negative inputs, facilitating a more balanced learning process. Models utilising Leaky ReLU demonstrated a notably reduced risk of overfitting, with error levels showing a more consistent trajectory. In summary, the four-layer Leaky ReLU-based LSTM model showcases superior performance, achieving the lowest SMAPE values. The advanced architecture allows for a more efficient understanding of long-term dependencies in time series data, while the Leaky ReLU activation function ensures stable weight updates and improves prediction accuracy. The results indicate that for long-term photovoltaic power forecasting and related time-series analyses, utilising deep LSTM architectures with the Leaky ReLU activation function can enhance the model's ability to generalise.

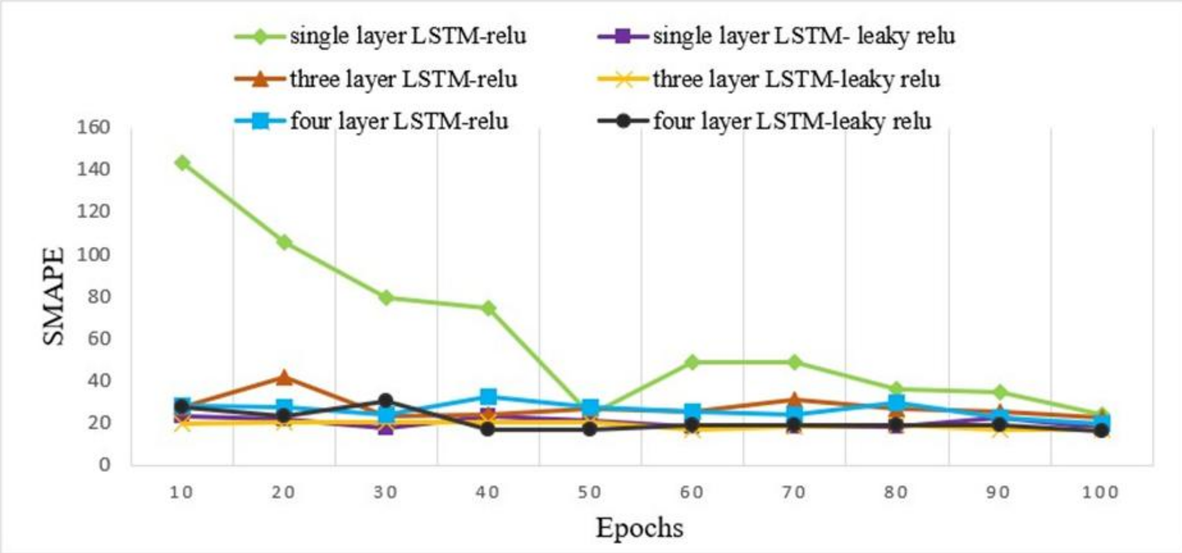


Figure 11. The Symmetric Mean Absolute Percentage Error (SMAPE) metric to assess the forecasting performance of single-layer, three-layer, and four-layer LSTM models

4. Conclusions

The rising global appetite for energy, fuelled by swift population expansion and unsustainable consumption habits, highlights the critical importance of precise predictions regarding future energy requirements. Among renewable energy sources, solar energy stands out as a highly promising option because of its abundance, sustainability, and seamless integration into contemporary power grids. For optimal grid functionality, energy management, and strategic economic planning, dependable long-term predictions of solar photovoltaic (PV) power generation are essential. Conventional forecasting techniques, such as statistical methods and those leveraging artificial intelligence, frequently fail to deliver the necessary accuracy and reliability for long-term predictions, especially in extensive photovoltaic systems connected to power grids. Our research tackles these challenges by introducing a sophisticated deep learning model that leverages Long Short-Term Memory (LSTM) networks, enhanced through the application of the Nadam algorithm. This research delivers an in-depth analysis of model performance in long-term PV power forecasting by integrating single-layer, three-layer, and four-layer LSTM architectures, while also assessing the effects of ReLU and Leaky ReLU activation functions. The results demonstrate that selecting the appropriate activation function has a substantial impact on the precision and reliability of predictions. Specifically, Leaky ReLU demonstrates superior performance compared to ReLU by addressing the dead neurone problem and facilitating better weight updates, which results in enhanced generalisation for time-series forecasting tasks. Moreover, our findings suggest that more complex LSTM architectures, especially the four-layer configuration, demonstrate enhanced effectiveness in capturing long-term dependencies in photovoltaic power data. Implementing Leaky ReLU in more complex architectures promotes consistent learning, minimising prediction inaccuracies across a range of assessment metrics, such as MAE, MSE, RMSE, and SMAPE. The results underscore the significance of fine-tuning model depth and activation functions in the development of LSTM-based forecasting models tailored for renewable energy applications. In summary, this research presents a strong and effective method for long-term photovoltaic power forecasting, showing that utilising deep LSTM architectures alongside the Nadam optimiser and Leaky ReLU activation can greatly improve predictive accuracy. The findings from this research offer significant benefits for energy planners and grid operators, enabling improved management of extensive PV systems. Future work can delve into further refinements, including hybrid deep learning models and additional optimisation techniques, to improve forecasting performance and facilitate the sustainable integration of solar energy into global power grids.

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