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Machine Learning Techniques for Solar Power Output Predicting

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Abstract- It is a challenge the world has never faced to shift away from energy sources that use fossil fuels and toward ones that are more sustainable and better for the environment. The development of solar photovoltaic (PV) systems is one of the most exciting developments in the field of renewable energy. However, because these devices operate inconsistently and only occasionally, integrating them into the energy grid presents several significant issues. Recent research examined how artificial intelligence (AI) and machine learning (ML) could be used to enhance the management, control, monitoring, maintenance, and performance of renewable energy systems. The aim of this article is to investigate if it is possible to predict the amount of power that photovoltaic (PV) systems will produce using machine learning long short-term memory (LSTM) neural networks and the Nadam optimizer. A particular kind of neural network that has performed well in time series forecasting is the long short-term memory (LSTM) design. The objective of this research is to develop a new method of weather forecasting that, when used over a time horizon of 24 hours, can produce reliable and precise projections of electricity output. The LSTM models are compared to the SARIMA and ARIMA time series models in the article. In comparison with modern approaches, the Nadam optimizer-based LSTM model provides predictions that are more accurate. In an attempt to enhance accuracy and dependability, the article also looks at how climate impacts predict solar energy. The Nadam optimizer and LSTM are combined in this work to anticipate solar power. The article's conclusions will assist in solar power system optimization, operation, and design, which will increase dependability and profitability.

Keywords: Solar photovoltaic, Long Short-Term Memory (LSTM), Nadam optimizer, time series forecasting.

1. Introduction

Solar PV systems are a reliable and sustainable energy source that can help us become less reliant on fossil fuels [1]. For the effective management and use of renewable energy resources, accurate solar PV power production forecasting is essential. Solar photovoltaic (SPV) power forecasting is crucial to the efficient integration and operation of SPV plants, particularly in the context of contemporary plants with greater capacity and their integration into the grid. When it comes to more recent plants, this is especially accurate. The majority of the research in SPV power forecasting, however, has focused on techniques with a short time horizon. These techniques fall short of what the contemporary SPV plants demand. As a result, there is an urgent need to shift the emphasis towards approaches that offer a power prediction for SPV systems over a long horizon. Additionally, the vast majority of research in this field has mostly concentrated on SPV plants with constrained capacity, neglecting to take into consideration the particular challenges provided by plants with greater capacities. The inadequacy of current methodologies for managing the complexity of higher-capacity SPV systems may be shown by the significant increase in the root mean square error (RMSE) that results from applying existing forecasting techniques to larger plants. Root mean square error is referred to as RMSE. Additionally, the short duration of meteorological and electricity data records as well as the potential for mistakes in these records create a challenge to their use in forecasting. It is hard to completely capture the range of meteorological conditions and variations in power production during the little time that data collection occurs. This has a detrimental effect on the precision and dependability of forecasting models.

Recent research examined how artificial intelligence (AI) and machine learning (ML) may be used to enhance the management, control, monitoring, maintenance, and performance of renewable energy systems [2]. The purpose of this article was to provide answers to the raised queries. The ability of ML to forecast the amount of power that PV systems will produce is crucial for integrating them into the energy grid [3]. It's crucial to create accurate projections in this field. Grid operators can increase dependability, reduce costs, and maximize the use of renewable energy with the aid of accurate forecasts [4].

Solar energy may easily be incorporated into existing power infrastructures and is a clean, economically viable, and healthy source of energy. It is a challenge the world has never faced to shift away from energy sources that use fossil fuels and toward ones that are more sustainable and better for the environment. The urgent need to mitigate the consequences of climate change and ensure that future generations will have a sustainable future is what is driving this transition. This transformation is being driven, namely, by how rapidly things must change. The development of solar photovoltaic (PV) systems is one of the most exciting developments in the field of renewable energy. However, because these devices operate inconsistently and only sometimes, integrating them into the energy grid presents a number of significant issues.

Integrating solar PV systems into the power grid presents significant challenges due to their variable and intermittent nature. Accurate solar power forecasting is crucial for maintaining grid stability and efficient energy management. Traditional forecasting methods, such as hybrid approaches, artificial neural networks (ANN), numerical weather prediction (NWP), and autoregressive integrated moving average (ARIMA), have predominantly focused on short-term predictions. While these methods suffice for smaller, standalone PV systems, they are inadequate for modern, larger-capacity, grid-integrated PV systems, which require more sophisticated, long-term forecasting techniques. Long short-term memory (LSTM) neural networks, a type of machine learning model, offer a promising solution for these challenges. LSTM networks excel in time series forecasting by effectively capturing temporal dependencies. By utilizing historical power production data, meteorological sequences, and advanced weather forecasts, LSTM models can provide more accurate and reliable long-term predictions of PV power output [5]. This capability is essential for enhancing grid reliability, optimizing energy management, and maximizing the utilization of renewable energy sources [6]. As we move away from fossil fuels and toward sustainable energy, developing precise and dependable solar PV forecasting systems becomes increasingly important. These systems facilitate better integration of solar energy into existing power infrastructures, thereby contributing to the mitigation of climate change and the creation of a sustainable future for generations to come [2]. Thus, shifting the focus from short-term to long-term forecasting approaches is imperative to address the unique challenges posed by high-capacity PV plants and ensure the continued growth and efficiency of renewable energy systems [3].

The purpose of this article is to investigate if it is possible to estimate the amount of electricity that photovoltaic (PV) systems will produce using machine learning long short-term memory (LSTM) neural networks. A particular kind of neural network that has performed well in time series forecasting is the long short-term memory (LSTM) architecture [5]. The objective of this research is to develop a new method of weather forecasting that, when used over a time horizon of 24 hours [6], can produce accurate and dependable projections of electricity output [7]. The suggested method's effectiveness will be evaluated using historical measurements of power production and sequences of meteorological data taken prior to the prediction horizon as input data. A separate set of information from an oracle weather forecaster will also be considered in addition to this. The purpose of this article is to evaluate the effectiveness of an LSTM model that has been trained on various types of input data to determine the best method for predicting the power output of PV systems. We'll look at the various data input types. The ultimate objective of this article is to contribute to the creation of solar PV power forecasting systems that are more precise and trustworthy. These ways of doing things can help make it easier to add green energy to the power grid.

To ensure smooth grid operations, effective energy management, and economical scheduling, an accurate solar photovoltaic (PV) power projection system is essential. Current popular prediction methods such as hybrid techniques, artificial neural networks (ANN), numerical weather prediction (NWP), and autoregressive integrated moving average (ARIMA) have shown limited success, being more suitable for short-term forecasts typically needed by smaller, standalone PV systems. However, with the increasing complexity of modern, grid-integrated PV systems, there is a pressing need for more reliable and enhanced long-term forecasting techniques. a detailed literature review reveals that many existing methods still rely on outdated solar photovoltaic (SPV) power projection techniques, neglecting crucial meteorological factors that significantly impact prediction accuracy. This oversight leads to suboptimal monitoring, maintenance, and control of power from renewable sources. Various studies employing techniques like NN [9], ARIMA/SARIMA [10], NWP [11], LSTM [12], and hybrid models [13] have assessed the accuracy of long-term solar power forecasts. Specific advancements include short-term forecasting methods [14], machine learning applications for solar generation prediction [15], and hybrid models that merge different approaches to improve accuracy [16]. Additionally, research has delved into optimizing solar energy systems and analyzing their cost-benefits [17], as well as using artificial neural networks to predict energy parameters [18]. These studies highlight the continuous efforts to enhance solar power forecasting to fulfill the requirements of advanced, grid-connected PV systems.

The structure of this study comprises several key sections: an introduction to the importance of accurate forecasting, a review of photovoltaic (PV) technology, a classification of existing forecasting methods, the proposed LSTM model, results and discussion, and a conclusion summarizing the research findings and their implications section titles are italic.

2. Photovoltaic Solar Power

A photovoltaic (PV) system is a combination of solar modules, each of which contains solar cell units capable of transforming the energy present in solar radiation into usable power. These systems are differentiated by their absence of greenhouse gas emissions and pollution as compared to the non-renewable energy sources that have historically been used on a regular basis, earning them the reputation of being ecologically advantageous. [19]. However, several factors can decrease the efficiency of photovoltaic (PV) systems that are connected to the grid. The condition of the surface, the quantity of solar irradiance, the degree of radiation intensity, and the amount of cloud cover must all be considered to obtain an accurate estimate of the potential power output of a PV system. Additionally, the temperature of the air around the solar cells has an impact since solar cells lose efficiency as the temperature rises. According to the random nature of several additional meteorological parameters, the power output of a photovoltaic (PV) system is not a simple linear function of the quantity of sun irradiation [20].

If one desires to accurately assess and foresee the performance of PV systems, one must fully comprehend this complexity and take them into account. By taking into consideration the aforementioned factors, researchers may create precise predicting models. These models consider the intricate workings of PV systems, which enhances the reliability and effectiveness of solar energy generation.

Since Edmond Becquerel discovered the photovoltaic phenomenon in around 1839 [21], The amount of people who have an affinity for photovoltaic solar energy has increased. The first solar cell was produced in 1876, but for a sizable period of time, technological developments were restricted to research done outside. Perhaps not until approximately 1960 did this kind of technology start to be produced on an industrial scale [21,22]. Two significant events were pivotal in the process and stimulated the development of solar technology. The first significant achievement was motivated by the need for alternate power sources to bring energy to rural locations. The so-called "space race," which utilized solar technology to power several pieces of equipment that were kept in space, was the second major event [21,22]. The increase in oil prices in the 1970s accelerated the advancement of solar technology. Early in the 2000s, countries began making substantial investments in the production of solar modules, finally taking the lead in this sector in 2009 [21]. According to CRESESB, the solar industry expanded at a rate of 54.2% each year between 2003 and 2014. [21]. In terms of solar power installed capacity, China is at the top in the world, followed by the US and Japan. (Improving Safety and Health in Micro-, Small and Medium-Sized Enterprises: An Overview of Initiatives and Delivery Mechanisms, n.d.). Around the world, 294GW of solar electricity has been built as of 2016. The widespread use of solar energy is still hindered by the cost of solar panels. [21].

Brazil installed solar power systems of 438.3 megawatts (MW) by the year 2017, dispersed throughout 15.7 thousand projects related to these systems [22]. Tax reductions, and support initiatives from public entities like the Brazilian Development Bank, some of the ways the nation aims to further stimulate the spread of solar installations include incentives for micro and distributed mini-generation systems. According to current predictions, solar energy will make up 9% of Brazil's whole national energy supply by the year 2050 [22]. The advancements in system efficiency that have been developed may be responsible for the increase in interest in solar production. Around 5% of solar panels were efficient at the time, and one peak watt of power cost $1.785 to produce. However, the cost of modules is currently $1.20 per peak watt, and their efficiency has increased to roughly 15% [22]. Considering silicon makes up over 95% of all photovoltaic cells produced globally, it is by far the most widely used material in the industry [21,22]. This is due to the fact that it is low-cost, readily available, and has well-established production methods. The three main types of photovoltaic cells that are offered for sale on the market are those made of monocrystalline silicon, polycrystalline silicon, and thin silicon film [21].

To appreciate the operation of a photovoltaic (PV) cell as well as the operation of a PV panel, one must be aware of both solar radiation and irradiance [23]. The phrase "solar radiation" refers to solar energy that is transmitted to Earth as electromagnetic radiation. The Earth can either directly or indirectly absorb this solar energy. According to [23], diffuse radiation is light that indirectly strikes a surface after being refracted and reflected. The term "direct radiation" refers to light that is directed in a straight line of advancement toward a horizontal surface. As shown in Fig.1., a photovoltaic cell's basic components include electrical connections that complete the circuit and let electricity flow as well as two different types of semiconductor materials known as N-type and P-type [23]. A photovoltaic cell generates electricity by following the photovoltaic principle, which specifies that the cell should convert the solar energy it absorbs into electric current.

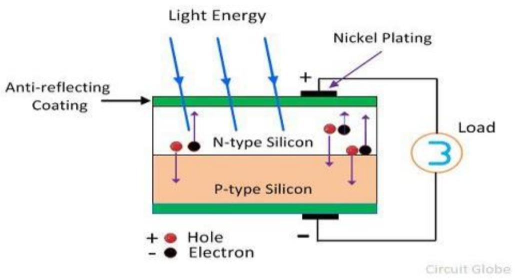

Fig. 1. Photovoltaic cell model.

Crystalline silicon has the capacity to absorb light when it comes in contact with its surface, changing the substance's electrical properties as a result. The electrons in the crystal's valence layer will get excited if there is sufficient energy, allowing them to move freely throughout the structure. Due to the attraction and mobility of valence electrons, which are produced as a result of the excitation of electrons, both electrons and holes can move through the crystal. As the energy of the radiation increases, the electrons and holes in the system become more unstable [23].

Since the potential barrier is in charge of separating free electrons from holes, the solar cell will have an excess of electrons on one side and an excess of holes on the other, necessitating the need for a potential barrier. If the correct circumstances are present, the electric field created by this difference in potential can be exploited to produce current. The potential barrier is created by the interaction of two boron-doped silicon shells, one that is positively doped (P-type) and the other that is negatively doped (N-type). The introduction of atoms with five valence electrons occurs when the material is negatively doped, whereas the introduction of atoms with one fewer electron in their valence shell occurs when the material is positively doped. Most electrons conveyed by the N-type material are followed by most holes carried by the P-type material [23]. Electrons from the N-type material fill the holes in the P-type material when the two types of materials come into contact. As a result, positive charge clusters form on the N side of the junction while negative charge clusters form on the P side [23]. When light strikes a material with an N-type atomic structure, the associated holes and electrons get separated, and the holes move quickly toward the barrier to unite with the negative charges on the P-type side. Similarly, whenever light contacts the P-type material, more electrons are produced in the N-type material. When the electrons leave the N-type material and recombine with the holes on the P-type side of the material, an electric current is created. When the cell is active, this procedure happens. The amount of current generated is proportional to the amount of light energy that is absorbed by the cell as well as the energy of the newly formed electrons [23].

3. Classification of Forecasting Methods

One of the most essential elements of predicting the future is forecasting. It is an efficient statistical approach that may be applied to predict a wide range of features, from short-term projections for the following few minutes to long-term estimations spanning several years. The choice of an appropriate forecasting technique in the context of solar photovoltaic (SPV) power forecasting depends on several factors, including the size of the PV plant, the necessary forecasting horizon, the location, and the presence of other climatic changes. To properly control the risks associated with predicting, it is crucial to choose the forecasting approach that is most suited. An extensive analysis of the different SPV forecasting approaches is given in the following sections. These sections provide information about the many SPV power forecasting approaches that are available. It is possible to examine the advantages and disadvantages of various forecasting approaches, paving the way for the selection of the approach that is most suited for creating precise and reliable SPV power predictions. This in-depth understanding guarantees the effective management of the inherent uncertainties and issues related to SPV power forecasting, which ultimately promotes improved decision-making and optimum performance in the renewable energy sector.

3.1. Horizon Forecasting

One of the most significant factors to take into account while deciding on the best technique for forecasting is the forecasting horizon, which refers to the time frame for which the SPV power output is predicted, as shown in Fig. 2., these forecasting techniques can be broadly categorized as short-, medium-, or long-term methods, each of which is tailored to meet certain deadlines and objectives. The focus of short-term forecasting techniques is on producing predictions for the very near or immediate future, frequently extending from a few minutes to a few hours. With medium-term forecasting, the prediction horizon is expanded to days or weeks and insights into somewhat longer-term trends in power generation are provided. Last but not least, by offering projections for the months, years, or even decades into the future, long-term forecasting methodologies improve strategic planning and policymaking in the SPV sector.

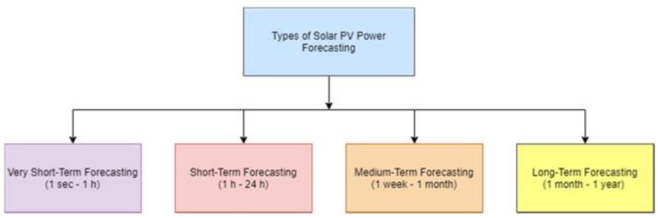

Fig. 2. Photovoltaic cell model.

3.2. Historical Data-based

Fig. 3. illustrates how many various forecasting methods have become available in the field of solar photovoltaic generation based on historical data. To produce reliable forecasting results, it is crucial to choose the right technique while taking the facts at hand and the desired time horizon into account. It is crucial to match the approach's suitability to the specific criteria that are required of it during the prediction process. The required time range, which can be short-, medium-, or long-term, should be considered when selecting a forecasting approach.

By providing a logical overview of the numerous options that are presently available, this thorough classification of forecasting approaches aids in the discipline's advancement. It empowers stakeholders to take informed decisions, which in turn promotes better energy management, more precise forecasting, and the best possible utilization of solar photovoltaic resources.

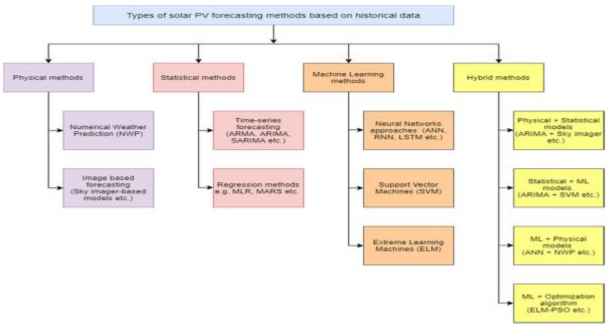

Fig. 3. Solar photovoltaic projections are categorized using past data

4. Methodology

The proposed method presents the new model, which is LSTM combined with the NADAM optimizer. the approach's goal is to provide a thorough understanding of both the models used for time series forecasting and the processes involved in their implementation.

4.1. Proposed Model: LSTM with NADAM Optimizer

4.1.1. Long Short-Term Memory (LSTM)

The Long Short-Term Memory (LSTM) model was applied in this investigation. It serves as an illustration of a recurrent neural network (RNN), which has been demonstrated to be capable of preserving temporal links in time series data. Fig. 4. demonstrates the deep learning tools available in MATLAB that may be used to create and train LSTM networks. The features and classes required to create and train these networks are provided by this toolkit. Memory cells, input gates, output gates, and forget gates are the components of the LSTM design. These gates assist the network in making precise predictions by assisting it in forgetting unimportant information and remembering crucial information. Tools that make designing the LSTM model simple to use may be found inside of MATLAB. These capabilities allow the user to choose the number of hidden layers, the number of LSTM units in each layer, and the activation of the layers.

Fig. 4. Shared circuitry of long- and short-term memory cells

4.1.2. NADAM Optimizer

In this paper, it uses the NADAM optimizer, a variation of the Adam optimizer. A technique called the Adam optimizer employs both momentum algorithms and variable learning rates. When dealing with data that is noisy or includes several curves, the NADAM optimizer employs the Nesterov Accelerated Gradient (NAG) approach to hasten convergence and increase effectiveness. The optimization toolbox in MATLAB, which contains a variety of different optimization techniques that may be used to train neural networks, is utilized to employ the NADAM optimizer. During training, the weights and biases of the LSTM model are modified using the NADAM optimizer. Depending on how steep the loss function's slopes are, these adjustments are done.

Historical data on solar power output and various meteorological factors were meticulously gathered and processed. The data cleaning phase involved handling missing values and scaling the data to a common range, ensuring consistency. Following this, the dataset was divided into training and testing sets. Traditional statistical models such as ARIMA and SARIMA were employed using Python's statsmodels library. Optimal parameters for these models were determined using the auto_arima function, and the models were then fitted to the training data. In parallel, a Long Short-Term Memory (LSTM) network was implemented. This required preprocessing the dataset and formatting it appropriately for LSTM input. The architecture of the LSTM model was defined by specifying the number of hidden layers and LSTM units. The model was trained using the NADAM optimizer, which dynamically adjusts the model's weights based on the gradient of the loss function. To evaluate the performance of the LSTM model, its predictions were compared with actual values from the testing set. Metrics such as root-mean-square error (RMSE) were employed to assess prediction accuracy. Additionally, the training time and the model's ability to handle data variability were analyzed. Different optimizers, including SGD, RMSprop, Adagrad, and Adam, were tested with the same LSTM architecture. These optimizers were evaluated based on loss function values, prediction accuracy, and training duration. The analysis showed that the LSTM model trained with the NADAM optimizer outperformed traditional ARIMA models in terms of accuracy and efficiency. This makes the LSTM-NADAM combination more suitable for forecasting solar power output in large-scale solar plants.

4.1.3. Comparison with Other Optimizers

- In addition to NADAM, MATLAB offers users a number of additional optimization techniques that may all be used to train LSTM models.
- Among the often-used optimizers are the Stochastic Gradient Descent (SGD) method, RMSprop, Adagrad, and

Adam. The rate of convergence and overall performance of the LSTM model can both be influenced by the update rules and adaptive learning rate approaches used by these optimizers.

- The same Long Short-Term Memory (LSTM) architecture and dataset may be used for experiments, allowing for performance comparisons across different optimizers. By analyzing variables like the loss function values, the precision of the predictions, and the training duration, we can gauge how effective each optimizer was in training the LSTM model. The advantages and disadvantages of several optimization strategies are discussed in this article, along with how successfully they may be applied to time series forecasting tasks.

- Based on the characteristics of their dataset and the unique requirements of their problem, academics and practitioners may benefit from this discussion in choosing the optimizer that is most appropriate for their time series forecasting challenge.

- Fig. 5. shows the main flowchart of the recommended method.

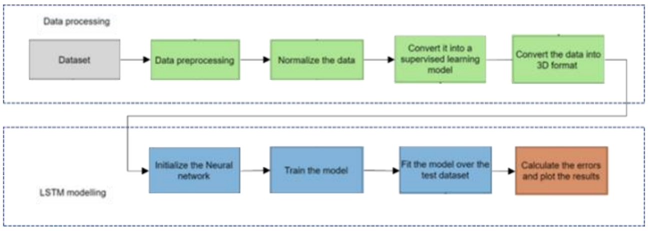

Fig. 5. The suggested model's data flowchart

5. Experimental Design

This section details the methodology employed to evaluate the effectiveness of ARIMA, SARIMA, and LSTM models in forecasting time series data. The experimental design includes several key steps:

1. Dataset Preparation: The data is preprocessed and organized to ensure it is suitable for model training and testing.

2. Implementation of ARIMA and SARIMA Models: These models are configured and applied to the dataset, following standard procedures to ensure accurate results.

3. Implementation of the LSTM Model with NADAM Optimizer: The LSTM model is set up and optimized using the NADAM optimizer, a process meticulously described to facilitate reproducibility.

Each of these steps is comprehensively detailed to provide clarity and enable others to replicate the study. The evaluation metrics used to compare the models' performance include root mean square error (RMSE), accuracy, and computing speed, ensuring a thorough analysis. Furthermore, the study examines the impact of various optimization algorithms on the LSTM model to evaluate improvements in accuracy and convergence. This holistic approach provides a robust comparison of the models' capabilities in time series forecasting.

5.1. Dataset Preparation

For this research, the "Pasion et al. dataset" was used. The first column of this set of data contains information regarding time. The data set is presented as a table, where each column denotes a particular variable or feature and each row denotes a specific time point. The dataset is initially prepared for research and cleaned up before the models are used. This calls for scaling the data, accounting for any missing values, and dividing it into training and testing sets.

5.2. Implementation of ARIMA and SARIMA Models

By employing the appropriate techniques from Python tools like stats models or arima, the "Pasion et al. dataset" is utilized to evaluate the ARIMA and SARIMA models. The parameters (p, d, q, P, D, and Q) are determined using the auto_arima technique before the models are "fitted" to the training set of data. The effectiveness of the models' future predictions is assessed using metrics including root-mean-square error (RMSE), accuracy, and processing speed.

5.3. Implementation of LSTM with NADAM Optimizer

The "Pasion et al. dataset" has to be preprocessed and converted into the proper format for LSTM input before the LSTM model can be utilized with the NADAM optimizer. The training and testing set of the dataset are then separated, and the LSTM network's architecture is described. The model is taught using the training set, and then the NADAM optimizer is used to improve the model. By contrasting the predicted values of the model with the actual values from the testing set, the LSTM model's accuracy is assessed.

6. Results and Discussion

6.1. Results using ARIMA

A variable dataset with 13 months of data was used to train the time-series method ARIMA model. Figure (6) The model had the lowest Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), and it also gave the best results. The RMSE values for the various days included in the dataset are comparable, as shown in Fig. 6.

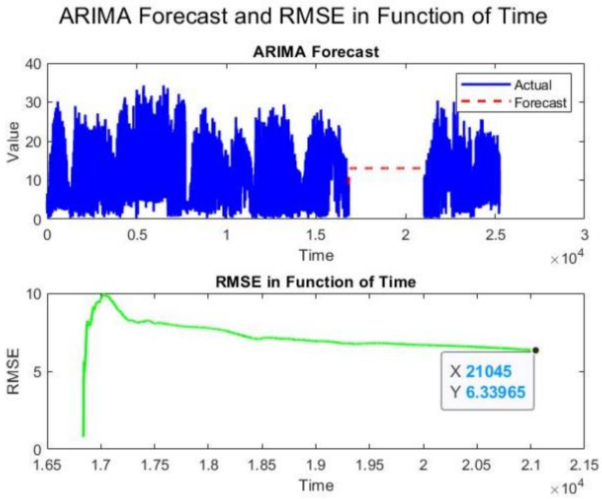

Fig. 6. ARIMA model data set featuring a forecast graph and Root mean squared error values over a range of days

6.2. Results using SARIMA

The time-series approaches used by SARIMA, which is relatively similar to ARIMA, were developed on data that spans thirteen months. Fig. 7. demonstrates that when the model was assessed during a training period, it had the best performance in terms of RMSE and MSE. Figure (7) demonstrates that the RMSE values for the various test dataset days were similar to one another.

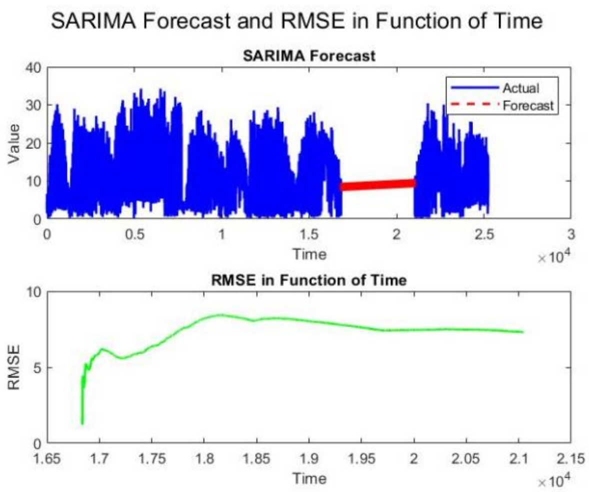

Fig. 7. SARIMA model data set featuring a forecast graph and Root mean squared error values over a range of days

6.3. Results using LSTM with NADAM

The neural network-based LSTM model was implemented successfully utilizing the provided strategy. The NADAM optimizer was used throughout through the training. Lower RMSE and MSE values were produced as a result of the LSTM model and NADAM optimizer combo since the predictions were more accurate. Fig. 8. displays the forecast that was produced using LSTM models, Fig. 9. displays the RMSE values that were computed for each day of the dataset. Each test dataset's RMSE curve remained within the same broad range the whole time.

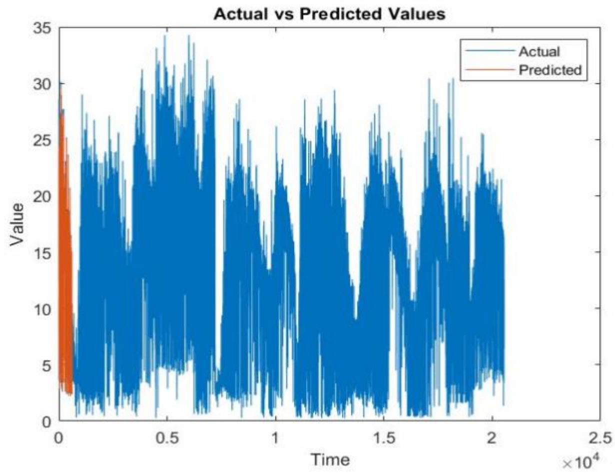

Fig. 8. NADAM LSTM

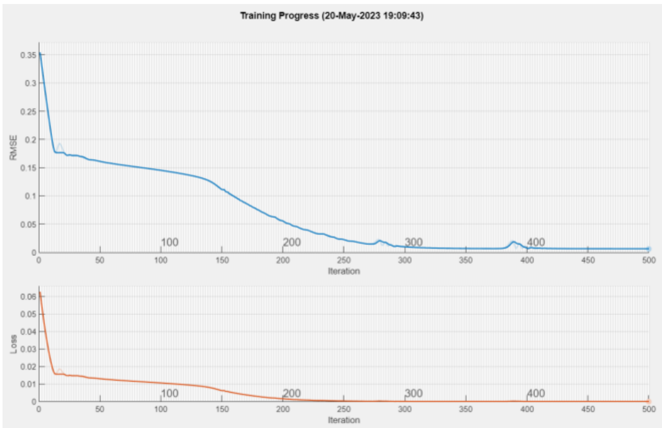

Fig. 9. NADAM LSTM RMSE

7. Comparison and Analysis of Results

To determine how effectively the data from the ARIMA, SARIMA, and LSTM models can forecast time series, they are contrasted and evaluated. The models' accuracy and running costs are calculated using the evaluation metrics, which also include root mean square error (RMSE), accuracy, and computing speed. The advantages and disadvantages of each model are discussed, and it is made clear how well they perform in projecting projects and with various types of time series data.

Table 1. Appearance properties of accepted manuscripts

Method	RMSE	Epoch	Time
NADAM LSTM	0.00756	500	26 second
ADAM LSTM	1.2279	500	72 min

SGD LSTM	0.75	500	70 min
RMSprop LSTM	0.8	500	75 min
ARIMA	6.3396	-	1 min
SARIMA	7.3102	-	1 min

To assess the effectiveness of ARIMA, SARIMA, and LSTM models in time series forecasting, we compare and analyze their performance using key evaluation metrics: root mean square error (RMSE), accuracy, and computing speed. This analysis highlights the strengths and weaknesses of each model across various scenarios. Additionally, we evaluate the impact of different optimization algorithms on the LSTM model, offering insights into their ability to enhance accuracy and convergence.

7.1. Comparison of ARIMA, SARIMA, and LSTM Models

To determine how effectively the data from the ARIMA, SARIMA, and LSTM models can forecast time series, they are contrasted and evaluated. The models' accuracy and running costs are calculated using the evaluation metrics, which also include root mean square error (RMSE), accuracy, and computing speed. The advantages and disadvantages of each model are discussed, and it is made clear how well they perform in projecting projects and with various types of time series data.

7.2. Comparison of Optimization Algorithms

The performance of the LSTM model using the NADAM optimizer is examined and compared to the performance of several optimization methods as shown in table 2, including SGD, Adam, RMSprop, and others. Utilizing the evaluation metrics, it is possible to assess how effective each optimizer is at improving the accuracy and convergence of the LSTM model. The results reveal how various optimization techniques used in time series forecasting impact the LSTM model's performance and provide some new insights.

After examining the output from several models, it is obvious that the optimization carried out using the NADAM optimizer was unquestionably required to get the forecast to the desired level of accuracy. The proposed LSTM model outperformed the ARIMA and SARIMA models as well as models that employed other optimization techniques when applied with the NADAM optimizer. The extensive comparison and analysis demonstrated how well the recommended LSTM model, when coupled with the NADAM optimizer, can forecast time series data.

Table 2. Comparison of Optimization Algorithms

Study	Year	Ref.	Forecasting para.	Forecasting Method	Forecasting Horizon
Sophie et al	2022	[24]	PV Power	LSTM with Nadam optimizer	30-60 days
Rana et al.	2016	[25]	PV Power	APSO-ELM	5-60 min
Abdel-Nasser et al	2019	[26]	PV Power	LSTM	1h
Lee et al.	2018	[27]	PV Power	LSTM - (CNN)	Next day
Jung et al.	2020	[28]	PV Power	LSTM	Monthly
Yongsheng et al.	2020	[29]	PV Power	Extreme Learning Machine -LSTM	1 day
Gao et al.	2019	[30]	PV Power	LSTM	1h
Mei et al.	2020	[31]	PV Power	LSTM-Quantile Regression Averaging (QRA)	Day ahead

8. Conclusion

This research introduces an innovative long-term solar power forecasting method that leverages the Nadam optimizer in conjunction with LSTM neural networks. Our approach surpasses conventional techniques by effectively addressing the specific challenges posed by large-scale SPV plants. By incorporating a range of meteorological variables, we achieve more accurate projections. The enhanced forecasting accuracy profoundly influences the design, operation, and optimization of solar power systems. It facilitates improved grid integration, energy management, and maintenance scheduling. This study provides a scalable solution that can be adapted to different climates and locations, which is vital for the expanding renewable energy industry. In summary, the integration of the Nadam optimizer with LSTM neural networks marks a significant advancement in solar power forecasting. Future research will aim to further refine the model, integrate additional data sources, and investigate applications in other renewable energy systems. This work supports the transition to sustainable energy and efforts to mitigate climate change.

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